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Application of geographical information system-based analytical hierarchy process as a tool for dengue risk assessment

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ABSTRACT

Objective: To highlight the use of analytical hierarchy process (AHP) in geographical information system that incorporates environmental indices to generate dengue risk zonation area.
Methods: The medical database considered for the study was referenced to the environmental data layers. Factors related to the risk of dengue fever (DF) were selected throughout previous research and were arranged in a hierarchical structure. The relative weights of factors were calculated, which were within acceptable range with the consistency ratio being less than 0.1. The outcomes from AHP based DF risk zonation area produced useful information on different levels of risks.
Results: As a result, factor weights used in AHP were evaluated and found to be acceptable as the consistency ratio of 0.05, which was < 0.1. The most influential factors were found to be housing types, population density, land-use and elevation. Findings from this study provided valuable insights that could potentially enhance public health initiatives. The geographical information system and spatial analytical method could be applied to augment surveillance strategies of DF and other communicable diseases in an effort to promote actions of prevention and control. The disease surveillance data obtained could be integrated with environmental database in a synergistic way, which will in turn provide additional input towards the development of epidemic forecasting models.
Conclusions: This attempt, if successful, will have significant implications that could strengthen public health interventions and offers priorities in designing the most optimum and sustainable control program to combat dengue in Malaysia.

1. Introduction

Dengue fever (DF) is a vector borne disease which generally emerges in certain season of the year. The major option in preventing the spread of DF is to control and monitor its vector by focusing on specific localization areas and via the destruction of suitable breeding environment. Spatial analysis is capable to identify localized cluster of the disease that is in excess of what would normally have been expected given the underlying population and demographic structure[1]. An analysis of the spatial distribution or dependencies of disease remains to be one of the most important public health interest[2-4]. Therefore, to better understand the distribution of DF in term of time and space, it is essential to develop spatial database, apply spatial statistics and link this information with environmental factors in an area.

The use of spatial analysis in geographical information system (GIS) for health purposes is becoming one of the major techniques to identify spatial association and has thus been adopted by several researchers worldwide[5-7]. The integration of an analytical hierarchy process (AHP) method in GIS for solving spatial planning problems has received considerable attention among multidisciplinary planners. The ability of GIS to integrate with AHP has been demonstrated in several studies related to natural and environmental management[8,9]. Multi-criteria decision making techniques can be used to make the process more explicit, rational and efficient. For such evaluation, AHP is used to determine the weights of each individual characteristic. Determination of weights in AHP depends on the pair-wise rank matrix which was developed based on expert opinion[10]. Systematic decision making process

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helps the decision maker to summarize and evaluate information effectively, define the right questions and determine the optimum and most appropriate solutions. The AHP method was applied to derive the weights of parameters because of its simple hierarchical structure, sound mathematical basis, widespread usage and its ability to measure inconsistencies in judgments[3,4,11].

The potential of GIS for disease mapping and risk zonation studies has been proven by several authors when it is integrated with AHP[12,13]. Nakhapakorn and Tripathi performed a study to explore the influence of physical environment factors on dengue incidence in Sukhotai Province, Thailand using the information value method which shows that a built up area has the maximum influence on the incidence of dengue compared to other land-cover of land-uses classes[5]. Rakotomanana *et al*. carried out a study using the multi-criteria evaluation method of weighted linear combination technique with GIS to determine risk zones from the malaria epidemic in the central highlands of Madagascar[14]. Kumar *et al*. used the pair-wise comparison method developed by integrating AHP and GIS based methods to develop the first volume of the Atlas which looks at the spatial distribution of 5 natural hazards (flood, landslide, wind speed, heat and seismic hazards)[15]. Faisal *et al*. used AHP methods to establish and optimize health case waste management systems[16]. Demesouka *et al*. adopted a map-based, interactive AHP implementation, which provided support in terms of methodology with exploratory geographic visualization[17].

