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Assessing the risk for dengue fever based on socioeconomic and environmental variables in a geographical information system environment

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Abstract. An important option in preventing the spread of dengue fever (DF) is to control and monitor its vector (*Aedes aegypti*) as well as to locate and destroy suitable mosquito breeding environments. The aim of the present study was to use a combination of environmental and socioeconomic variables to model areas at risk of DF. These variables include clinically confirmed DF cases, mosquito counts, population density in inhabited areas, total populations per district, water access, neighbourhood quality and the spatio-temporal risk of DF based on the average, weekly frequency of DF incidence. Out of 111 districts investigated, 17 (15%), covering a total area of 121 km², were identified as of high risk, 25 (22%), covering 133 km², were identified as of medium risk, 18 (16%), covering 180 km², were identified as of low risk and 51 (46%), covering 726 km², were identified as of very low risk. The resultant model shows that most areas at risk of DF were concentrated in the central part of Jeddah county, Saudi Arabia. The methods used can be implemented as routine procedures for control and prevention. A concerted intervention in the medium- and high-risk level districts identified in this study could be highly effective in reducing transmission of DF in the area as a whole.

Keywords: *Aedes aegypti*, dengue fever, environmental and socioeconomic risk factors, geographical information system, Saudi Arabia.

Introduction

With no drug or vaccination to stop the spread and danger of dengue fever (DF), the major option for prevention is to control and monitor its vector (*Aedes aegypti*) by focusing on localisation and destruction of suitable breeding environments. To better understand DF distribution in terms of time and space (Ward, 2007), it is important to develop spatial databases, apply spatial statistics (Eisen and Lozano-Fuentes, 2009) and to link this information with environmental, climatic, entomological and socioeconomic factors for a given area. Geographical information systems (GIS) and high-resolution satellite imagery are useful for collecting data for the study of factors affecting DF and its vector distribution in areas where millions of people are at risk of contracting DF (Keiser et al., 2004, Srivastava et al., 2009; Khormi and Kumar, 2011a).

GIS has been used to visualize and identify spatial heterogeneity of DF in risk by short-time interval spatial approaches (e.g. Siqueira-Junior et al., 2008), using household surveys, spatial point pattern analysis and risk factor assessments, demonstrating that low-prevalence areas can easily shift to high-risk areas from one year to the next. GIS and statistical methods can play an important role in formulating control activities, assessing changes in transmission over time and determining resources to control prevalence, particularly in areas of high or persistent transmission (Allen and Wong, 2006; Bautista et al., 2006; Achu, 2008; Bhandari et al., 2008).

Most previous studies employed GIS and high-resolution satellite images to model DF risk, predicting risk based on a limited number of variables such as mosquito counts only, or alternatively two such as environmental variables either integrated with DF incidence or with mosquito counts. In contrast, we used multiple variables, i.e. clinically confirmed DF cases, mosquito counts, population densities in inhabited areas, population per district, neighbourhood quality, role of subsurface water, and estimating the monthly spatio-temporal risk of infection based on average weekly frequency. We have previously modelled DF risk based on mosquito counts and clinically

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confirmed DF cases using socioeconomic factors (Khormi and Kumar, 2011b) or a frequency index of DF cases (Khormi et al., 2011b). In this study, we pioneered using all these variables together in a global model. Our main aim was to develop a system where current DF and *A. aegypti* data can be used to assess current risk areas correlating mosquito counts and DF cases with environmental and socioeconomic parameters. The emphasis is thus more on current risk and less on future developments.

Materials and methods

Study site

The study was conducted in Jeddah county, Saudi Arabia, centred on latitude 21°32'33" N and longitude 39°10'22" E, and located on the coast of the Red Sea. Jeddah is home to about 3.5 million people, consists of 12 sub-municipalities and 111 districts and covers approximately 1,100 km^2. The study area (Figs. 1-3) contains the locally highest incidence of mortality and morbidity due to DF.

Data sources

From 2006 to 2010, the Jeddah municipality acquired daily adult *Aedes* mosquito samples by means of black hole traps, distributed based on population density and various environmental factors as described earlier (Khormi et al., 2011b). Clinically confirmed DF case registries have been collected systemically since 2006 by the Dengue Fever Operation Room of Jeddah Health Affairs and by the Jeddah municipality. Weekly case notifications, including district and coordinates, age, sex, nationality and day of disease onset for each case were provided.

