Optimizing distribution of droneports for emergency monitoring of flood disasters in China

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Funding information
National Natural Science Foundation of China, Grant/Award Number: 41771388; National Key Research and Development Program of China, Grant/Award Number: 2017YFB0503005; China Postdoctoral Science Foundation, Grant/Award Number: 2018M640170

Abstract
Floods occur frequently, impacting large areas, displacing thousands of people and causing great losses. Unmanned Aerial Vehicle (UAV) remote sensing is easy to obtain high-resolution image that is immensely helpful to timely assess the flood situation and provide scientific decision-making for emergency rescue. The important roles of UAV remote sensing have been widely recognized. However, the sudden onset of floods and lack of UAV resources deployed nearby have restricted rapid response of UAVs in emergency rescue. A UAV remote sensing observation network on a regional scale has been proposed to deal with these emergencies. However, how to build this UAV network and where to deploy UAV resources are still mysterious. In this study, the Maximum Covering Location Problem (MCLP) model was improved to distribute a series number of droneports in China. Finally, 81 droneports were selected from 268 potential facility points, which covered 61.84% risk of total demand area. Droneports have been allocated near flood-prone areas and most floods in China can be monitored within 2 hours, which is critical for saving lives and reducing losses. The construction of UAV airport networks will surely contribute to an integrated disaster emergency observation system combining satellite, airplane, UAV, and ground observations in China.

KEYWORDS
droneports, facility location problem, flood rescue, UAV remote sensing observation network

1 | INTRODUCTION

Flooding is one of the most frequent and devastating natural disasters worldwide (Jongman et al., 2015). They submerge farmland, demolish buildings, and most importantly displace or worse kill thousands of people annually. These risks have significantly affected our assets and physical well-being, as well as regional infrastructure and...
economies (Willner, Levermann, Zhao, & Frieler, 2018). Unfortunately, trends in global flood losses have been increasing over the past decades due to increasing population growth and economic development in flood-prone areas (Bouwer, Crompton, Faust, Hoeppke, & Pielke, 2007). Shifting rainfall patterns and intensities under climate change will further increase flood risk worldwide (Kundzewicz et al., 2014; Milly, Wetherald, Dunne, & Delworth, 2002).

To minimize the impacts of floods, a lot of new technologies have been used (Kabenge, Elaru, Wang, & Li, 2017). In recent years, satellite remote sensing plays an important role in monitoring the flood situation, risk assessment, and loss evaluation (Gao, Shen, Zhou, & Li, 2018; Kaku, Aso, & Takiguchi, 2015). But, it is often very difficult to acquire clear satellite images timely when floods occur, due to the fixed orbit and revisit times of satellites, and generally cloudy conditions (Lu et al., 2017). The unmanned aerial vehicles (UAVs) remote sensing technology developed in recent years has effectively overcome these shortcomings. UAVs can be deployed and flown below the clouds to quickly take images and videos. Furthermore, they are less expensive with lower operational costs, lower risk, and more flexible in hosting different kinds of sensors (Torresan et al., 2017). All these factors make them attractive to disaster management agencies. Hence, UAVs have received great attention over the last few years (Erdelj, Krol, & Natalizio, 2017).

The response time of search and rescue personnel in a disaster is the key factor for saving life. We cannot underestimate the importance of timely access to data, as floods can cause great loss of life and property in a short time, and the survival probabilities of victims will decrease with time (Tang et al., 2018). Unfortunately, in the current most UAVs are of little help when floods occur, unless specialized UAV resources were stationed and deployed nearby. A multi-UAV observation network has been proposed as an efficient and effective way to overcome this deficiency (Liao et al., 2015). That is a promising idea, but research of multi-UAV observation networks stayed in the stage of conceptual. Many questions are not solved, such as how to build this network on a regional or national scale? Where and what kind of drones should be deployed? Droneport was proposed in this study and defined as a site used for landing and taking off UAVs, as well as the necessary infrastructure, such as hangars, airstrips, charging stations, service hall and parking, and so on. A droneport is also a node of UAV observation network, which stores a lot of UAV platforms and related sensors. We would like to determine where and how to select a series of reasonable sites in China to deploy UAV resources, such that they can reach a disaster site within the shortest time when a flood occurs. Improper selection of these locations will seriously decrease the efficiency of UAV services (Rahman & Smith, 2000).

