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Integrating Spatial Risk Factors with Social Media Data Analysis for an Ambulance Allocation Strategy: A Case Study in Bangkok

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Abstract: Emergency medical service (EMS) base allocation plays a critical role in emergency medical service systems. Fast arrival of an EMS unit to an incident scene increases the chance of survival and reduces the chance of victim disability. However, recently, the allocation strategy has been performed by experts using past data and experiences. This may lead to ineffective planning due to a lack of consideration of a recent and relevant data, such as disaster events, population density, public transportation stations, and public events. Therefore, we propose an approach of the integration of using spatial risk factors and social media factors to identify EMS bases. These factors are combined into a single domain by using the kernel density estimation technique, resulting in a heatmap. Then, the heatmap is used in a modified maximizing covering location problem with a heatmap (MCLP-Heatmap) to allocate ambulance base. To acquire recent data, social media is then used for collecting road accidents, traffic, flood, and fire incidents. Additionally, another data source, spatial risk information, is collected from Bangkok GIS. These data are analyzed using the kernel density estimation method to construct a heatmap before being sent to the MCLP-heatmap to identify EMS bases in the area of interest. In addition, the proposed integrated approach is applied to the Bangkok area with a smaller number of EMS bases than that of the existing approach. The simulated results indicated that the number of covered EMS requests was increased by 3.6% and the number of ambulance bases in action was reduced by approximately 26%. Additionally, the bases defined by the proposed approach covered more area than those of the existing approach.

Keywords: emergency medical service base allocation; covering model; kernel density estimation; social media information

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1. Introduction

At present, rescue squads in many countries are encountering the problem of coping with incidents that cost people lives and properties, e.g., natural disasters, terrorism, political protests, chemical storage explosions or diseases. In a rescue squad, an emergency medical service (EMS) is vital for victims [1–3]. Recent research reveals that survival rate was increased and severe injury chance was reduced for the victim when an EMS unit reached the scene of the incident within 8 min [4,5]. Therefore, it is necessary that the EMS unit must always be ready and on stand-by close to the incident scene so that the service can reach the scene as soon as possible. Generally, an EMS base is defined by the experienced officer. Their decision primarily relies only on the demand factor. The decision for the allocation of EMS bases is irrespective of other factors that may not be suitable for an ever-changing environment.

In Bangkok, there are currently 49 EMS bases (http://ws.niems.go.th/ITEMS_DWH/: information technology for emergency medical systems of Thailand, accessed on 1 April 2020). Proportional to the area, 49 bases is a very high number because it was designed such that the travelling time from the nearest base to the incident scene can be minimized regardless of whether this number (49 bases) is optimal or not. Not only the number of EMS bases can affect the travelling time, but a base location that is allocated closed to high-population areas can also reduce the travelling time [6]. In Bangkok, the ratio between population and an EMS base is 108.16, compared to that of Vienna, Rome, and Amsterdam, which are 360.51, 279.0, and 545.3, respectively [7–10]. The ratio of Bangkok is the lowest, implying that the EMS unit travelling times are high because the unit cannot respond to real-time incidents due to base location, traffic, protocol, and management [11]. Recently, EMS bases have been allocated based on the management person's experience. This allocation strategy is unlikely to be optimal [12]. By using their experience, the management person reduced the high travelling time by adding new EMS bases. However, the growth in the number of EMS bases seems to overly consume the resources. Therefore, the allocation strategy must be changed to reduce the number of EMS bases and also the travelling time.

Recent research presents mathematical models, i.e., the covering model, for EMS base allocation problems that mostly considered demand factors and the population density factor, so called spatial risk factor, which is a vital factor for EMS base planning [13]. This is consistent with research by [14,15] that examined factors affecting the planning of EMS base, which can be divided into two types: firstly, demographic factors, for example, housing density population in each area, workplaces with a high number of employees, community sites, or public events with many participants. Secondly, geographic factors, such as areas at risk of flooding, areas that are at risk of accidents, etc. Those factors are related to the opportunity to call for EMSs.

Social media is emerging as an important technology for emergency response. [16] proposed an integration of social media data streams to efficiently identify a real-time EMS base from the data stream from social media such as Twitter [17]. As an alternative to GIS data [18], Social media can be thought of as social sensors that closely investigate incidents or disasters such as a flood or earthquake [19]. Although social media factors and spatial factors were proposed, they have not been integrated to construct a covering model for an effective EMS base allocation. Therefore, this paper proposes integration of spatial risk factors and social media factors to generate heatmaps of risk. Then, a mathematical model, an improved MCLP-LF, is developed to make a decision for the EMS base allocation based on the density generated by the heatmaps.