Previously, most studies employed GIS and high resolution satellite images to model DF risk by predicting the risk based on a limited number of variables such as mosquito counts. Alternatively, environmental variables would be integrated with DF incidence or with mosquito counts. Such technique has it's limitation and for this reason, we propose the use of multiple variables (*i.e.* confirmed DF cases, population densities, micro-land-use and elevation) to formulate DF risk zones. This study assesses the correlation of DF risk with environmental factors and analyzes the dynamic of DF cases. With those references, this study aims to use environmental variables to develop a DF risk zonation in Subang Jaya using AHP in GIS.

2. Materials and methods

2.1. Study design

Criteria and indicators were evaluated by applying GIS techniques coupled with physical-environment and demographic factors in association with DF incidence locations.

2.2. Determination of preliminary list of criteria

Previous researchers used several factors to analyze the influence of DF incidence such as physical environment, land cover types, location of DF affected, climate factors and population data[5,18-22]. Satellite images and environmental and epidemiological data were also frequently used[23,24]. In tandem, the following physical environment factors were considered in this study (Figure 1).

Data for DF cases were obtained from 2006 to 2010 in order to formulate buffers of specific sizes, affected by DF cases. This buffer was used to identify the geographic environmental conditions such as land-use, water bodies and surrounding conditions of the areas. The buffer distance was considered due to the flight distance factors covered during the lifespan of *Aedes mosquitoes*[25]. The average lifespan of the female mosquitoes is about 8–15 days and it can fly at an average speed of 30–50 m per day. This indicated in general that the female mosquitoes are capable to move about a range of 240–600 m in their life time[26,27].

The land-use map had been used in this study to determine area activities and socio-economic status (residential/housing types). There were various types of land-use classes in the Subang Jaya Municipality including residential, industrial, commercial area, cleared land, dumping site, forest and others. A housing type of classification was used whereby; the house class was been given an attribute based on the possibility and potential of the dengue disease transmission and distribution with the types of houses. Classes of houses were based on the estimation of the level potential of the dengue transmission and the distribution for each houses class. It was important to consider commercial areas as an attribute due to the real situation in the ground where it was found that for some areas, residential houses were located in the same building as the commercial shop. Then, the housing types were classified as interconnection houses, mix houses, independent houses, commercial area and none residential area.

Subang Jaya area had variable topography. Elevation was considered to reflect its influence in risk zonation. Elevation data were created using the Shuttle Radar Topography Mission data collected from the Malaysian Remote Sensing Agency. Annual population data in each locality in Subang Jaya for the period of 2006–2010 were obtained from the Department of Statistics. The data included a variety of population characteristics including educational level.

2.3. The AHP

AHP is a multiple decision making tool which was used in this study to evaluate the environmental assessment towards developing dengue susceptibility risk map based on environmental characteristics. The first step in the AHP methodology was to break down the decision problem into a hierarchy of interrelated decision elements (*i.e.*, to define a goal and identify criteria and sub criteria relevant to identify DF risk zone areas). A hierarchical structure was established to interrelate and chain all decision elements of the hierarchy from the top level down[8,28]. The main objective (DF risk zones) was placed at the top of the hierarchical structure. The lower level of the hierarchical structure consisted of more detailed elements, which interrelated to the criteria in the next higher level. The hierarchical structure of the decision tree was presented in Figure 2.

After the hierarchical structure was established, the relative importance of all decision elements was captured and revealed through pair wise-comparison by creating a ratio matrix. Pair-wise comparisons of the main and the sub-criteria within the same hierarchical level were established. The numerical scales as proposed by Saaty and Vargas ranging from 1 to 9 were used in the pair-wise comparison matrices (Table 1)[29]. AHP was introduced as the most appropriate method because it allowed partitioning the problem and focusing on smaller decision sets one at the time.