The location of droneport is essentially a facility location problem (FLP). A lot of FLP models have been proposed including set covering problem (Toregas & ReVelle, 1972; Toregas, Swain, ReVelle, & Bergman, 1971), maximum covering location problem (MCLP) (Church & ReVelle, 1974), bi-objective maximal covering location problem (BMCLP) (Grubesic & Murray, 2002), backup coverage model (Hogan & ReVelle, 1986), P-median model (Maranzana, 1963; ReVelle & Swain, 1970), hierarchical facility location problems (HFLPs) (Sahin & Sural, 2007), multilevel facility location problems (MLFLPs) (Ortiz-Astorquiza, Contrerasn, & Laporte, 2018). Each of these models was proposed to solve a practical problem. So every model has its own unique objective functions and constraints. A set covering problem tries to cover all the demand points regardless of resources. An MCLP maximizes the number of covered demand points with limited resources. The backup coverage model tries to cover the same location with more than two facilities. The objective of P-median problems is to minimize the total traveling or waiting time, or costs. An HFLP is used when facilities exist in hierarchical systems, for example, not a single-level facility type. When facilities are partitioned into multiple levels, then MLFLP is used. MLFLP goal is to determine which facilities to open simultaneously at each level, so that customers are assigned to one or multiple sequences of opened facilities, while optimizing an objective function. All in all, FLPs have been widely used in the location selection of hospitals, fire stations, emergency relief and of course the UAVs. Pulver, Wei, and Mann (2016) developed a geographic approach based on an MCLP model to create a network of medical drones, equipped with an automated external defibrillator, designed to minimize travel time to victims of out-of-hospital cardiac arrest. In order to overcome the deficiencies of MCLP, Pulver and Wei (2018) developed a new spatial optimization model, the backup coverage location problem with complementary coverage to aid in the deployment of a network of automated external defibrillator-enabled medical drones. Hong, Kuby, and Murray (2017) present a coverage model that can optimize the location of recharging stations for delivery drones as well as ensure construction of a feasible delivery network that connects the stations and covered demand based on continuous space shortest paths.

In this study, we would like to develop a new geographic approach to the placement of a network of UAV airports, such that UAVs deployed nearby can quickly and timely reach flood areas to facilitate rescues when floods occur. The spatial character of floods, population distribution, and GDP were regarded as the most important
factors affecting the distribution of droneports. Results are presented to demonstrate the capability and efficiency of the new location model. The distribution of droneports is of great significance to flood relief and of great importance to comprehensive and coordinated satellite-airplane-UAV-ground remote sensing observation system.

2 | DATA AND METHODS

Figure 1 presents a flowchart outlining the methodology used in this study. The data mainly include Chinese administrative division data, the field observation stations of Chinese Academy of Sciences, the spatial distribution of flood risk in China, Chinese population, and GDP data and remote sensing UAV database. Multifactors maximum covering location problem (MF-MCLP) model was used to locate these droneports. The data and method will be introduced in detail in Figure 1.

