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Urban structure and dengue fever in Puntarenas, Costa Rica

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Abstract

Dengue is currently the most important arboviral disease globally and is usually associated with built environments in tropical areas. Remotely sensed information can facilitate the study of urban mosquito-borne diseases by providing multiple temporal and spatial resolutions appropriate to investigate urban structure and ecological characteristics associated with infectious disease. In this study, coarse, medium and fine resolution satellite imagery (Moderate Resolution Imaging Spectrometer, Advanced Spaceborne Thermal Emission and Reflection Radiometer and QuickBird respectively) and ground-based data were analyzed for the Greater Puntarenas area, Costa Rica for the years 2002–04. The results showed that the mean normalized difference vegetation index (NDVI) was generally higher in the localities with lower incidence of dengue fever during 2002, although the correlation was statistically significant only in the dry season ($r=-0.40$; $p=0.03$). Dengue incidence was inversely correlated to built area and directly correlated with tree cover ($r=0.75$, $p=0.01$). Overall, the significant correlations between dengue incidence and urban structural variables (tree cover and building density) suggest that properties of urban structure may be associated with dengue incidence in tropical urban settings.

Keywords

Costa Rica; dengue; normalized difference vegetation index (NDVI); QuickBird; remote sensing; urban environment

Dengue is the most important arboviral disease in terms of worldwide morbidity and mortality with an estimated 50 to 100 million cases and 12 000 to 24 000 deaths per year (WHO, 2002; Gibbons & Vaughn, 2002). The principal mosquito vector, *Aedes aegypti*, lives in close association with humans mostly in urban and suburban environments where larvae commonly develop in water-filled artificial containers such as drums, buckets, tyres and flower pots (Focks & Chadee, 1997; Gubler, 1998; Calderon-Arguedas *et al.*, 2004). The recent dissemination of dengue viruses and *Ae. aegypti* throughout the tropics has been influenced by such factors as increasing global trade, migration and travel, population growth and uncontrolled or unplanned urbanization (Kuno, 1995).

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Dengue incidence in Costa Rica is one of the highest in Central America, with over 45 000 reported cases from 2006 to 2008 (close to 26 000 cases in 2007 alone) (PAHO, n.d.). In comparison, next in ranking over the same period, Honduras and El Salvador reported slightly over 30 000 and 26 000 cases respectively. Whereas the incidence rate per 100 000 population for 2007 in Costa Rica was 815, it was 445 in Honduras and 195 in El Salvador (PAHO, n.d.). Although *Ae. aegypti* and dengue were eradicated from the country in 1960, the vector recolonized in 1993 and dengue cases were reported soon after (WHO, 1994). Since then, there have been more than 140 000 cases reported (Ministerio de Salud, *et al.* 2004), including almost 38 000 cases in 2005 (Ministerio de Salud, n.d.). Dengue currently represents the most important vector-borne disease in Costa Rica.

Remotely sensed data, together with geographical information systems (GIS), have been used to study vector-borne diseases, mostly in ex-urban settings (Hay *et al.*, 1997; Bergquist, 2001; Correia *et al.*, 2004). The study of vector-borne diseases in urban environments poses particular challenges owing to urban spatial heterogeneity and structural complexity, complex movement of hosts and vectors, and anthropogenic creation of vector habitats. The launch of commercial imaging satellites such as IKONOS and QuickBird offers new opportunities to assess urban habitats for disease vectors by providing very high spatial resolutions (1 m and 0.62 m respectively) for identification of city blocks, individual roads, trees, roadways, buildings and rooftops (Jensen & Cowen, 1999). While such imagery produces a fine-scale representation of urban environments, near-nadir observations are relatively infrequent compared to other orbital sensors that possess coarse spatial resolution such as the Advanced Very High Resolution Radiometer (AVHRR) and the Moderate Resolution Imaging Spectrometer (MODIS). These latter instruments enable the study of seasonal factors, including humidity, vegetation greenness and temperature, that control physiological variables related to vector and pathogen phenology (Goetz *et al.*, 2000; Tatem *et al.*, 2004; Hay *et al.*, 2006).

Few studies have used satellite imagery to investigate environmental factors associated with dengue fever. Recent studies involving remote sensing for dengue surveillance have employed coarse spatial resolution data from AVHRR (Peterson *et al.*, 2005; Rogers *et al.*, 2006; Kolivras, 2006), as well as medium resolution imagery and land use/cover maps derived from Landsat Enhanced Thematic Mapper+ (ETM+; 30 m spatial resolution) (Nakhapakorn & Tripathy, 2005; van Benthem *et al.*, 2005) and SPOT (20 m spatial resolution) (Tran & Raffy, 2005). Using Landsat ETM+, spatial determinants of dengue infection were studied in specific rural and peri-urban areas (van Benthem *et al.*, 2005). For other mosquito-borne diseases such as malaria, data obtained from very high resolution multispectral bands have been used to study disease risk (Sithiprasasna *et al.*, 2005) and anopheline larval habitats (Mushinzimana *et al.*, 2006; Jacob *et al.* 2006). However, studies that have used satellite imagery with very high spatial resolution (<5 m) in multispectral bands to assess *Ae. aegypti* habitats within urban areas appear to be lacking.