Following this, a weighted linear combination (WLC) method, which was one of the most often used techniques for tracking spatial multi-attribute decision making was applied to identify specific DF risk zonation[30]. The method of WLC was used to assess the

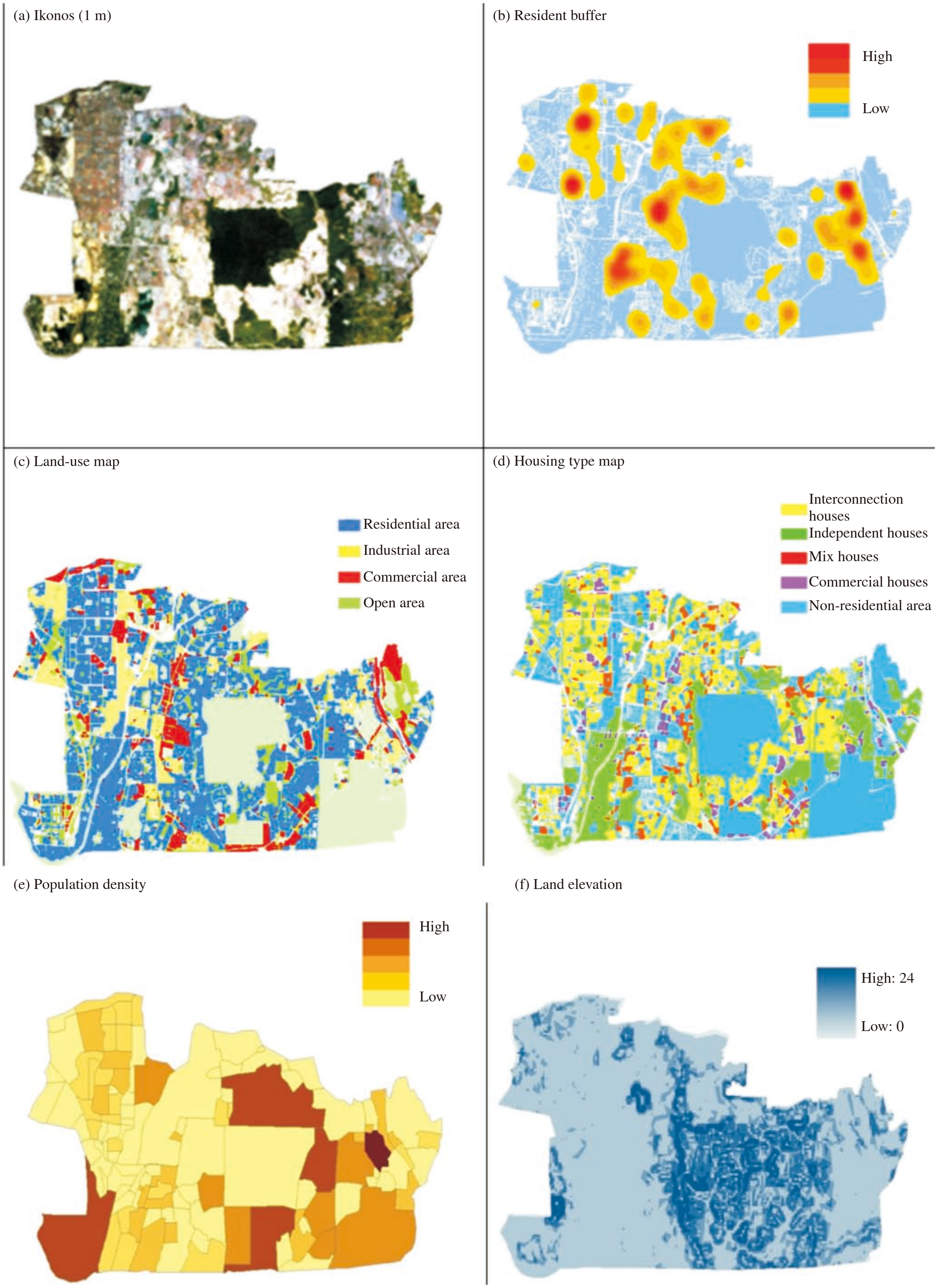


Figure 1. Factors considered in the DF analysis composed of five sub-factors that interacted with each other's.