Annual population data for each district in each sub-municipality of Jeddah was obtained from the Central Department of Statistics and Information. Data regarding the differences in population characteristics included the number of Saudi and expatriate residents in each district, as well as the numbers of males and females. A map of the different levels of subsurface water in Jeddah, with the associated risk for each level, was provided by the Saudi Geological Survey. SPOT satellite (http://en.wikipedia.org/wiki/SPOT_(satellite) images of the study area for 2010 (2.5 m spatial resolution), obtained from King Abdul-Aziz City of Science and Technology, were digitized and used to demarcate the inhabited areas in each district as a proxy indicator for accurate population density and neighbourhood quality in all Jeddah districts (Khormi and Kumar, 2011b).

Data analysis

In this study, we used all the techniques and variables published earlier (Khormi and Kumar, 2011b; Khormi et al., 2011b) to analyze the data with the overall aim to create a DF model covering all aspects of interest for controlling the disease. We used Getis-Ord Gi* statistics to model the annual hotspots for the human cases and the *A. aegypti* vector (Khormi et al., 2011b). A matrix containing the name of each district and its level of risk was created using the results of the hotspot analysis, the relationships modelled between socioeconomic factors (neighbourhood quality, total population per district and population density), the DF cases (Khormi and Kumar, 2011b), the monthly spatio-temporal risk (Khormi et al., 2011b), and the risk due to the depths of subsurface water wells. Each level of risk was assigned a different class, ranging from 1 to 3 (low to high). Average risk levels were calculated for each district by adding the risk level for each category for each district and then dividing by the total number of risk factors (i.e. 5) (Table 1). Each risk category was given the same weight. The average risk level results ranged from 1 to 12. We assigned districts that had a total average from 1 to 3 (inclusive) as of very low risk, from 3-6 as of low risk, from 6-9 as of medium risk and from 9-12 as of high risk.

Results

Spatial patterns of DF

Areas with various risk levels were identified in different geographic locations (districts) for the different epidemics (years) using Getis-Ord Gi* (Fig. 2). The districts depicted with dark and light red shades were found to comprise high and medium spatial clusters with high and medium risk levels, respectively. The DF spatial patterns were similar over most of the study period, especially in the high-risk areas in the old Jeddah districts (Fig. 2) except in 2007, when the risk decreased in those areas and the high-risk zone shifted to districts north of Jeddah, such as Al Safa. The hotspot areas, classified into four classes according to the level of risk, showed high risk with around 654 recorded cases (z-scores 3-6) in 14% (67 km^2) of Jeddah districts in 2006. Medium risk level was identified in 11% (80 km^2) of the districts with around 207 recorded cases, low risk in 16% (174 km^2) with

Table 1. Example of the simple matrix used for modeling dengue fever based on multiple variables (only five of the 111 Jeddah districts are shown).

District	Level of *Aedes aegypti* risk						Level of dengue fever risk					
	2006	2007	2008	2009	2010	Average	2006	2007	2008	2009	2010	Average
Al Andulus	0	3	3	2	3	2.2	0	0	0	0	1	0.2
Al Azizeyyah	1	2	2	3	2	2	1	3	1	2	2	1.8
Al Rehab	0	0	1	2	1	0.8	0	3	1	2	2	1.6
Al Hamrah	1	3	3	2	3	2.4	0	1	1	1	1	0.8
Me Shrefah	1	2	3	1	3	2	1	2	1	2	2	1.6

District	Monthly level of spatio-temporal risk													SW*	RSDF**	Total average
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average			
Al Andulus	0	1	0	1	0	0	0	0	1	2	1	0	0.6	3	1	7.0
Al Azizeyyah	3	3	3	2	2	2	2	3	3	3	3	3	2.6	2	3	11.4
Al Rehab	2	1	2	2	1	1	1	2	2	1	3	3	1.8	2	2	8.2
Al Hamrah	0	1	1	2	1	1	1	1	3	2	2	2	1.7	3	1	8.9
Me Shrefah	1	2	2	2	2	2	1	2	3	2	3	3	2.2	2	2	9.8

*Sub-surface water risk level; **Risk level based on association between socioeconomic factors and dengue fever.

around 214 cases and very low risk in 59% (839 km^2) with a total of 80 cases. In 2007, the percentage of areas at high risk decreased to 5% (54 km^2) with a total of 118 cases (z-scores 3-5), medium risk level in 31% (163 km^2) with around 244 cases, low risk levels in 17% (204 km^2) of the districts with around 85 cases, while only 20 cases were recorded in 47% (737 km^2) of the districts classified as very low risk.