Our paper is organized as follows: Section 2 presents the background of some related works, a utilization of spatial and social media data, multivariate density estimation, and a covering model. The proposed approach of allocating EMS bases by using social media and spatial factors is depicted in Section 3. The viability of our approach is demonstrated in the Bangkok area, and its results are discussed in Section 4. The discussions are presented in Section 5. Section 6 presents the conclusions and the future research direction.

2. Background

The strategy of the EMS allocation is divided into three levels to help the vehicle to reach the incident scene effectively, namely strategic level, tactical level and operational level [20]. Managing the standby site allocation in this study is considered as the strategic level. Two levels of data are required: static (gradually changed data, e.g., annual data) and dynamic (frequently changed data, e.g., monthly, weekly, daily or real-time data) [16]. In this paper, we present an allocation strategy integrating a covering model with utilized spatial and social media information for collecting data in the form of both static and dynamic characteristics. All the data are analyzed using the kernel density estimation method to construct a heat map. Then, the map is used in the modified maximizing covering location problem.

2.1. A Utilization of Spatial and Social Media Data

There have been several studies utilizing spatial and social media data in both static and dynamic environments. The data were used to plan for emergency situations. [21,22] suggested that most people interact via social media in daily life. They not only talk to others, share their memorable moments or run their businesses on social media, but also use it as a place to report incidents or emergency situations such as disasters, terrorism or exhibitions being crowded. The authors suggest that the use of social media provides a lot of benefits over the existing approach. For example, the collection of data can be performed quickly or in real time. Due to this advantage, there are several studies that used the data from social media to plan for EMS bases.

Refs. [14,23] studied the factors that affect the management of EMS. They defined two types of factors, which are: 1. Demography, which is the factor describing population and habitation in the area. 2. Geography; this factor describes a correlation between number of medical service requests and other parameters such as population habitation and geography. The authors concluded that a rise in the population increases the number of medical service requests. They also studied the relationship among multiple factors such as vehicle speed, road conditions, traffic, weather, population, workplace, temperature, special events, etc. In addition, in the case of images containing demography and geography data, some data extraction techniques based on deep learning method may be used [24,25].

Refs. [26,27] used data from social media to develop a decision-making tool to allocate EMS bases. The results showed that an event that shares data on social media can be used as a data source for computing a chance of medical service requests. The study developed a mathematical model utilizing geographical data to support the decision. This is in accordance with [28], who utilized social media and spatial data to develop a risk assessment model for medical service requests. They also constructed an EMS base allocation model based on multiple factors, i.e., the number of accidents, type of accident, population, number of elderly people, and number and size of public events.

2.2. Multivariate Density Estimation

Multivariate density estimation is a statistical technique used in geographical analysis. It describes spatial data such as population distribution, population density, and risk map. Ref. [29] proposed spatial density estimation, which consists of two major components: 1. Statistical techniques used to estimate the density and distribution of the data and 2. Visual presentation

Refs. [30,31] investigated multivariate spatial density estimation methods, i.e., histograms, naive estimator, kernel estimator, and the nearest neighbor method. The results showed that the most frequently used was histograms and kernel estimator. These techniques can accurately predict the incident area and allocate the EMS base.

Refs. [32,33] suggested that EMS bases for road accidents should be allocated using accident history and risk maps constructed using kernel estimator. Kernel estimator provides three advantages: 1. It does not require an expert to estimate the maps and interpret the results. 2. This technique requires less computational time than the other techniques compared. 3. It provides more accuracy than the other techniques compared. Recent research shows that kernel estimator is one of the most frequently used techniques that is used to predict EMS requests. It is also used to construct heatmaps.

Refs. [34,35] used kernel estimator to estimate the chance of crime in an area of interest by using criminal history to construct a heatmap that describes frequency of crime. Likewise, [28,36] constructed a heatmap to investigate unusual events represented by the color. The author used color temperatures to describe the risk of receiving EMS.

Kernel Density Estimators

Kernel density estimators (KDE) are nonparametric estimators of both univariate and multivariate densities. There are several articles about its properties. It has been used in a wide range of applications [29,31,37]. The KDE technique is also used to estimate the spatial density between two points to determine the density of the area.

The general form of a kernel estimator is:

$$\hat{\lambda}(s) = \sum_{i=1}^{n} \frac{1}{\tau^2} k\left(\frac{s - s_i}{\tau}\right) \tag{1}$$

where $\hat{\lambda}(s)$ is the estimate of the density of the spatial point pattern measured at location s, s_i is the observed ith event, $k()$ represents the kernel weighting function, and τ is the bandwidth. Figure 1 illustrates parameters used to compute KDE $\hat{\lambda}(s)$.

