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Modeling spatio-temporal risk changes in the incidence of dengue fever in Saudi Arabia: a geographical information system case study

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Abstract. The aim of this study was to use geographical information systems to demonstrate the Dengue fever (DF) risk on a monthly basis in Jeddah, Saudi Arabia with the purpose to provide documentation serving to improve surveillance and monitor the *Aedes aegypti* mosquito vector. Getis-Ord Gi* statistics and a frequency index covering a five-year period (2006-2010) were used to map DF and model the risk spatio-temporally. The results show that monthly hotspots were mainly concentrated in central Jeddah districts and that the pattern changes considerably with time. For example, on a yearly basis, for the month of January, the Burman district was identified as a low risk area in 2006, a high-risk area in 2007, medium risk in 2008, very low risk in 2009 and low risk in 2010. The results demonstrate that it would be useful to follow the monthly DF pattern, based on the average weekly frequency, as this can facilitate the allocation of resources for the treatment of the disease, preventing its prevalence and monitoring its vector.

Keywords: Dengue fever, frequency index, Getis-Ord Gi , temporal risk, geographical information systems, Saudi Arabia.

Introduction

Dengue fever (DF) is a major public health issue around the tropical and subtropical part of the world that can cause significant morbidity and mortality (Kongsomboon et al., 2004). The infectious agent, belonging to the Flaviviridae group of RNA-viruses, exists as four serotypes (DEN 1, 2, 3 and 4) (Briseno Garcia et al., 1996; Fakeeh and Zaki, 2003). Its main vector is the *Aedes aegypti* mosquito (Gubler, 1997). In recent years, the incidence of DF infection has increased in Saudi Arabia, particularly in Jeddah. Over the past 5 years, approximately 8,000 people have been infected, and there is now a dire need to control and prevent the DF. However, since neither chemotherapy nor a vaccine exists, a different control strategy is required.

Health-related, spatial studies have been used to locate and define health catchment areas in Saudi Arabia, evaluating the demand and supply of health facilities. However, while the published literature indicates limited application of geographical information systems (GIS), remote sensing and spatial analysis for mosquito-borne diseases in the country, this approach should be useful with respect to DF epidemiology. These techniques can be used to spatio-temporally determine the endemic areas, including the hotspots, e.g. spatial analysis can estimate the risk for DF across affected areas and offer insight into the nature of DF disease clusters (Bithell, 1999). For example, kernel estimation was used to analyse the spatial pattern of DF and its biological vector in Rio de Janeiro (Lagrotta et al., 2008), and the results of this study demonstrated five specific areas of mosquito breeding sites characterised by high and medium density of the *Ae. aegypti* vector. The authors highlighted small clusters with high larval density and recommended this approach for DF surveillance. GIS and spatial analysis techniques have also been used to stratify a city for the occurrence of hyper-endemic dengue hemorrhagic fever DHF, to improve the application of surveillance and control measures (Barrera et al., 2000). In Thailand (Sukhothai province), Nakhapakorn and Jirakajohnkool (2006) applied autocorrelation statistics such as Moran's *I* to map local risk areas, showing how spatial patterns change from the past to the present, while Tipayamongggghholgul and Lisakulruk (2011) used the K-order nearest neighbour method to find social-geographical factors that influence the local vulnerability

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to DF. This study revealed a trend of increasing DF in rural areas subjected to increasing urban influence as compared to more remote areas. In general though, researchers who turned to GIS for the identification and visualization of disease clusters did not integrate both spatial and temporal techniques for producing accurate spatio-temporal map layers.

Mapping of DF hotspots, or patterns of uneven events, often ignore the temporal kinetics. As a result, without the temporal dimension, decision makers find it difficult to assess whether or not a dengue epidemic has broken out or how well existing DF transmission has been controlled. Earnest et al. (2005) and Zeger et al. (2006) used autoregressive integrated moving average (ARIMA) models to forecast the spread of uneven cases and predict incidence values, but this and other similar approaches had difficulties identifying the spatial risk. Wen et al. (2006) proposed a spatio-temporal risk approach to map uneven events based on temporally defined indices. In their study, three temporal risk indices were introduced and a local spatial auto-correlation index to identify areas at risk was proposed. However, the dataset collected was limited, covering a span of only 9 months, i.e. from April to December 2002. Galli and Neto (2008) used the approach pioneered by the previously mentioned authors to locate high-risk DF areas in southeastern Brazil. However, this study only involved annual classifications for at-risk areas.