Areas with a low risk for DF had a low mean population density (2,107 per km^2), while areas of medium risk had a medium mean population density (12,880 per km^2) and areas of high risk had the highest mean population density (19,728). The ratio between Saudi and expatriate population was found to be 65% to 35% in the low-risk areas, 49%-51% in the areas of medium risk, it was 47%-53% in areas of high risk.

Vector abundance

From 2006 to 2008, most of the districts that had high DF risk levels were identified as of medium risk with respect to *A. aegypti* abundance, while districts with medium DF risk levels were identified as of high-risk for mosquito abundance, especially in the central districts of Jeddah (Fig. 2). In 2009 and 2010, new high-risk districts with respect to the vector were detected in some parts of the study area for the first time since 2006, especially in the eastern and northern parts of old Jeddah districts.

Subsurface water

Forty-seven percent of the Jeddah districts were classified as of low risk (≥5 m) with respect to the distance down to the water surface, 18% as of medium risk (2.5-5 m), and 35% as of high risk (≤2.5 m). Most of the high-risk districts were concentrated along the coast of the Red Sea, and a few were in some districts in the eastern part of Jeddah (Fig. 3) due to the presence of Al Musk Lake, the place where all the sewage water from Jeddah is dumped (Haddad, 2009).

DF risk

Based on a combination of environmental and socioeconomic variables, such as DF cases, mosquitoes capture, population, population density, neighbourhood quality, monthly spatio-temporal of DF incidence and the depth of subsurface water levels, a model of DF risk was developed (Fig. 4). Most of the high-risk areas were found in the central part of Jeddah. Out of 111 districts investigated, 17 (15%) with a total area of 121 km^2 were identified as of high risk, 25 (22%) with a total area of 133 km^2 were identified as of medium risk, 18 (16%) with a total area of 180 km^2 were identified as of low risk and 51 (46%) with a total area of 726 km^2 were identified as of very low risk (Fig. 4). DF risks, ranging from low to high, were identified in all of the districts in many sub-municipalities (Khuzam, Al Balad, Al Jameah, Al Azizeyyah, Al Sharafyah, Al Matar and