2.1 | The field observation stations of CAS

A droneport is not only a launching and landing site for UAVs, but also includes a lot of supporting infrastructures. It will be a huge cost for a department to build many droneports. Meanwhile, it should be noted that many observation networks have been built in China, such as meteorological, surveying and mapping, ecological, flux stations and so on. CAS has built 268 scientific experimental stations throughout the whole country. Many stations have complete infrastructure facilities, such as convenient transportation and vacant experiment space. Furthermore, many stations have their own UAVs and conducted a lot of researches within their own domain (Bian et al., 2017; Wan et al., 2014). If droneports could be built by multiple parties to make full use of existing stations, great cost will be reduced. The CAS established research center for UAV application and regulation (UAV center in short) in April 2017, whose purpose is to coordinate and manage UAV resources of CAS stations to build a UAV application and control network system by setting a series of rules and building a shared data acquisition and processing platform. The network was expected to provide vital technical support for the application of UAVs in several domains, including land and ocean monitoring, agricultural and forestry protection, environmental protection, and emergency response. In recent years, UAV center has done a lot of work in UAV remote sensing observation network. They applied 13 long-term fixed UAV experiment airspace from the Chinese air force, and built a series number of UAV verification field. Jingjinxincheng UAV verification field is currently one of the most famous places and it can be seen in Figure 2. Based on the preliminary work of the UAV center, we will take field stations of the CAS as ideal facilities points for droneports in this study. These stations can be seen in Figure 3.

2.2 | Chinese administrative division data

Chinese administrative division data were used to define demand points and restrict its boundary. These data were downloaded from resource and environmental data cloud platform. Downloaded data were firstly projected to Asia_North_Albere_Equal_Area_Conic. That is standard coordinates and projection of Chinese map, with the Krasovsky ellipsoid, two standard parallel 47°N and 25°N and central meridian 105°E. All the data used in this study will be projected onto this coordinate system to ensure the data consistency. A fishnet tool with interval 0.5 longitude and latitude was used to discretize the whole China into
3,847 grids. Central points of these grids were extracted to represent the grid area. 90 km was assumed to be the fixed maximum service distance of droneport. It should be noted that it is impossible to cover all the grid central points. At most 1,417 central points can be covered if all the stations were used (Figure 3). It is meaningless in using these stations to consider what cannot be covered, so only the covered 1,417 points will be regarded as the demand points in this study.

### 2.3 The spatial distribution of flood risk in China

The spatial distribution of floods in China can be summarized as more occurring frequently in the eastern, coasts, plain, east, and south slope of mountains and less frequently in the western, inland, plateau, west, and north slope of mountains (Gu & Gu, 2012). Major floods mainly occurred in the seven rivers basin (including the Yangtze, Pearl, Huang, Huai, Hai, Songhua, and Liao rivers) and inner city. Figure 4 shows a flood prevention level distribution map obtained from the Chinese Office of State Flood Control and Drought Relief Headquarters, which is used to guide the deployment of flood prevention and relief resources. The whole China is divided into three levels: serious, general, and rare affected by floods.

### 2.4 Population and GDP data

Population and GDP data are important factors revealing social and economic development. They are important basis for flood prevention and risk assessment (Amadio, Mysiak, & Marzi, 2018). The greater the population and the better the economy, the more important for disaster prevention. Population and GDP data usually are collected by the National Bureau of Statistics based on administrative districts. It is difficult to show population distribution in detail. These data should be converted to certain fine spatial unit. Liu, Jiang, Yang, and Luo (2005) proposed a method using three factors including land cover, night-lighting luminance, and population distribution weight of residential density to spatialize population and GDP data. They were calculated as follows:

\[
P_{ij} = P \times \left( \frac{Q_{ij}}{Q} \right),
\]

where \(P_{ij}\) is the population or GDP value after spatialized for the \(i\)th line and \(j\)th column pixel. \(P\) is the demographic or GDP data counted by county-level administrative unit where the grid unit is located. \(Q_{ij}\) is the total weight of land cover, night-lighting luminance, and density of residential area of the grid unit. \(Q\) is the total...
weight of land cover, night-lighting luminance, and density of residential area of the county administrative unit.

The population and GDP data of 2015 year in $1 \text{ km} \times 1 \text{ km}$ scale were used in this article, which can be seen in Figures 5 and 6. This data also can be downloaded from the resource and environment data cloud platform (Xu, 2017).