The aim of the present study was to demonstrate the changing DF temporal risk based on monthly data for an unusually long period (from January 2006 to December 2010) with the view to provide documentation that could improve DF surveillance.

Materials and methods

Study site

The study was conducted in 111 districts (around 1,100 km²) in Jeddah county of Saudi Arabia (Fig. 1), located on the coast of the Red Sea in the western part of the country and home to about 3 million people. Jeddah is the most important commercial city and the main gateway to the two holiest cities in Islam (Mecca and Al Medina). According to Jeddah Health Affairs, this area contains the highest levels of DF mortality and morbidity in Saudi Arabia.

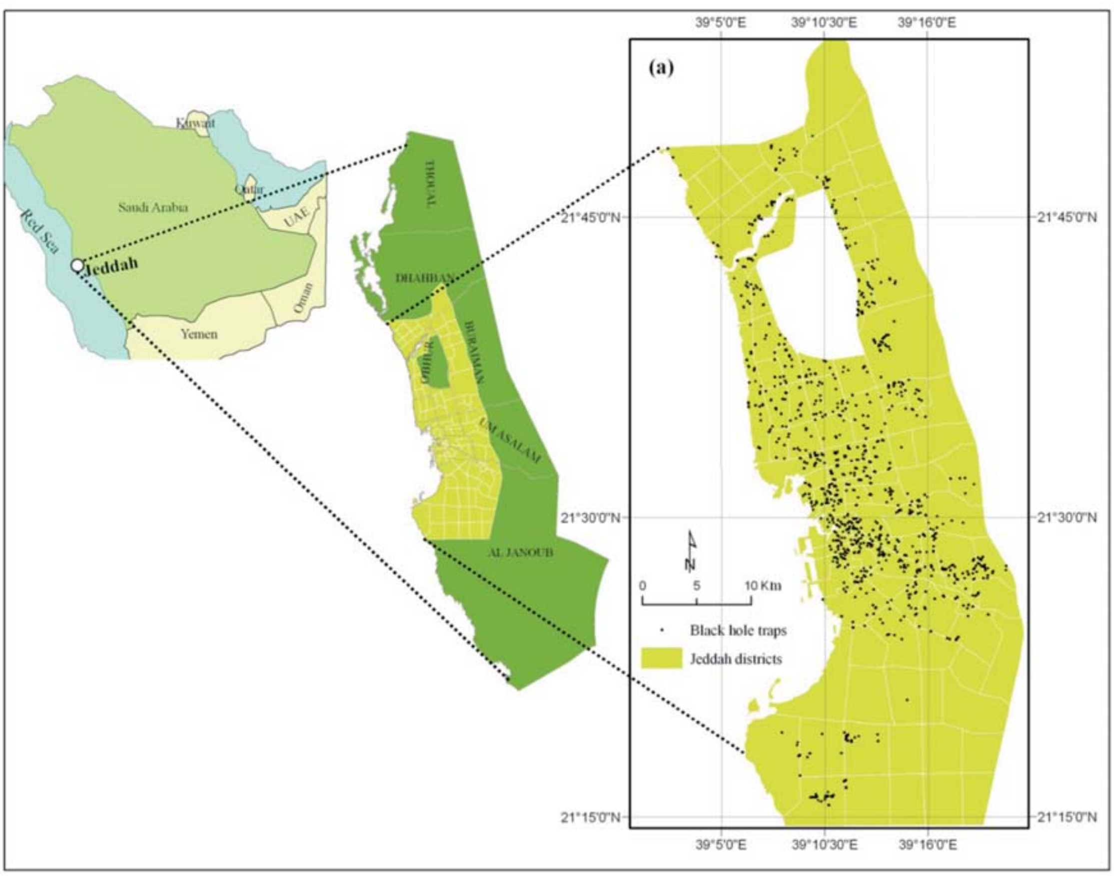

Fig. 1. Location of the study site with the positions (a) of the black hole traps.