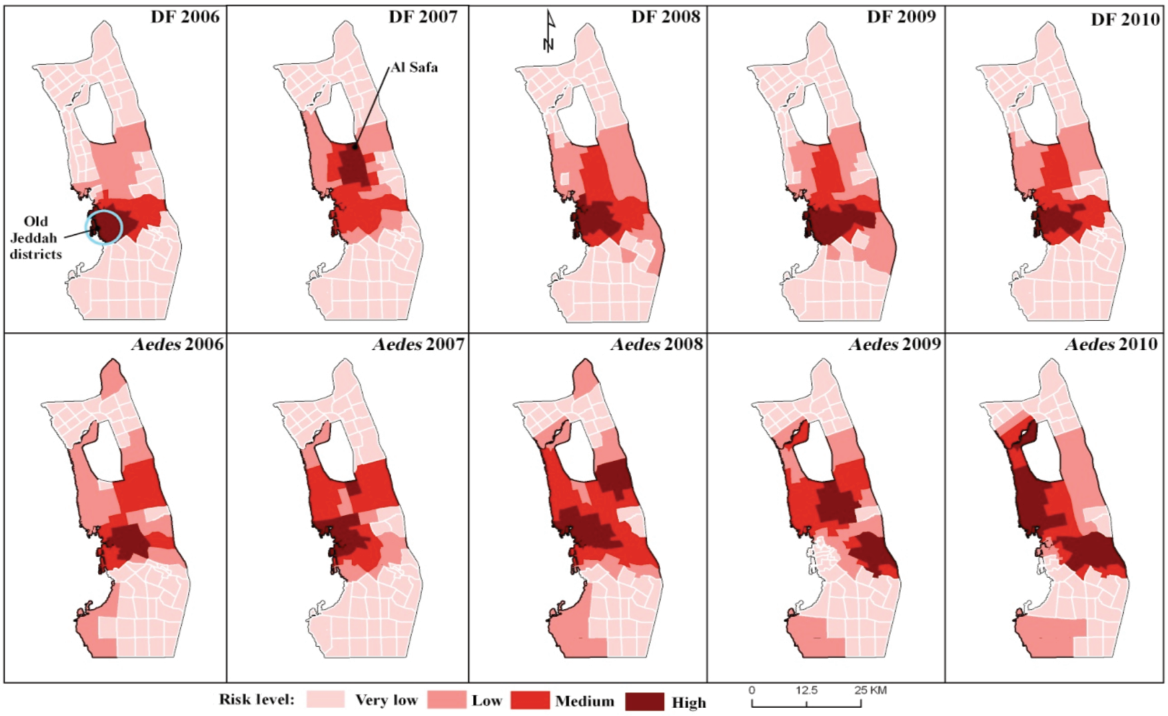

Fig. 1. Model of hotspots and risk levels based on recorded cases of dengue fever and captured *Aedes* mosquitoes.

Jeddah Al Jadeedah). For example, Khuzam (32 km²) has eight districts: 12% of low risk, 38% of medium risk and 50% of high risk, whereas Al Balad (18 km²) has eight districts: 62% of them medium-risk areas and 38% high-risk areas. On the other hand, the overall risk was clearly lower in other neighbourhoods, e.g. in Um Asalam where it was high in only 16% of the districts, medium in 16% low in 16% and very low in 50%. Obhur had an even better situation with no high risk districts, 40% of low risk and 60% of very low risk, while Buraiman had 7% of medium risk 14% of low and 79% of very low risk.

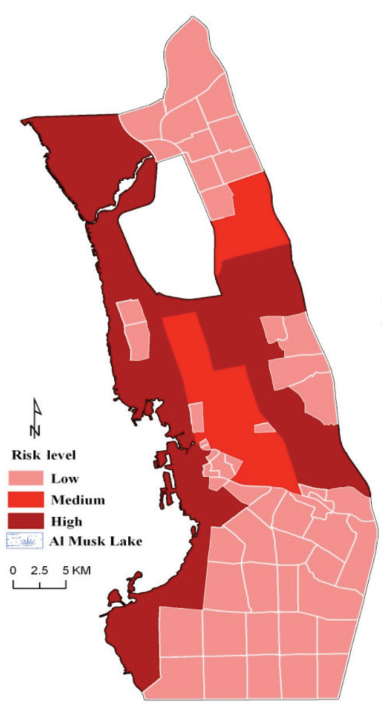

Fig. 2. Risk levels based on subsurface water in Jeddah districts, Saudi Arabia.

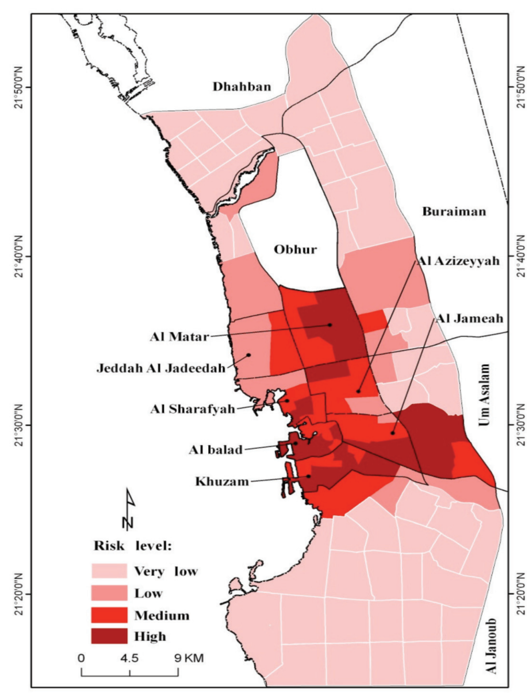

Fig. 3. Risk model for dengue fever based on a combination of environmental and socioeconomic variables.