Table 1

Scales for pair-wise comparison.

Variables	Verbal terms	Explanation
1	Equally importance	Two elements had equal importance regarding the element in higher level
3	Moderate importance	Experience or judgement slightly favored one element
5	Strong importance	Experience or judgement strongly favored one element
7	Very strong importance	Dominance of one element proved in practise
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation
2,4,6,8	Intermediate values between adjacent scales values	Compromise was needed

weighting for factors and to map the risk in the various zones, based on the concept of the weighted average, where the relative weights were assigned to each attribute[14]. The weight of each main-criterion was multiplied by the weights of the sub-criteria within the same hierarchical level and aggregated to determine the total scores with respect to each criterion, using following formula presented below:

$$w_i^S = \sum_{j=1}^{j=m} w_{ij}^S w_j^a \quad \text{(Equation 1)}$$

where, w_i^S is the total weight of the criteria i; w_{ij}^S and w_j^a are vectors of priorities of the main criteria and sub-criteria respectively, m is the number of criteria and *j* criterion is equally or more important than the other criterion. Consequently, the consistency ratio (CR) values of all comparisons were calculated by the methodology proposed by Saaty and Vargas[29].

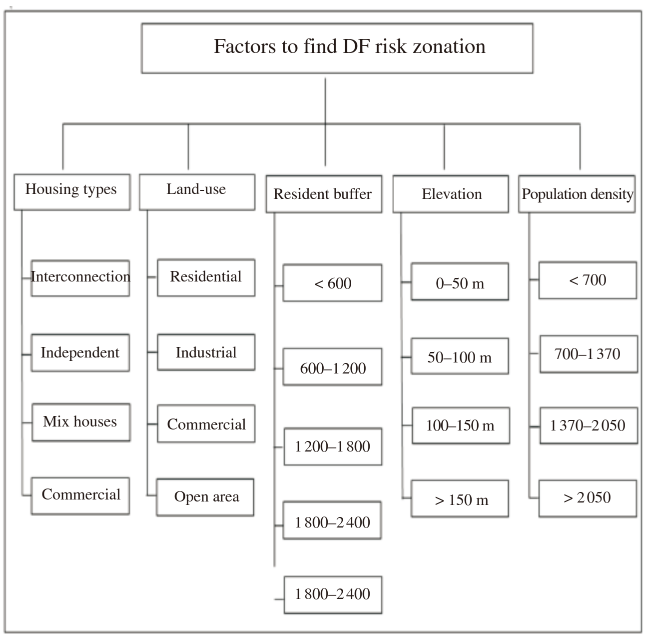


Figure 2. Decision tree for determining the main and sub-criteria for DF risk zonation.

Subsequently, the risk zone based on environmental characteristics was created using 19 input maps as decision factors layers. All vector maps associated with the selected main criteria and sub-criteria were converted to raster map. Each raster was then re-classified for all criteria and sub-criteria values. In order to generate the dengue risk zonation areas, the normalized weights of the main criteria were multiplied with the normalized weights of the sub-criteria to generate output layer by using the following formula stated in Equation 2 which was modified from Equation 1.

$$\text{DRZM} = \frac{\sum (F_{HT}C_I + F_{LU}C_I + F_{RB}C_I + F_E C_I + F_{PD}C_I)}{\sum w_I} \quad \text{(Equation 2)}$$

where, DRZM is dengue risk zone model, *F* is a factor weight of housing types (*HT*), land-use (*LU*), resident buffer (*RB*), elevation (*E*) and population density (*PD*), C_I is a class weight of sub-criteria and w_I is a total weight of the main criteria.

These multiple layer was merged to a single layer using union operation to perform dengue risk zone index layer. The above process was performed by overlay analyses in GIS environment. The integration of the GIS and AHP was performed by using the AHP extension in the Arc GIS 9.3.