Human data

The data on clinical cases of DF were obtained from the Jeddah Health Affairs department. The department keeps systemic records of confirmed cases of DF since 2006. These records include age, sex, nationality, district, coordinates and the week of disease onset for each case.

Entomological data

Daily mosquito samples for each district were acquired using 504 black hole traps, considered to be the most efficient for the study area (Aburas, 2007). These traps capture mosquitoes by producing carbon dioxide (CO_2) that significantly increases the collection rate of *Ae. aegypti* (Russell, 2004). The traps were returned to the mosquito laboratory for filtering and sorting according to species, sex, date of collection, location coordinates and number of mosquitoes for each place. Since only female *Ae. aegypti* mosquitoes can function as vector, this research and analysis are based on female specimens only. Identification and counting were done by the Jeddah Municipality mosquito laboratory. The black hole traps were distributed geographically based on population density and environmental factors (Fig. 1a). The study took place from January 2006 to December 2010, providing data over a 5-year period.

Data organization and analysis

To assess the frequency of transmission per month in each district, a frequency index (f) was adopted and calculated weekly, monthly and then yearly for each district. However, it was based on the number of cases recorded daily as follows: for one or more confirmed DF cases per day, the occurrence for that day would be 1, while it would be 0 if no cases were found (Giesecke, 2001, Wen et al., 2006). We defined the index as ED/TD, where ED is the total number of days in which one or more cases occurred during the period and TD is the total number of days during the period (TD). For example, if over one week, DF cases were reported on three days, the occurrence would be 3, resulting in a frequency index of 3/7. In this study, the index was calculated on a weekly (AWFI), monthly (AMFI) and annual (AYFI) basis. With the frequency index value ranging from 0 to 1, values close to 1 indicate the possibility of disease occurrence being high, while values close to 0 indicate the possibility of the disease occurrence being very low. We also carried out a similar exercise using female *Ae. aegypti* mosquitoes instead of DF cases, but did this only for January of each year. Since the number of black hole traps differed from district to district, the number of female mosquitoes was divided by the number of traps for each district, thus yielding the average number of vectors per trap.

The AMFI of each district was analysed spatially using Getis-Ord Gi* statistic to model the monthly risk levels in each district. This approach looks at each feature within the context of neighbouring features. If a feature value is high, and the values for all of its neighbouring features are also high, the conclusion is that it is part of a hot spot. Equation 1 below was applied to examine the local level of monthly temporal risk in order to model districts, where values of the DF frequency index and the numbers of mosquitoes were extreme and geographically homogenous. This study identified extreme index hotspots across the 111 districts in Jeddah. First, the spatial relationships relating case locations and female *Ae. aegypti* concentrations in districts were conceptualised and calculated using the fixed distance band. This included frequency index of the DF cases and the number of mosquitoes inside the boundary of the study area, but excluded everything outside that boundary. This approach was chosen as it has been shown to be generally more appropriate than inverse distance conceptualisation (Mitchell, 2005). Secondly, Euclidian distance was used to give an output of a z-score and p-value for each district in Jeddah. Districts with high z-scores and small p-values indicated spatial clustering of a high level of DF hotspots (a high temporal risk in a given period). Districts with low z-scores and high P values indicated a spatial clustering of a low level of DF hotspots (a low temporal risk in the given period). Based on the previous steps, one model was created for each month of the 5-year period to identify the areas of very low, low, medium and high infection probability in recorded DF cases (Fig. 2). The areas were classified based on z-score values: z-scores ≥3 indicating high risk areas, z-scores 2-3 indicating medium risk areas, z-scores 1-2 indicating low risk areas and z-scores ≤1 indicating very low risk areas.

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}\, x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{s\sqrt{\dfrac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}},$$

where x_j is the attribute value for feature j, $w_{i,j}$ the spatial weight between i and j and n equal to the total number of features.