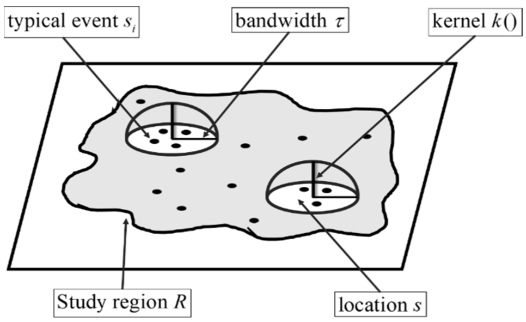

Figure 1. Parameters used to estimate kernel density function.

The KDE function allows one to estimate the intensity of a point pattern and to represent it by means of a smoothed three-dimensional continuous surface that represents the variation in density of point events across the study region. The procedure can be organized in three steps [38]:

1. A fine grid is placed over the study region and the distribution of events;
2. A moving three-dimensional function visits each cell and calculates weights for each point within the function's radius (threshold or bandwidth). In most of the kernel functions considered, events closer to the center are given a higher weight than those located at the edge of the search function, therefore contributing more to the reference cell's density value; and
3. Grid cell values are calculated by summing the values of all surfaces for each location.

The routine therefore calculates the distance between each of the reference cells and the event's locations, evaluates the kernel function for each measured distance, and sums the results for each reference cell.

2.3. A Covering Model

The location-allocation problem is an approach that optimally organizes the service locations to sufficiently serve the demands in the area of interest [39]. This problem has drawn a large portion of interest in recent research [40].

Generally, there are two models used to solve location-allocation problems: the p-median model and covering model. For p-median, a number of service spots, called p, are allocated in the area of interest such that travelling time from the nearest service spot to the demand point is minimized [41], while the covering model aims to establish service spots such that the travelling time or distance from the nearest service spot to the demand point is under the threshold [42].

In this research, we prefer the covering model because we have set the travelling time threshold at 8 min, referring to [4,5] that the survival rate was increased and severe injury chance was reduced for the victim when an EMS unit reached the incident scene within 8 min.

For the covering model, to solve EMS base allocation problems, [43,44] proposed covering models to allocate EMS bases to sufficiently serve the need of medical services in a specific area. A model for the location set covering problem (LSCP) proposed by [45] is regarded as the first covering model. It was developed to minimize the number of ambulances and their bases that sufficiently provide a service in the area of interest. Then, [46] proposed the maximum covering location problem (MCLP) to allocate EMS bases to cover the need in a specific area with limited resources. [11] proposed the maximum covering location problem with location forced (MCLP-LF). This model describes the forced selection of an area as an EMS base from a control chart that is constructed based on data from social media. In this study, maximum covering location problem with location forced (MCLP-LF) was chosen as a model for improvement by applying spatial factors and social media information.

3. Our Proposed Approach

Parameters:

γ_j: The density level of the area j obtained from kernel density estimation.
R_i: The lowest density level that is used to forcibly select the standby site in area i.
d_i: Demand in area i.
p: Number of possible EMS bases.
M: A large number.

Decision Variables:

$$x_j: \begin{cases} 1 & \text{If area } j \text{ is allocated for a standby site.} \\ 0 & \text{Otherwise.} \end{cases}$$

$$y_i: \begin{cases} 1 & \text{If area } i \text{ is covered by at least one standby site.} \\ 0 & \text{Otherwise.} \end{cases}$$

Indices:

i: Area index; $i \in V$.
j: Possible EMS base index; $j \in W$.

Sets:

V: A set of area.
W: A set of possible EMS bases.
W_i: A set of EMS bases that covers area i.

As described earlier, our proposed approach is an integration of spatial risk factors and social media factors to generate heatmaps. Then, the density from the heatmaps is used in the decision-making process using an improved MCLP-LF. To demonstrate our proposed approach, we divide it into four steps: data collection, data preparation and analysis, decision making, and model validation using simulation, as shown in Figure 2.