3. Results

In the process of developing dengue risk zonation in Subang Jaya, 19 factors were classified into five types according to the nature and roles in the decision making process were identified. All factors were clustered according to their domain of influence, namely, land-use, housing types, dengue buffers, land-elevation and population density. Table 2 depicts the 21 criteria which were assigned by different rating on the scale: 1 (low relationship towards dengue outbreak) to 7 (high relationship towards dengue outbreak) according to comprehensive analysis of the local data.

Table 2

Decision factors and rating used to generate input layers in the analyses.

Decision factors		Rating	References
Housing types	Mix houses	1	[19,31-33]
	Commercial houses	2	
	Independent houses	4	
	Interconnection houses	7	
Land-use	Open area	1	[5,30,31,34]
	Commercial area	3	
	Industrial area	2	
	Residential area	7	
Resident buffering	< 600 m	1	[26,29,35]
	600–1 200 m	2	
	1 200–1 800	3	
	1 800–2 400 m	4	
	> 2 400 m	6	
Elevation	0–50 m	1	[32,34,36]
	50–100 m	3	
	100–150 m	2	
	> 150 m	2	
Population density	< 700	1	[27,36-38]
	700–1 370	3	
	1 370–2 050	4	
	> 2 050	7	

By using the approach of pair-wise comparison, AHP provided a way for calibrating a numerical scale, particularly in new areas where measurements and quantitative comparison did not exist[29,39]. The pair-wise comparison matrices for all criteria along with weights were calculated. The pair-wise comparison elements were decided in consultation with expert and field knowledge. The advised scores for each element in important Saaty and Vargas's scale were applied in the matrix. The weight of all factors group and criteria obtained after evaluation were summarized in Tables 3–7 along with the values of consistency index (CI) and CR values. The value of CR for sub-criteria of location of DF affected area (resident buffer), land-use, housing types, elevation and population densities were 0.04, 0.09, 0.07, 0.06 and 0.07 respectively. Based on the result obtained, the CR was less than 0.1 which indicated that the calculated values were in acceptable range.

Table 3
Pair-wise comparison elements and weight of residential buffer.

	< 600	600–1 200	1 200–1 800	1 800–2 400	> 2 400	Normalized weight	Consistency measures
< 600	1.00	2.00	3.00	4.00	6.00	0.4424	5.049
600–1200	0.50	1.00	2.00	2.00	3.00	0.2345	5.044
1200–1800	0.33	0.50	1.00	1.00	2.00	0.1324	5.053
1800–2400	0.25	0.50	1.00	1.00	1.00	0.1096	5.028
> 2400	0.16	0.33	0.50	1.00	1.00	0.0811	5.038

CI = 0.04; CR = 0.04 (CR and CI of 0.1 or below was considered acceptable)[30].

Table 4
Pair-wise comparison elements and weight of land-use.

	Open area	Commercial area	Industrial area	Residential area	Normalized weight	Consistency measures
Open area	1.00	0.33	0.50	0.14	0.0769	4.000
Commercial area	3.00	1.00	1.50	0.43	0.2308	4.000
Industrial area	2.00	0.67	1.00	0.29	0.1538	4.000
Residential area	7.00	2.33	3.50	1.00	0.5385	4.000

CI = 0.06; CR = 0.09 (CR and CI of 0.1 or below was considered acceptable)[30].

Table 5
Pair-wise comparison elements and weight of housing types.

	Mix houses	Commercial houses	Independent houses	Independent houses	Normalized weight	Consistency measures
Mix houses	1.00	0.50	0.25	0.14	0.0871	3.6813
Commercial houses	2.00	1.00	1.00	0.29	0.2054	3.7950
Independent houses	4.00	1.00	1.00	0.57	0.2768	3.8894
Interconnection houses	7.00	1.00	1.75	1.00	0.4308	4.0155

CI = 0.06; CR = 0.07 (CR and CI of 0.1 or below was considered acceptable)[30].