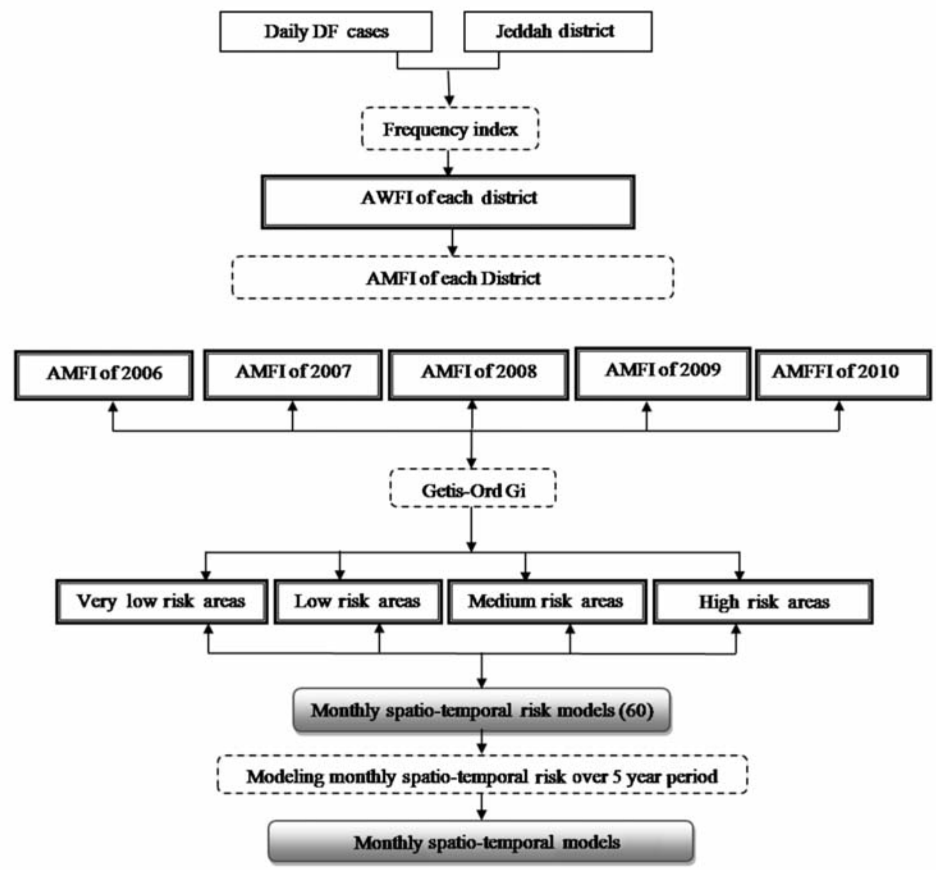

Fig. 2. Schematic representation of the study framework.

Results

Monthly spatio-temporal models 2006 to 2010

The results are presented on a monthly basis for 60 months (January 2006 to December 2010) with Fig. 3 indicating the locations of hotspots with significantly high frequency index findings. The spatio-temporal monthly hotspots shown in Fig. 3 were distributed in most of districts in central Jeddah, in particular in the districts of Old Jeddah (marked as 1) and the Alsafa district (marked as 2), areas identified for high or medium risk in most study months (red circles). Fig. 3 also shows that the pattern of risk changes with time, e.g. for the month of January (from an annual point of view), the Burman district (marked as 3) was identified as a low-risk area in 2006, a high-risk area in 2007, medium risk in 2008, very low risk in 2009 and low risk in 2010. Looking at the pattern changes over the span of a year instead, choosing 2010 as example, a very low risk was found in June, July, September, October, November and December, a low risk in January, March, April, May and August, and a high risk in February (marked with a red star in Fig. 3). During some months, e.g. January and February in 2009, hotspot patterns and high-risk areas display a shift to new districts, not identified in previous years. In addition, the risk of DF increased during November, December and January (Fig. 3).