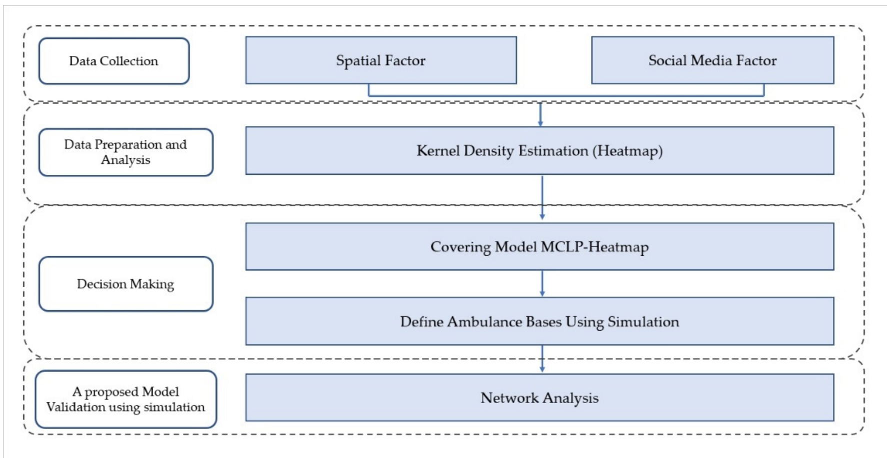

Figure 2. Our proposed approach.

3.1. Data Collection

There were two types of factors collected in this work:

1. Spatial factors were collected from the department of public works and town and country planning. The factors include hospital location, community location, etc.

2. Social media factors were obtained from social media users (verified Twitter users), such as Thailand traffic radios, e.g., JS100 Station (@js100radio). Their Twitter accounts report traffic and unusual events (accident, exhibition, public event).

Figure 3 shows the data transformation process from social media (Twitter) to the location of an incident after receiving message reports with unusual incident events being tweeted, such as accidents, fires, or floods. Usually, those messages are in text format and contain unnecessary text for analysis, for example, retweeted posts or advertising. Therefore, before using the data, the tweeted text must be cleaned by eliminating these irrelevant details. Then, we must identify where incidents occur by locating road names or places in the cleaned messages. Next, the accidents with their location will be transformed to a spot on a real map.

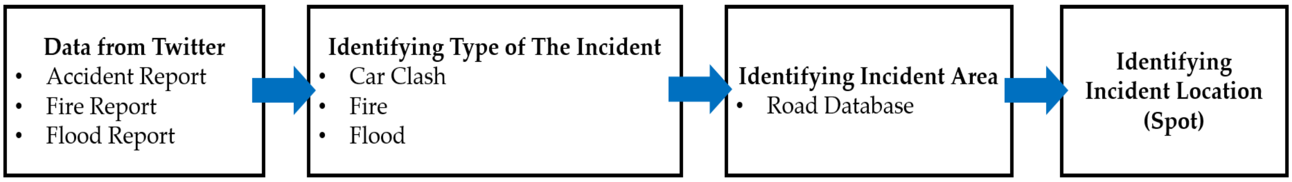

Figure 3. Transformation process of data from Twitter to location of incident.

3.2. Data Preparation and Analysis

In this step, spatial and social media data are taken into kernel density estimation. The results obtained from kernel density estimation are presented in a heatmap. The colors in the map represent the density of risk factor in such an area, ranging from a red color, representing a high density of risk factors to a dark green color, representing a low density of risk factors. In this work, five levels of density are defined with five different colors, as used in [47], which identify and prioritize the most critical regions in an area prior to the occurrence of the natural disaster. The meaning of each level is shown in Table 1.

Table 1. Colors representing density levels and meaning of each level.

Color	Meaning	Density Level
Red	Very high chance of emergency medical service request	5
Orange	High chance of emergency medical service request	4
Yellow	Moderate chance of emergency medical service request	3
Light Green	Low chance of emergency medical service request	2
Dark Green	Very low chance of emergency medical service request	1

3.3. Decision Making

After the map is generated, a covering model [11] will forcibly select the EMS base in very-high- and high-density areas on the map. Then, the other standby sites will be identified using a covering model. However, in this work, we proposed a constraint to the model (Equations (2)–(7)) to select the standby site. Our assumptions of the modified covering models include that the demands in different time periods are independent; in each time period, the demand is deterministic and determined by data collected from social media (Twitter application). Note that in real-time situation, the demand can be forecasted [48]; all location bases must be available to set as an ambulance base; it is assumed that social media and communication infrastructure are available at all areas; and for each location, only one ambulance/base can be assigned. The modified covering models are described as follows:

Objective Function

$$\text{Maximize } \sum_{i \in V} d_i y_i \quad (2)$$

Equation (2) is the objective function used to maximize the area that is covered by the EMS bases which is subjected to the following constraints.