Table 6
Pair-wise comparison elements and weight of elevation.

	0–50 m	5–100 m	100–150 m	> 150 m	Normalized weight	Consistency measures
0–50 m	1.00	3.00	2.00	2.00	0.3209	4.651
50–100 m	0.33	1.00	2.00	2.00	0.2137	4.443
100–150 m	0.50	0.50	1.00	2.00	0.1667	4.426
> 150 m	0.50	0.33	0.50	1.00	0.0980	4.197

CI = 0.05; CR = 0.06 (CR and CI of 0.1 or below was considered acceptable)[30].

Table 7
Pair-wise comparison elements and weight of population density.

	< 700	700–1370	1370–2050	2050–2720	Normalized weight	Consistency measures
< 700	1.00	0.33	0.25	0.14	0.0517	4.014
700–1370	3.00	1.00	0.50	0.33	0.1320	4.001
1370–2050	4.00	2.00	1.00	0.50	0.2204	4.033
2050–2720	7.00	3.00	2.00	1.00	0.3959	4.023

CI = 0.06; CR = 0.07 (CR and CI of 0.1 or below was considered acceptable)[30].

From the pair-wise comparison analysis, the DF incidence was highest in interconnection houses and in residential areas, analysis of land-use type indicated that residential area provided greatest risk of DF. Similarly, high levels of DF were also found in the buffer zone of 600 m around the affected residential areas. Elevation map was developed in order to characterize the locality based on elevation. It was found that the highest risk of DF was in area with less than 100 m elevation.

The results obtained from the preliminary analysis of all factor groups and criteria after evaluation were summarized in Table 8. The most striking result to emerge from the data was that the significant factors were housing types, population density, land-use, residential buffer and elevation respectively. The high levels of DF were found in the interconnection houses. The result indicated that each factor group had their own role in enhancing dengue transmission. The CR values that were lower than 0.1 indicated that the use of weights was suitable parameters. Finally, the dengue risk map for the environmental criteria was derived by following the weighted linear combination method.

Table 8
Weights of all decision processes.

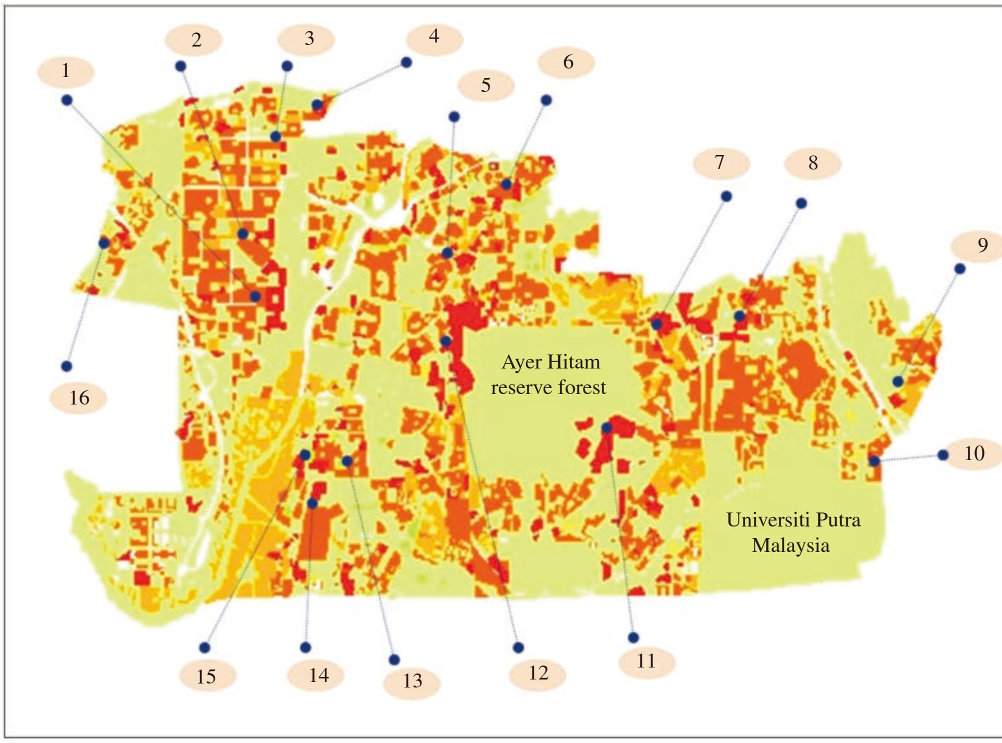
Factor groups	Weight	Criteria	Weight
Housing types	0.2996	Mix houses	0.0871
		Commercial houses	0.2054
		Independent houses	0.2768
		Interconnection houses	0.4308
Land-use	0.1498	Open area	0.0769
		Commercial area	0.2308
		Industrial area	0.1538
		Residential area	0.5385
Residential buffer	0.1498	< 600 m	0.4424
		600–1200 m	0.2345
		1200–1800 m	0.1324
		1800–2400 m	0.1096
		> 2400 m	0.0811
Elevation	0.1344	0 to 50 m	0.3209
		50 to 100 m	0.2137
		100 to 150 m	0.1667
		> 150 m	0.0980
Population density	0.2663	< 700	0.0517
		700 to 1370	0.1320
		1370 to 2050	0.2204
		2050–2720	0.3959