Overall spatio-temporal model based on monthly risk models over the 5-year study period

The average monthly risk over the 5-year period shows most of the hotspots in central Jeddah. Based on average 5-year DF frequencies, most of old Jeddah was identified as carrying a high risk for most months, while all northern and southern districts were identified as very low risk areas (Fig. 4). The risk levels also changed from one month to another. For example, the districts within the red circle in Fig. 4 (three in all) were identified as having low, medium and high risk levels, respectively, in January and very low, low and medium risk levels, respectively in February and the risk levels continued to change for the remaining months. This finding provides a good understanding of the temporal risk variations during the year.

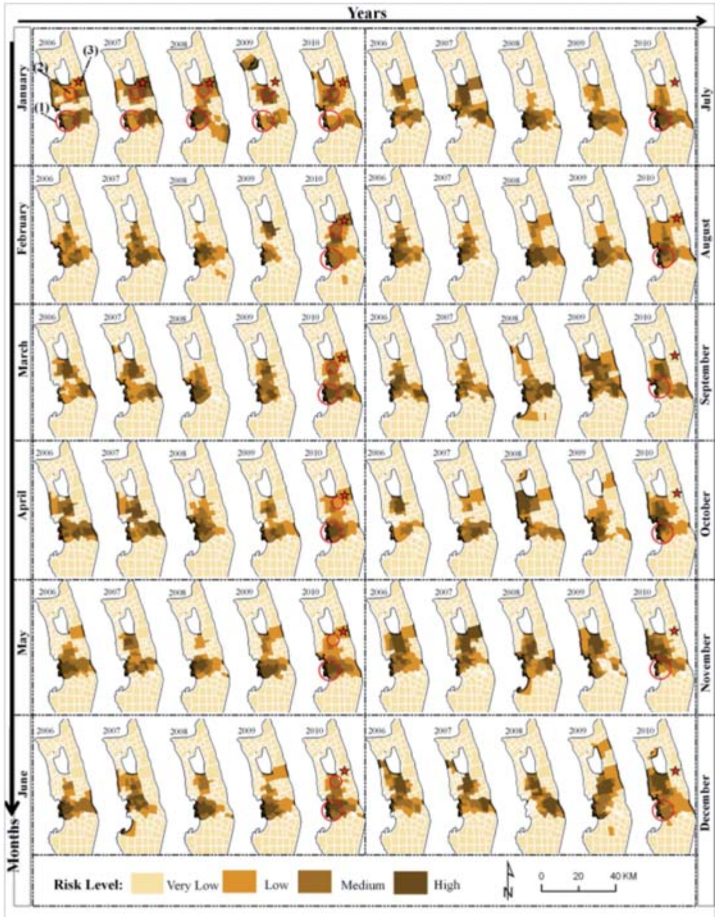

Fig. 3. Spatio-temporal monthly risk models of the study districts from 2006 to 2010. The red circles and stars are examples showing risk changes with time.

The percentage of districts with low- to high- risk ranged from 12% to 18% in most months, and those with very low risk from 48% to 61% (Fig. 5). Outliers were observed in the percentage of high risk, showing a decrease during February and December and, with respect to medium and low risk, an increase in September.

Impact of the vector on the monthly change in the DF numbers

Fig. 6 shows an example of the impact of the *Ae. aegypti* levels on the monthly changes in DF risk. Generally, most DF hotspots were also the vector hotspots, with some differences in the risk level pat-

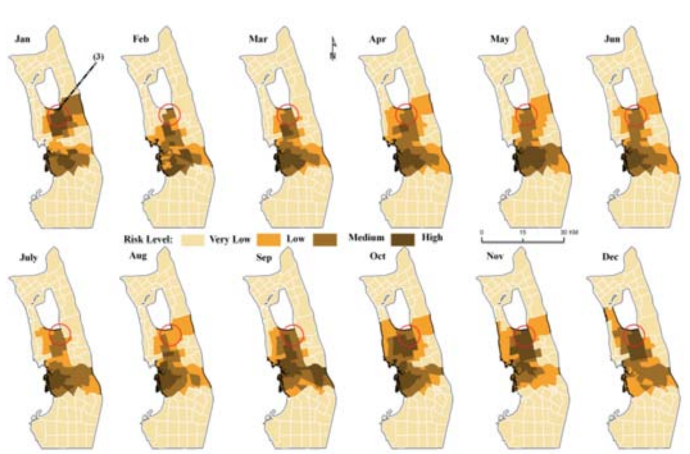

Fig. 4. Overall spatio-temporal model of monthly temporal risk over the 5-year epidemic period.