Subject to

$$\sum_{j \in W_i} x_j \geq y_i;\ i \in V \quad (3)$$

Equation (3) is a constraint that describes that an area needing medical service (y_i) must be covered by at least one EMS base x_j (x_j).

$$\sum_{j \in W_i} x_j \leq p \quad (4)$$

Equation (4) says that the total number of allocated EMS bases (x_j) must not exceed the total number of allocable EMS bases (p).

$$\beta_j \leq x_j;\ j \in W \quad (5)$$

In Equation (5), an unusual situation area or an area that lies outside the boundary in the control chart (β_j) must be forced to allocate an EMS base (x_j).

$$x_j \in \{0, 1\};\ j \in W \quad (6)$$

$$y_i \in \{0, 1\};\ i \in V \quad (7)$$

Equations (6) and (7) say that (x_j) and (y_i) are binary variables.

Although MCLP-LF utilizes data from social media to select an area, it lacks efficiency in utilizing spatial data because the model considers the request for medical service only from recipients calling. Therefore, this research proposes an improvement in the MCLP-LF by changing from a forced selection of an area by using a control chart to a forced selection of an area by using the spatial density, which is approximated using the data from social media.

$$\gamma_j - R_i \leq M \cdot x_j - \left(1 - x_j\right);\ j \in W,\ i \in V \quad (8)$$

This constraint forces that a standby site must be placed on any area that has a density level γ_j higher than R_i.

3.4. Model Validating Using Simulation

In this step, the effectiveness of the assigned standby sites using the proposed approach and the existing standby sites are compared. Network analysis is used to analyze the distance to reach an incident scene. The distance is measured from the standby site to the incident scene along possible roads in the area of interest. The analysis tool used in this step is the location-allocation technique. The testing steps are as follows and are shown in Figure 4:

1. Determine the ambulance bases obtained from the proposed covering model and the ambulance bases allocated by the existing approach (management person's experience) for use in the simulation.
2. Determine EMS request (empirical distribution)
3. Analyze the road network using the location-allocation technique based on real roads.
4. Compare the results in terms of bases, demand access, and average distance.

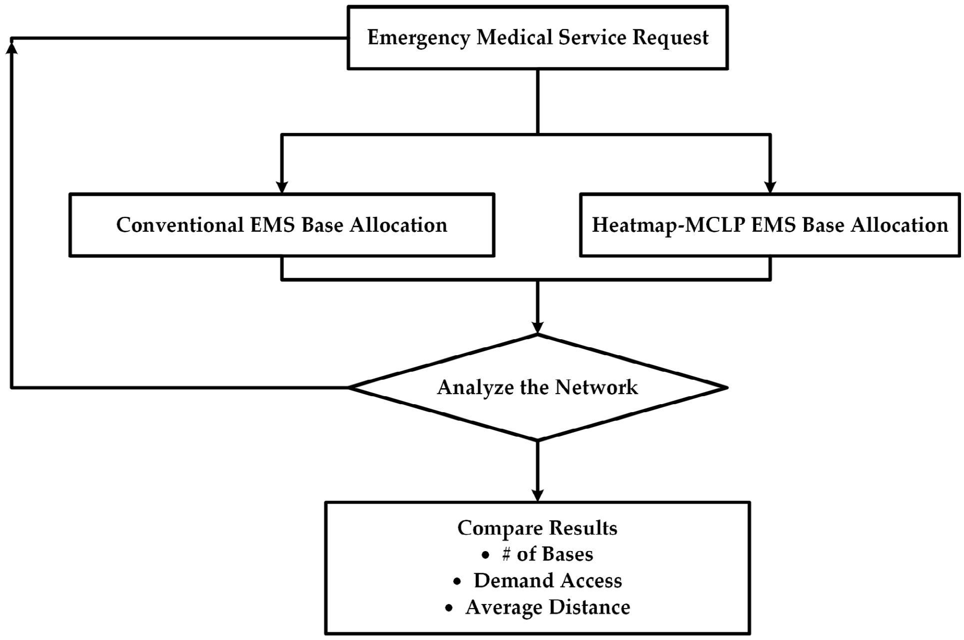

Figure 4. Model validation using simulation.

4. A Demonstration in Bangkok Area and Its Results

4.1. General Data of the Area of Study

In this study, Bangkok, Thailand is selected as the area of interest. It has 50 districts covering 1568.74 km^2. The population is 5,993,656. According to a report from Road Accident Victims Protection Company Limited (Accessed: 15 April 2020) [49], there were 52,187 cases of road accidents in 2020, which caused 61,960 deaths and injuries combined. Primarily, Emergency Medical Foundation of Thailand (EMFT) is responsible for EMS in Bangkok. In 2020, EMFT had 156 EMS units in Bangkok, of which 59 were advanced emergency service units. There were 133 medical service requests/day. The number of incident scenes reached was 22,968 times/year. The time taken to reach the incident scene was 9 min or longer.