Discussion

GIS and spatial statistics are valuable for modelling the risk for DF based on multiple variables since they visualize the association between socioeconomic factors and DF prevalence, explain the variance and predict the risk for DF transmission. The application of these tools improves our understanding of the monthly spatio-temporal risk, which provides the foundation for control management. This study integrated DF records with information on *A. aegypti* abundance and Jeddah districts identifying hotspots based on z-scores resulting from Getis-Ord Gi*, socioeconomic factors as described by Khormi and Kumar (2011b) and monthly spatio-temporal risks as shown by Khormi et al. (2011b).

From 2006 to 2008, the prevalence of DF and mosquito abundance was strongly associated. For example, most of the DF cases were recorded in the districts with high or medium risk levels with regard to the vector. However, in 2009 and 2010, most DF cases were identified in high-risk districts with low to very low mosquito abundance. There are several plausible explanations for the nearly simultaneous appearance of DF cases in those districts. First, teenagers and young adults (91% and 92% were between 15 and 60 years old in 2009 and 2010, respectively) were predominant among those infected. These people are highly mobile and are often outside their districts for work or visiting relatives and friends in districts with high *A. aegypti* densities. Second, most of the victims were expatriates, around 66% in 2009 and around 77% in 2010. Their wages are about four times lower than those of Saudis (Al Sahemey, 2011), forcing them to inhabit low-quality neighbourhoods, which favour mosquito breeding (Khormi and Kumar, 2011b) thus exposing them to a higher DF risk (Khormi and Kumar, 2011b).

The increase in hotspots and mosquito abundance observed was due to the high rainfall that fell in Jeddah during the winter season (November to January); around 90 mm in 2009 and 111 mm in 2010 as compared to around 50 mm recorded between 2006 and 2008. Higher rainfall not only creates hotbeds for *Aedes* reproduction, but also increases the vegetation index (Khormi et al., 2011a). It is well-known that high relative humidity with high temperatures and heavy rainfall has a positive impact on the survival and breeding conditions of mosquitoes (Kuno, 1997; Hales et al, 2002; Khormi et al., 2011a).

The overall model of DF risk level in Jeddah districts, based on the combination of multiple variables used here, shows that the hotspots and risk areas were mostly confined to the districts located between latitudes 21º 41´ 9.163˝ N and 21º 24´ 35.675˝ N (Fig. 4), where there is limited access to water, high population density high building density, and low neighbourhood quality. Several studies (Honório et al., 2003; Lagrotta et al., 2008; Siqueira-Junior et al., 2008; Khormi and Kumar, 2011b), found that *Aedes* mosquitoes and DF risk cases increase in areas with high human population density and high concentrations of dwellings. Similar results were also found by da Costa and Natal (1998), who stated that people from low socioeconomic backgrounds are more affected and at a greater risk of contracting DF.

A reasonable assumption is that population and population density directly influence the risk of DF outbreaks. The present study confirmed that DF is more prevalent in districts with predominant expatriate population, low neighbourhood quality and high population density, as compared to those characterized by a high percentage of Saudi population, better neighbourhood quality and lower population density.

Limited access to water supplies leads residents in districts of mainly low neighbourhood quality to store water in containers at ground level where it favours *Aedes* breeding. In a study of *A. aegypti* pupae in an area of Havana, Cuba, out of 1,000 samples, the immature stages of *Aedes* were found in 70 containers, and the pupae of this species were found in 52 containers (Bisset et al., 2006). Of these, 74.1% of the pupae were collected from ground-level water storage tanks, and 19% were found in miscellaneous small containers.

The model predicts that any future population increase, particularly of expatriates, 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-makers in choosing which areas should be under intensive treatment to counter mosquito breeding and reduce prevalence. However, future risk will depend on future developmental areas and changing environmental and socioeconomic conditions.

Conclusions

The models developed in the present study comprise a highly effective approach to DF control and prevention that can be utilized for control management and improved surveillance. The study resulted in the following conclusions and recommendations:

(i) The hotspot model based on annual data provides excellent overviews of high-impact areas by DF, while spatio-temporal risk modelling, based on monthly and weekly frequency indices, identifies rapid changes.

(ii) Risk models of DF, based on a combination of environmental and socioeconomic variables, can help to define the causes behind the prevalence of the disease.

(iii) Elimination of mosquito breeding sites and providing vulnerable populations with window screens, safe water containers and better access to water supplies are likely to lower DF transmission.

(iv) The overall model can be used by the decision makers in Jeddah municipality for prioritizing when carrying out the major infrastructure projects planned in Jeddah.

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