Fig. 5. Variation of risk by calendar month, i.e. the percentages of districts at each level of risk (high, medium, low and very low) based on the five-year average.

terns. Forty-eight Jeddah districts (43%) were identified as hotspots for DF incidence (Figure 6a), and 59 Jeddah districts (54%) were identified as *Ae. aegypti* hotspots (Figure 6b). The former figure shows that approximately 14% of Jeddah districts were at high risk for DF, while the latter shows that approximately 10% of the districts were at high risk with regard to the vector. Fifteen percent of the districts were identified as medium risk and 13% as low risk for DF (Figure 6a), while 22% were identified as medium risk for *Ae. aegypti* and 24% at low risk (Figure 6b). The figure also shows areas (marked with red circles) where a high DF risk was associated with a medium mosquito risk (marked as 1) and areas with medium DF risk associated with medium mosquito risk (marked as 2).

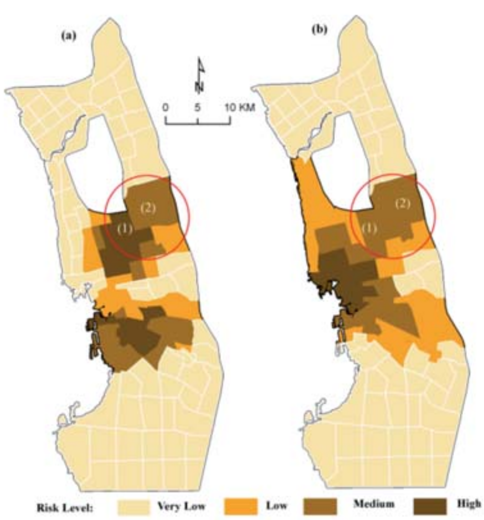

Fig. 6. Districts at risk of DF incidence (a) and at risk for *Ae. aegypti* intensity levels (b) in January. The red circles represent various associations between DF incidence and presence of *Aedes* mosquitoes.

Discussion

The approach chosen to map DF temporal risk characteristics and model monthly risk areas was the application of Getis-Ord Gi* statistic, a type of analysis particularly helpful for resource allocation and decision making, combined with a frequency index, which has not been used together before for mapping DF temporal risk characteristics and modeling monthly risk changes. This study is also the first to attempt modeling areas for the monthly risk levels of the disease over a long term (5 years) based on daily data on DF occurrence, while previous studies are based on short-term data.

This study identified extreme index hotspots across the 111 districts in Jeddah using a frequency index for identifying the spatio-temporal risk to improve visualization of the progress of epidemics. The results indicate that epidemiologists can identify case clusters when factoring in temporal properties such as the number of DF cases occurring within a specific time. The spatio-temporal risk details presented in this research confirm that the temporal risk model, based on a daily frequency index, produces a better understanding of the changes, compared with previous yearly-based studies. This should provide insights for improving the DF surveillance system and leading to better DF control interventions in Jeddah.

Monthly hotspot patterns of DF were similar for most months based on the average monthly frequency index of each month during the 5-year period (Fig. 3). However, changes in the risk level patterns occurred. Most high and medium risk areas during the 60 months studied were mainly concentrated in the central districts of Jeddah. Most of these districts have limited access to water supply, which forces residents to use water storage containers. Bisset et al. (2006) reported that immature stages of *Aedes* were found in 70 containers, and the pupae of this species were observed in 52 containers out of the total sample they used (around 1,000). They also found that 74% of the pupae were collected from ground level water storage tanks and that 19% were found in miscellaneous small containers.