4.2. Spatial Data and Social Media Data

4.2.1. Spatial Data

We collected general data and road data in Bangkok from [50–52] and take the data of interest as suggested by [53]. The total number of roads in the area is 2413 and several types of places in the area are shown in Table 2.

Table 2. Spatial Data in Bangkok.

No.	Type of Place	Number
1.	Risky Intersection	81
2.	Community	2011
3.	BTS (skytrain)	30
4.	MRT (metro)	18
5.	Fresh market	148
6.	Flood area	323
7.	Shopping mall	127
Total		2738

4.2.2. Social Media Data

Twitter is an extremely trendy social media platform in Thailand, with over 5.3 million users (18% increase since 2015), and most of these users are active on mobile devices (EPC Global Social Media Trends 2015). In this research, social media data were used from official/reliable news agencies, i.e., @JS100radio, @Thairath_News, and @FM91_Trafficpro. The collection began with searching keywords related to road accident reports, fire reports, and flood reports in the Bangkok area. The data were collected for 1 month in March 2020 with a total of 3521 messages, and after that the redundant and irrelevant messages were cleaned/filtered for representation in a heatmap (Table 3); moreover, the 1-month accident data pattern is used to demonstrate monthly service demand. In this work, the importance of each incident is assumed to be equal since we cannot guarantee the seriousness of the damage occurring in each incident.

Table 3. Data collected from social media.

Incident	Keyword	Report Frequency
Road Accident	Two-car clash	6
	Car-motorcycle clash	5
	Car hit Street-isle	3
	Two-motorcycle clash	5
	Lost-controlled motorcycle	7
	Fallen motorcycle	3
	Two-truck clash	7
	Truck fall off the road	1
	Car, truck and motorcycle clash	1
	Flipped SUV	1
	Lost-controlled car	1
	A car clash	19
	Lost-controlled car hit	2
	Lost-controlled soil grader	1
	Motorcycle clash	25
	Car clash	31
	Van-motorcycle clash	1
	Trailer clash	5
	Lost-controlled trailer	1
	Truck clash	11
	Lost-controlled clash	2
	Accident	95
	Total	233
Fire	Fire	73
	Total	73
Flood	Flood	7
	Water waiting to drain	3
	Total	10
	Total Incident	316

4.2.3. Kernel Density Estimation

The results from kernel density estimation are the density values that will be used to identify the temperature of each sub-area in the heatmap shown in Figure 5. The whole area is divided into 187 sub-areas (blocks). The estimated density in each sub-area is matched with the density level. Then, the level color is painted onto the sub-area.

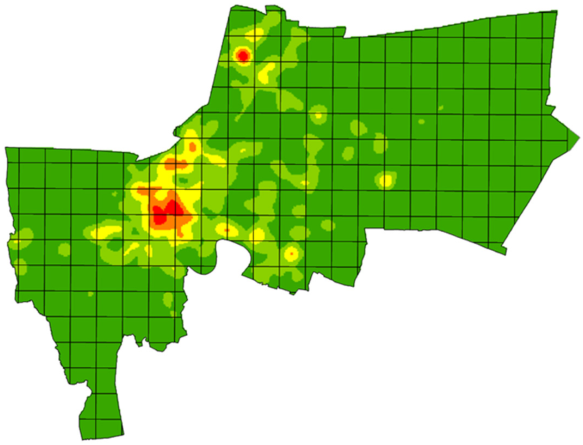

Figure 5. A heatmap representing the incident density in Bangkok.

4.2.4. EMS Base Allocation

To allocate the standby site, an MCLP-heatmap model is used. From the optimization results, 48 standby sites are allocated, which cover 369 possible EMS request spots throughout Bangkok, as shown in Figure 6. Figure 7 shows the heatmap with sub-area numbers. The red crosses in sub-areas represent the allocated standby sites. A summary of the allocated standby sites is illustrated in Table 4.

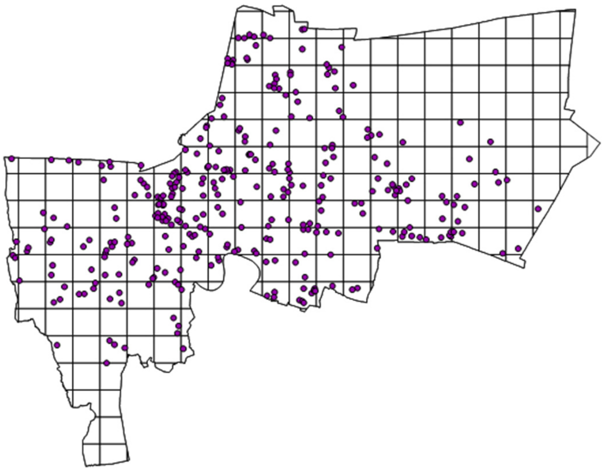

Figure 6. EMS request spots throughout Bangkok (represented by dots).