2.5 Remote sensing UAV database

In order to better understand the current development of UAVs in China, the National Remote Sensing Center of China has built a national UAV remote sensing system database in 2012. To date, it has recorded more than 740 UAV models, covering nearly all the remote sensing UAV models in China. The database also contains mainly performance parameters of all the UAVs, such as flying speed, duration of flight, energy, weight, ability of wind resistance, etc. There are also differences among different kinds of UAVs. Electrically powered drones fly more steadily, but duration time is commonly less than an hour. The duration time for oil-motored drones can reach 8 hours, but their engine vibrates and the platform is less stable. Multiple rotors can spot hover, but they are less resistant to wind. The speed of fixed-wing UAVs can reach 140 km/h, and have wind-resistance abilities. Understanding these differences and selecting appropriate UAV are very important to flood monitoring. High-quality images and videos are essential and can be used

**FIGURE 4** Flood prevention level distribution map of China

**FIGURE 5** One-kilometer grid population distribution data of 2015 year
to detect flood extent and therefore guide rescue work. Oil-motored powered, fixed-wing drones were regarded as the best choice. In this study, we assumed a 2-hour response time. The UAV must reach the flood area in 1 hour, and finish the preliminary observations in another hour. The fixed maximum service distance for each droneport was assumed to be 90 km, which was a conservative estimate in flood condition.

2.6 Multi factors - maximum covering location problem (MF-MCLP)

MCLP is suitable to solve such a problem, under the condition of limited resources to achieve the maximum coverage of requirements. Therefore, MCLP was used in this study to solve the location of droneports. A mathematical formulation of MCLP can be stated as follows:

\[
\begin{align*}
\text{max} f &= \sum_{i \in I} w_i y_i, \\
\text{s.t.} \quad &\sum_{j \in N_i} x_j - y_i \geq 0 \quad \forall i \in I, \\
&\sum_{j \in J} x_j = P, \\
&x_j, y_i \in \{0, 1\}, \quad \forall i \in I, j \in J,
\end{align*}
\]

where \(i\) represents the \(i\)th demand point, \(j\) represents the \(j\)th facility point. \(x_j\) and \(y_i\) are two bool values. If the \(i\)th demand point could be covered by any facility, then \(y_i = 1\), otherwise \(y_i = 0\). If the facility was selected as an airport, then \(x_j = 1\), otherwise \(x_j = 0\). \(w_i\) represents the weight of the \(i\)th demand point. \(N_i\) represents all the facilities set covering the \(i\)th demand point, namely \(N_i = \{j | d_{ij} \leq R\}\). \(d_{ij}\) represents the distance between the \(i\)th demand point and the \(j\)th facility point. \(R\) represents the maximum covering distance of the facility. \(P\) is a fixed value, which represents the number of facilities.

The objective Equation (2) is to maximize the value of covering demand points. Equation (3) constraints that if the \(i\)th demand point would like to be covered, the \(j\)th facility must be selected first. Equation (4) means the total number of facilities. Equation (5) limits the value of \(x_j\) and \(y_i\) either 0 or 1.

It is very difficult for MCLP model to solve the location of droneports, as many factors will affect the distribution of droneports. The key is to define the description of \(w_i\). Grubesic and Murray (2002) ever used a bi-objective extension of MCLP, which was called BMCLP to integrate two aspects of demand points. \(w_i\) was replaced by \(\beta a_i + \lambda b_i\). \(a_i\) and \(b_i\) represent two attributes of demand points. \(\beta\) and \(\lambda\) represent the weight of each attribute. Along this way, when many factors are concerned, \(w_i\) can be expressed as Equation (6) and it is constrained by Equation (7).

\[
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&x_j, y_i \in \{0, 1\}, \quad \forall i \in I, j \in J,
\end{align*}
\]
attributes were standardized and that the weight of each attribute was clear set. In this article, factors include population, GDP and flood risk were limited to a range of 1–4. A value of 1 indicates the least demand for service and a value of 4 indicates the most demand for service.