There is a reasonable assumption that population and population density directly influence the risk of DF outbreaks. Khormi and Kumar (2011) previously found that areas in Jeddah with a low risk for DF also have a low mean population density (2,107 per km²), whereas areas of medium risk have a medium population density (12,880 per km²) and areas that carry the highest risk have a very high population density (19,728 per km²). This is borne out in this study as

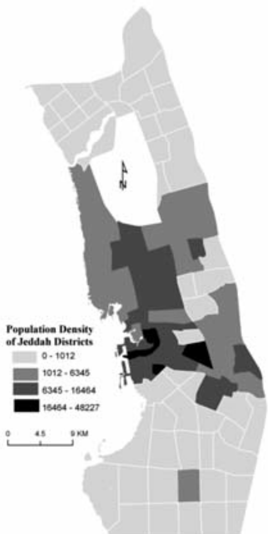

Fig. 7. The population density in the various districts of Jeddah.

many districts in Jeddah have a population above 6,345 per km² (Fig. 7) and the results are also corroborated by other reports (Honorio et al., 2003; Lagrotta et al., 2008; Siqueira et al., 2008).

One of the reasons behind the continued DF occurrences, shifts and changes between districts reported in this study is probably the failure of current control approaches (that have been in use since 2006) to limit the spread of DF in spite of achieving reduced transmission. Other, possible reasons are that mosquito breeding sites may have been overlooked or may not have been identified as risk areas. In addition, the current strategy may be based on cumulative DF incidence alone, which would explain the frequent weekly occurrences of the disease due to the presence of *Ae. aegypti*.

There is an increased risk of DF during November, December and January due to climate conditions such as rainfall, relative humidity and temperature changes, which are known to change from 20-25 ºC in the winter to 30-40 ºC in the summer. Rain creates puddles or swamps that serve as suitable breeding sites and this stagnant water also increases humidity, which enhances *Ae. aegypti* mosquito survival as reported by Kuno (1997) and Hales et al. (2002) who found that high relative humidity with high temperatures and heavy rainfall positively affect the survival and breeding conditions of the mosquitoes.

Conclusions

The GIS approach and the spatio-temporal analysis techniques reported here were found to be useful for mapping, analysing and understanding DF risk, a technique that also lends itself for the study of other vector-borne diseases. The application of average weekly frequency indices makes it possible to recognize monthly disease patterns, which facilitates the assessment of the strengths and weaknesses of current control measures.

We propose a simple, inexpensive technique, based on case notification data, for early warning, categorization and identification of at-risk areas that can be incorporated into the routine monitoring by the health authorities. The approach prevents DF prevalence, helps monitoring *Ae. aegypti* population levels and can also be used to identify mosquito hotspots for the elimination of mosquito breeding sites. DF presence detected in relatively unpopulated areas should also be occasionally monitored for the presence and density of the *Ae. aegypti* vector.

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References

Aburas HM, 2007. Aburas index: a statistically developed index for dengue-transmitting vector population prediction. Proceedings of World Academy of Science, Engineering and Technology 23, 151-154.

Barrera R, Delgado N, Jimenez M, Villalobos I, Romero I, 2000. Stratification of a hyperendemic city in hemorrhagic dengue. Rev Panam Salud Publica 8, 225-233.

Bisset JA, Marquetti MC, Suarez S, Rodriguez MM, Padmanabha H, 2006. Application of the pupal/demographic-survey methodology in an area of Havana, Cuba, with low densities of A*edes aegypti*. Ann Trop Med Parasitol 100, 45-51.

Bithell JF, 1999. Disease mapping using the relative risk function estimated from areal data. In: Lawson A, Biggeri A, Böhning D, Lesaffre E, Viel J-F, Bertollini R (Eds). Disease Mapping and Risk Assessment for Public Health, John Wiley & Sons, LTD, pp. 247-255.

Brisenogarcia B, Gomezdantes H, Argottramirez E, Montesano R, Vazquezmartinez AL, Ibanezbernal S, Madrigalayala G, Ruizmatus C, Flisser A, Tapiaconyer R, 1996. Potential risk for dengue hemorrhagic fever: the isolation of serotype dengue-3 in Mexico. Emerg Infect Dis 2, 133-135.