CI = 0.05; CR = 0.06.

From the DF risk zones map (Figure 3) generated, it was found that most of the high risk areas were found circulating all areas in Subang Jaya and most likely influenced by the environmental condition, related to the ecology of *Aedes mosquitoes*. Strong evidence of DF risk zones was found when a total of 16 localities showed a high risk in terms of their incidence rate per 1 000 population (Table 9).

Table 9
Intensity of DF incidence of priority localities generated from AHP.

ID	Localities	No. of accumulated DF cases	Population density	Incidence rate/1000 person
1.	USJ 11	210	14 165	14.82
2.	USJ 6	67	11 560	5.79
3.	PJS 7	157	6 040	25.99
4.	PJS 9	207	4 325	47.86
5.	Taman Puchong Jaya	128	55 095	2.32
6.	Taman Kinrara	197	40 045	4.92
7.	Taman Serdang Jaya	95	18 190	5.22
8.	Taman Serdang Raya	103	13 120	7.85
9.	Taman Sg Besi Indah	135	8 295	16.27
10.	Taman Seri Serdang	89	14 360	6.20
11.	Taman Universiti Indah	85	14 330	5.93
12.	Bandar Puteri	91	23 770	3.82
13.	Taman Puchong Perdana	216	19 296	11.19
14.	Taman Puchong Indah	77	9 430	8.17
15.	Kampung Batu 13	146	9 734	14.99
16.	Taman Batu 3	32	2 809	11.39



Priority area classification based on DRZM

LID	Name of localities
1	USJ 11
2	USJ 6
3	PJS 7
4	PJS 9
5	Taman Puchong Jaya
6	Taman Kinrara
7	Taman Serdang Jaya
8	Taman Serdang Raya
9	Taman Sg Besi Indah
10	Taman Seri Serdang
11	Taman Universiti Indah
12	Bandar Puteri
13	Taman Puchong Perdana
14	Taman Puchong Indah
15	Kampung Batu 13
16	Taman Batu 3

Figure 3. Dengue risk zones (model 1) based on environmental characteristic in Subang Jaya, Malaysia.
LID: Localities identity.

4. Discussion

Many studies have noted that environmental parameter is one of the contributing factors in dengue transmission and distribution. The impact of environmental parameters on the transmission pattern of DF can be both direct and indirect exposure. A direct impact may describe the changes of environmental condition which influences the trend of the dengue transmission and distribution pattern. There are several examples of environmental parameters which give indirect impacts to the trend of dengue transmission and its distribution such as human population dynamics and their effects on exposure risk and other landscape features.