3 | RESULTS

3.1 | Droneports provision

Figure 7 depicts the cost-effectiveness curves, which were generated for a range of \( p \) values using a maximum service distance of \( S = 90 \) km. The coverage percentage of total risk is calculated by Equation (8) and the change of coverage risk produced by the \( p \)th droneport can be calculated by Equation (9).

\[
r_p = \frac{\sum_{i=1}^{p} \sum_{j=1}^{m} w_{ij}}{\sum_{i=1}^{n} \sum_{j=1}^{m} w_{ij}} \times 100, \tag{8}
\]
\[
\Delta c_p = r_p - r_{p-1} \tag{9}
\]

\( r_p \) represents the coverage percentage of total risk when \( p \) droneports were built. \( p \) represents the number of droneports to be built. \( i \) represents the \( i \)th droneport. \( m \) represents the total number of demand points serviced by the \( i \)th droneport. \( j \) represents the \( j \)th demand points serviced by the \( i \)th droneport. \( n \) represents the total number of potential droneport. \( a_{ij} \) represents risks of the \( j \)th demand points covered by the \( i \)th droneport. \( \Delta c_p \) means the change of coverage risk produced by the \( p \)th droneport.

As the number of droneports increases, more and more demand points will be covered and the change of coverage risk produced by \( p \)th droneports will decrease. At the point of \( p = 188 \), all the 1,417 demand points were covered and the coverage risk produced by 188th droneport will decrease to 0. At the point of \( p = 81 \), the number of facilities is about 30.22% of all the stations, but it has covered nearly 61.84% of total risks and the coverage risk caused by that droneport has decreased to 0.64%. Therefore, the optimal number of UAV airports was identified as 81 in this study.

3.2 | Distribution of droneports

In order to certify the effectiveness of the proposed method, the original form of MCLP was used as a contrast experiment. The result of MCLP was meaningful, because it covered the maximum area and the most amount of demand points (Figure 8). But it is difficult to consider many important factors such as the floods risk, population GDP and so on. More emphasis should be paid on those areas more prone to flooding, having greater population and higher GDP than other areas. The result with MF-MCLP can be seen in Figure 9, which is different from the result of MCLP. In the original form of MCLP, we note that most facility points located in the open and vast areas. The overlap areas of different droneports are minimized. When MF-MCLP was used, we could see that most facility points are located in the eastern and middle areas of China, and covered nearly all the main river basins. This result is more practical and meaningful, because it can permit the UAVs to reach most flood areas and finish the primary observations in 2 hours.

FIGURE 7  The cost-effectiveness curves for a range of \( p \) values (a) and change of coverage risk produced by the \( p \)th droneport (b)
4 | DISCUSSION

4.1 | The distribution of droneports

In view of the great destruction and severe disasters caused by flooding (Alahacoone, Matheswaran, Pani, & Amarnath, 2018), it is of great importance to timely and rapidly observe the flooding situation. Construction of UAV observation network is not only advanced, but also of great practical value to rescue. A reasonable distribution of droneports means that UAVs can reach flood areas in a very short time and assess the flood situation quickly, such that they can play important roles in the supporting rescue and relief work. Furthermore, deployed UAV resources in the droneports must be highly efficient. They should not leave unused for a long time, thereby wasting resources. In view of this, drones should be located in areas prone to flooding and where populations and economies are more concentrated. From Figure 10, we can see that a total of 57 droneports selected by MCLP and MF-MCLP are same. However, 24 droneports are different. Droneports selected by MCLP are more broad and balanced, which can be found in the Tibetan Plateau region, Xinjiang region, and other border regions. Compared to the results of MCLP, droneports selected by MF-MCLP are mainly located in the area with high flood risk, more population and GDP, such as the middle and lower reaches of Yangtze river. The service
area of selected facilities by MF-MCLP has covered nearly all the serious flood areas and most general flood areas, in eastern of China. The main basins, such as the Yangtze, Pearl, Huang, Huai, Hai, Songhua, and Liao rivers, also have been covered. The UAVs can reach these areas within an hour, which can meet the time requirement of flood emergency rescue.