Earnest A, Chen MI, Ng D, Sin LY, 2005. Using autoregressive integrated moving average (arima) models to predict and monitor the number of beds occupied during a SARS outbreak in a tertiary hospital in Singapore. BMC Health Serv Res 5, 36.

Fakeeh M, Zaki A, 2003. Dengue in Jeddah, Saudi Arabia, 1994-2002. Dengue Bull 27, 13-17.

Galli B, Neto FC, 2008. Temporal-spatial risk model to identify areas at high-risk for occurrence of dengue fever. Rev Sau Pub 42, 656-663.

Giesecke J, 2001. Modern infectious disease epidemiology. Arnold 280, London, UK.

Gubler DJ, 1997. Dengue and dengue hemorrhagic fever: its history and resurgence as a global public health problem. Dengue and Dengue Hemorrhagic Fever, pp. 1-22.

Hales S, De Wet N, Maindonald J, Woodward A, 2002. Potential effect of population and climate changes on global distribution of dengue fever: an empirical model. Lancet 360, 830-834.

Honorio NA, Silva WD, Leite PJ, Goncalves JM, Lounibos LP, Lourenco-de-Oliveira R, 2003. Dispersal of *Aedes aegypti* and *Aedes albopictus* (Diptera: Culicidae) in an urban endemic dengue area in the state of Rio de Janeiro, Brazil. Mem Inst Oswaldo Cruz 98, 191-198.

Khormi H, Kumar L, 2011. Modeling dengue fever risk based on socioeconomic parameters, nationality and age groups: GIS and remote sensing based case study. Sci Total Environ 409, 4713-4719.

Kongsomboon K, Singhasivanon P, Kaewkungwal J, Nimmannitya S, Mammen MP, Nisalak A, Sawanpanyalert P, 2004. Temporal trends of dengue fever/dengue hemorrhagic fever in Bangkok, Thailand from 1981 to 2000: an age-period-cohort analysis. Southeast Asian J Trop Med Public Health 35, 913-917.

Kuno G, 1997. Factors influencing the transmission of dengue viruses. Dengue and Dengue Hemorrhagic Fever, pp. 61-88.

Lagrotta MT, Silva WD, Souza-Santos R, 2008. Identification of key areas for *Aedes aegypti* control through geoprocessing in Nova Iguacu, Rio de Janeiro State, Brazil. Cad Saude Publica 24, 70-80.

Mitchell A, 2005. The ESRI guide to GIS analysis. ESRI, Press 2.

Murad A, 2008. Defining health catchments areas in Jeddah city, Saudi Arabia: an example demonstrating the utility of geagraphical information systems. Geospat Health 2, 151-160.

Nakhapakorn K, Jirakajohnkool S, 2006. Temporal and spatial autocorrelation statistics of dengue fever. Dengue Bull 30, 177-183.

Russell RC, 2004. The relative attractviness of carbon dioxide and octnol in CDC and EVS-type light traps for sampling the mosquitoes *Aedes aegypti* (L.), *Aedes polynesiensis* marks and *Culex quinquefasciatus* say in Moorea, Franch Polynesia. J Vector Ecol 29, 309-314.

Siqueira JB, Maciel IJ, Barcellos C, Souza WV, Carvalho MS, Nascimento NE, Oliveira RM, Morais-Neto O, Martelli CM, 2008. Spatial point analysis based on dengue surveys at household level in central Brazil. BMC Public Health, 8, 361.

Tipayamongkholgul M, Lisakulruk S, 2011. Socio-geographical factors in vulnerability to dengue in Thai villages: a spatial regression analysis. Geospat Health 5, 191-198.

Wen TH, Lin NH, Lin CH, King CC, Su MD, 2006. Spatial mapping of temporal risk characteristics to improve environmental health risk identification: a case study of a dengue epidemic in Taiwan. Sci Total Environ 367, 631-640.

Zeger SL, Irizarry R, Peng RD, 2006. On time series analysis of public health and biomedical data. Annu Rev Public Health 27, 57-79.