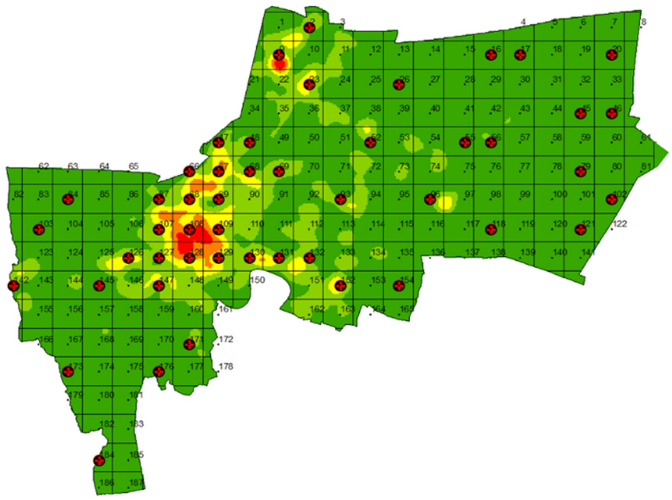

Figure 7. A heatmap with allocated EMS bases (represented by black circles with red crosses).

Table 4. Summary of the EMS base allocation.

Subarea	Standby Site
2, 9, 16, 17, 20, 23, 26, 45, 46, 47, 48, 52, 55, 56, 66, 67, 68, 69, 79, 84, 87, 88, 89, 93, 96, 102, 103, 107, 108, 109, 118, 121, 126, 127, 128, 129, 130, 131, 132, 142, 145, 147, 152, 154, 171, 173, 176, 184	Allocated (48 bases)
1, 3, 8, 10, 14, 21, 22, 24, 25, 28, 29, 31, 32, 34, 42, 44, 49, 50, 51, 65, 70, 71, 73, 75, 76, 77, 78, 80, 82, 83, 86, 91, 92, 94, 95, 99, 104, 106, 110, 111, 112, 113, 114, 115, 117, 119, 120, 122, 123, 124, 125,133, 135, 137, 138, 140, 141, 143, 144, 146, 148, 149, 151, 153, 155, 156, 157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169, 170, 172, 174, 175, 177, 178, 179, 180, 181, 182, 183, 185, 186, 187	Not Allocated (139 bases)

Table 4 presents the allocated and unallocated EMS bases in Bangkok. Based on the generated blocks, there are 48 allocated areas and 93 unallocated areas.

4.2.5. Simulation Results

The results obtained from the MCLP heatmap are validated by a simulation technique. The events with EMS requests were simulated. A total of 187 daily requests were randomly generated with 10 replicates, as shown in Table 5. In the simulation model, the number of standby sites in action was 36.6–36.7 bases with 95% confidence interval, which was approximately 26% less than the existing standby sites (46.8–49.6 bases).

Table 5. The comparison for the results between MCLP heatmap and current EMS bases.

No.	MCLP-Heatmap (48 Locations)				Current Emergency Ambulance Bases (59 Locations)			
	Bases	Demand Access	Avg. Dist. (Meter)	SD.	Bases	Demand Access	Avg. Dist. (Meter)	SD.
1	40	183	3554.91	1912.85	46	175	2922.16	2135.74
2	38	184	3437.11	1814.99	47	179	3162.5	2338.56
3	34	182	3473.40	1811.34	45	179	3234.4	2424.14
4	38	186	3446.99	1887.49	49	178	3094.18	2188.60
5	39	183	3389.75	1994.36	51	174	3026.53	2100.30
6	37	179	3555.87	1934.54	49	174	3157.67	2363.94
7	36	183	3215.01	1875.58	48	179	3104.8	2337.71
8	40	185	3461.70	1833.09	50	177	3062.48	2287.46
9	41	184	3432.11	1916.46	50	176	3299.99	2542.19
10	38	182	3619.93	1992.12	47	175	3290.46	2497.60
CI 95%	(36.6, 36.7)	(181.7, 184.7)	(3387, 3562)	-	(46.8, 49.6)	(175.1, 178.1)	(3019, 3235)	-

Then, the traveling distances from the standby sites allocated by two approaches to the incident scenes are compared. The standby sites allocated using the proposed approach yielded a traveling distance of 3387 m to 3562 m, while the existing approach yielded a traveling distance of 3019 m to 3235 m.