This study produced results which corroborates the findings of previous work in this field. AHP techniques were applied in assessing the risk areas of DF. AHP has gained wide popularity and acceptance in GIS analysis for its robustness in the allocation of stable weight using pair-wise comparison. The CR was 0.031 which is less than 0.1 and hence acceptable. These weights were used in a WLC method to develop DRZM for Subang Jaya. The main advantage of the AHP is its ability to rank choices in the order of their effectiveness in meeting conflicting objectives. It is interesting to note that the analysis of the physical-environment factors such as land-use types and housing types with the DF incidence can be utilized to identify the relationship between built-up areas and risk zones, and thus define the causes behind the prevalence of this disease.

The overall model of DF risk in Subang Jaya, based on the combination of multiple variables using AHP showed that the risk area was mostly confined to the area where there is a high population density, high building density and low neighbourhood quality. This finding is in agreement with several studies, which stated that DF risk cases were increase in high population density and high concentration of dwellings[3,4,40-43]. Similar results were also found by Siqueira-Junior *et al.* who stated that people from low socio-economic background are more affected and at a greater risk of contracting DF[42]. It can thus be suggested that any future population increase will be associated with increased DF risk in areas which already accommodate this disease environmentally, climatically and socioeconomically. Future risk could be modelled using the same methods. This would help decision maker in choosing which areas should be under intensive treatment to counter mosquito breeding and be reduce the prevalence of DF.

In managing an effective dengue control program, it is necessary to assess the population at risk, vector ecology and the virus surveillance of the area. The concept of epidemiological triangle of disease is well known by public health practitioners. The host, agent and environment need to co-exist in order to facilitate disease transmission. In the absence of any of these three elements, the transmission cannot be taken place.

As it relates to dengue transmission, the host is human, the agent is the dengue virus and the environment is represented by the vectors and climatic parameters. All three elements are required for the transmission of dengue which are presented in Subang Jaya on a permanent basis and for that reason, the disease has become periodically. The main dengue vector in Subang Jaya are *Aedes aegypti* and *Aedes albopictus* mosquito. Since the environmental conditions (temperature, humidity, rainfall and altitude) are within the ideal ranges in all localities, therefore the entire area in Subang Jaya is likely to be at risk of dengue transmission. The level of risk is determined more by life style and socioeconomic condition of the communities than by geographical location[44].

The ability to accurately predict local and regional DF outbreaks has rapidly improved due to advances in technology. This has allowed a better understanding of the interaction between spatial and the temporal distribution of DF as well as stimulating research interest on epidemic prediction modelling. The present system of prediction of dengue outbreak relies on the use of various entomological indices such as the house (premises) index, the Breteau index, *etc*. However, it has been observed that these indices may not be suitable for outbreak prediction due to the absence of epidemiological component in the process. As systematic mosquito data were not available in the study area, this study explored the development of a dengue forecasting model based on the environmental and epidemiological variables.

In addition, GIS and spatial temporal modelling method can display and model the spatial relationship between cases and disease. Spatial temporal modelling can help us to understand the distribution of dengue outbreaks in space and time due to the powerful application of GIS technology to superimpose the temporal and spatial distributions based on ecological determinants such as landscape ecology, climate, vector population and human presence and activity. Improved surveillance coordination for dengue control activity, such as the issue of timing for control strategies, can lead to an integrated management model for public health intervention based on a sound ecological understanding of the disease. Endemic area of DF/dengue hemorrhagic fever would expand in both time (length of season) and space (geographic area) under socio-environmental condition (*e.g.* optimal climate, inadequate urban planning, ecosystem change *etc*.).

Conflict of interest statement

We declare that we have no conflict of interest.

Acknowledgments

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