4.2 Why the stations of CAS were selected as droneports

The field stations of CAS mainly focus on scientific research. They were regarded as potential droneport based on the following reasons. Firstly, the CAS setup UAV application and control research center in 2017, aiming to build the national UAV application and control network through coordinating the UAV resources and strengthening the cooperation within and outside the CAS. Secondly, the field stations of the CAS are distributed all over China. A broad global vision and complete infrastructures make them perfect alternatives to droneports. Thirdly, many stations of CAS are in the fields of geology, resources, and environment. They have a certain number of remote sensing UAVs themselves. They are pleased to cooperate with UAV center expand their drone fleet. Finally, UAV center has built good cooperative relationships with many CAS stations. They have made a lot of productive work such as apply for airspace from air force, build droneport base, and so on. All these efforts should be inherited, so the stations of CAS were regarded as potential facility points.

It should be noted that this UAV network is a spatially distributed but uniformly managed network. It is not closed but open to social organisations. So, in the future, the water resource department, emergency rescue department, meteorological department and so on can join the network and play to their roles.

4.3 Prospect and outlook

The UAV remote sensing observation network can adopt a three-level networking framework, namely “UAV control main center—droneports sub-center—UAV performance center”. The UAV control main center is the flood relief headquarters, which can dispatch UAV resources, observe flood situation and make rescue plans, etc. The droneport sub-center stores UAV platforms and sensors resources provide places and conditions for UAV flight experiment. The UAV performance center carries out UAV remote sensing observation experiment and maintenance of UAVs at ordinary time, and will execute UAV observation tasks when receiving observation commands from the main center. The main center, sub-center, and UAVs are connected through satellite communication link or mobile communication link, ensuring the main center will be able to observe real-time images and videos obtained from UAVs. Since the UAV resources deployed nearby, they can reach flood area quickly and get the first-hand information. The data obtained by UAVs can be quickly processed to extract flood inundation area information and estimate losses caused by flood. Furthermore, various sensors can be loaded on the UAV platform to perform a specific task. Infrared camera can be used to search for signs of life, the video camera allows people to feel the disaster firsthand. In this way, the UAV remote sensing network will play important roles in flood rescue.
5 | CONCLUSION

In this study, an MF-MCLP model was proposed and utilized to distribute a series of droneports in China to form a UAV remote sensing network, which can respond quickly to flood disaster. Cost-effectiveness curves were used to decide the suitable number of droneports. On the basis of a lot of preliminary work of the UAV center, the stations of CAS were regarded as the ideal places for droneports. Finally, 81 droneports were selected based on their flood risk, population and GDP level. Although the number of droneports accounts for 30.22% of total stations, they covered 61.84% risk of total demand area. The selected droneports were allocated near flood-prone areas, such that most floods in China could be monitored within 2 hours, which is critical for saving lives and reducing losses. In conclusion, this study further deepens and expands the MCLP model, making it more widely applicable. It is also of great importance to flood emergency rescue and construction of an integrated disaster emergency observation system combining satellite, airplane, UAV, and ground observations in China.

ACKNOWLEDGEMENTS

This study was supported by the National Natural Science Foundation of China (41771388), the National Key Research and Development Program of China (No. 2017YFB0503005) and China Postdoctoral Science Foundation (2018M640170).

DATA AVAILABILITY STATEMENT

I confirm that my article contains a Data Availability Statement even if no data is available (list of sample statements) unless my article type does not require one. I confirm that I have included a citation for available data in my references section, unless my article type is exempt.

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**How to cite this article:** Lu M, Liao X, Yue H, et al. Optimizing distribution of droneports for emergency monitoring of flood disasters in China. *J Flood Risk Management*. 2020;13:e12593. [https://doi.org/10.1111/jfr3.12593](https://doi.org/10.1111/jfr3.12593)