However, the standby sites allocated by the proposed approach covered 181.7 to 184.7 EMS requests, while those of the existing approach covered 175.1 to 178.1 EMS requests (3.6% increased).

In summary, the standby site allocation using the proposed approach is different from that of the existing approach with 95% confidence interval. The number of standby sites provided by the proposed approach is lower than that of the existing approach. However, with the proposed approach, the traveling distance to reach the incident is longer than that of the existing approach because there are fewer standby sites, but they are better distributed. An example of the simulation of the MCLP heatmap model is shown in Figure 8.

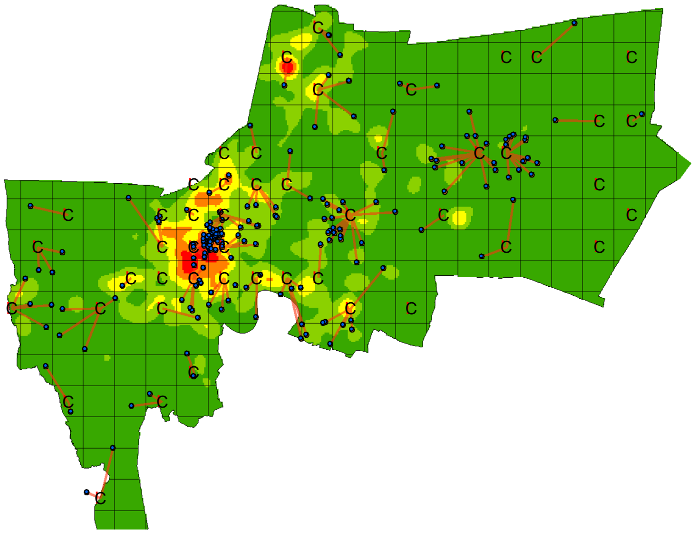

Figure 8. An example of the simulation of the MCLP heatmap model where "C" represents EMS base, dot represents EMS-requested location and red line represents the distance from an EMS base to an EMS-requested location.

5. Discussion

Recently, most EMS bases have been planned using expert experiences. The incident report history was the only factor used to allocate the EMS bases. Other factors that can affect the chance of requesting EMS were not considered, such as spatial and social media data. However, at present, data from social media can be utilized to better plan EMS bases because the data are fresh and real-time. There have been studies [16,25,26] that utilized social media data to monitor emergency incidents and capture it as data for EMS base allocation. However, those works did not use the data to create a decision-making tool. This work used social media data to create a decision pattern for EMS base allocation.

This study also utilizes geographical analysis. Kernel density estimation was used as an analysis tool because it is not complicated and provides as good results as the other complex methods. The results from the estimation were then used with an optimization technique to construct a visualization tool, a heatmap that was a decision-making tool. This is in accordance with [32]. The author used the kernel density estimation to assess risk of emergency incident occurrence in an area of interest.

In the decision-making step, we proposed an MCLP heatmap model to identify the EMS bases. Similarly, [11] proposed a mathematical model to identify the minimum number of EMS bases to cover an area of interest. However, those authors considered data from accident history and traffic to identify the standby site, while this work relied on social media and spatial data. We believe that the model proposed by the two studies can provide comparable results. Users may use these works as reference and select factors that are suitable for the area of interest to achieve the best results.

6. Conclusions and Future Work

This paper presents integrating spatial risk factors with social media data analysis for an EMS base allocation strategy in Bangkok. These factors are combined into a single domain by using kernel density estimation techniques, resulting in a heatmap. Then, the heatmap is used in a modified maximizing covering location problem with a heatmap (MCLP heatmap) to allocate an EMS base. The results indicated that the number of covered EMS requests was increased by 3.6% and the number of EMS bases in action was reduced by approximately 26%. Although the cost of emergency planning management should not be considered the highest priority, efficient planning should be considered simultaneously. As a result, the bases defined by the proposed approach covered more area than that of the existing approach and responded to a higher number of service requests. Our approach can be used as an alternative for EMS base allocation planning.

Since the data used in this work are in a near real-time environment, the allocated EMS bases were not relocated according to real-time incidents. Additionally, a decision-making tool for real-time EMS base relocation is still missing. However, in the future, if our proposed approach is applied to larger areas, applied to larger populations or used with more factors or real-time environments, additional tools can be used to help reduce the computational time, such as K-means clustering. Currently, the proposed approach can be used to plan EMS bases in Bangkok and other areas, which may have different factors affecting the decision. Additionally, weighting techniques can be applied to each factor to rank the importance, which is applicable for other applications. In addition, the number of accidents was collected from only Twitter, but using it as the main source of information could be biased. Therefore, other sources such as traffic congestion should be considered.

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