In this study, relevant spatial and seasonal determinants of dengue incidence were investigated for the Greater Puntarenas area, Costa Rica, for the years 2002–04. The approach involved a series of exploratory data analyses of static urban structural features (houses and other buildings, roads, parks, and so on) as well as dynamically changing variables (such as greenness and rainfall) derived through remote sensing and ground data. The choice of variables was informed by a number of factors including the likelihood of obtaining acceptable classification accuracies for relevant urban objects such as trees, houses and paved surfaces, as well literature on modelling and epidemiological analyses that incorporated static and dynamic spatial variables to explain spatial patterns of dengue incidence and spread (Nakhapakorn & Tripathy, 2005; Tran & Raffy, 2005; Kolivras 2006). Thus, the purpose of our study was threefold. First, to obtain basic spatial information on the urban environment of Greater Puntarenas using satellite and ground-based data. Second, to correlate this information to epidemiological data gathered by local public health authorities. And third, to explore relationships between specific urban structural metrics and disease parameters to further our understanding of urban features that may favour the spread and persistence of dengue fever in the tropics.

Materials and methods

Study site background

Our study focused on the Greater Puntarenas area of Puntarenas Province, Costa Rica, which is a term used to refer to the area comprising the districts of Puntarenas, Chacarita, El Roble and Barranca (Figure 1). Populated areas within districts are mapped as localities (localidades), the smallest unit within the health system, which in Costa Rica is jointly managed by the Ministry of Health and Social Security Bureau. The provincial capital is centred in Puntarenas City, an urban area encompassing a narrow peninsula (Puntarenas District) and nearby mainland areas (Chacarita District) on the Pacific coast. Within approximately 20 km^2, census data from 2000 indicate a population close to 100 000 people with approximately 20 000 houses (INEC, 2002). Because the main government offices, commercial buildings and amenities are located here, much of the population of the Greater Puntarenas study area and even the province is concentrated in Puntarenas City. Most of the area is classified as urban (>95 per cent), although habitations vary greatly in size density and construction quality (INEC, 2002). The main economic activities are related to the port, tourism, fishing and commerce (Impoinvil *et al.*, 2007). Although much of the population in Puntarenas City are settled communities, there is a small percentage of migrants constantly moving to and from other parts of Costa Rica and also neighbouring Nicaragua.

Puntarenas City is the site of dengue reintroduction to Costa Rica in 1993 (WHO, 1994) and the disease has been endemic in the area since. From 2002 to 2005, more than 7000 cases of dengue were reported for the Greater Puntarenas area (Ministerio de Salud, n.d.); most cases reported after 2000 have been caused by the DEN-1 serotype. Compared with other health regions of the country, the Central Pacific Region of the Ministry of Health, which Puntarenas Province falls under, registers some of the higher social burdens: the poverty level is 26.4 per cent and the unemployment rate of 6.8 per cent is the second highest in the country. The climate is moist tropical: mean minimum and maximum daily temperatures are 22°C and 32°C respectively, with a marked wet season (May to mid-November) and a dry season (mid-November to April). Combined with the tropical environmental characteristics, relatively populous Puntarenas City is a potentially high-risk area for vector-borne diseases

Population data and dengue case reports

The weekly number of dengue cases reported in 2002, 2003 and 2004, and data on the number of households, estimated population and line drawings of the geographical boundaries for each of the 30 localities in Greater Puntarenas were obtained from the Central Pacific Region Directorate of the Ministry of Health located in downtown Puntarenas. Each locality has at least one small clinic and/or basic health team that collects weekly surveillance and case data (as diagnosed by qualified physicians) and reports this to central clinics (that come under the Social Security Bureau), which then group the data and send it to the Regional Directorate of the Ministry of Health. House density (houses per km^2) was determined for each locality. Dengue incidence data per 100 population was calculated as:

$$[\text{total number of cases reported (in a year or season) / total population}]^{*}100$$

The total population was assumed to be constant during all three years. To assess local climate and weather conditions during those same years, daily observations on rainfall, maximum, minimum and mean temperatures for Puntarenas City were obtained from the headquarters of the National Meteorological Institute in San Jose.

Information derived from satellite imagery

Seasonality and vegetation greenness was evaluated at a monthly time scale during 2002 using the enhanced vegetation index (EVI) obtained from MODIS (500 m spatial resolution). The EVI provides greater sensitivity to changes in vegetation greenness than other widely used vegetation indices (VIs) as it reduces atmospheric and background effects that may introduce significant errors in VI time series. EVI is given as:

$$\mathrm{EVI}=G\,[\mathrm{NIR}-\mathrm{red}]/[\mathrm{NIR}+C_1\times\mathrm{red}-C_2\times\mathrm{blue}+L]$$

where NIR (near infrared), red and blue correspond to the surface reflectance for the respective band, L=1 and is the canopy background adjustment, C_1=6 and C_2=7.5 and are coefficients of the aerosol resistance term, and G=2.5 and is the gain factor (Huete *et al.*, 2002).

Multitemporal EVI data were obtained from a series of co-registered image tiles downloaded from the US Geological Survey EROS Data Center server (http://edcimswww.cr.usgs.gov/pub/imswelcome/). In addition, four cloud-free scenes from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) (15 m spatial resolution) acquired during the dry and wet seasons respectively of 2002 were obtained, and the individual multispectral bands were georeferenced using a Landsat image of 30 m spatial resolution obtained from the Global Landcover Facility (http://glcf.umiacs.umd.edu/index.shtml). The normalized difference vegetation index (NDVI) was calculated from the ASTER multispectral bands (NDVI = [NIR-red]/[NIR +red]), and the mean NDVI was extracted for each of the 30 localities using Idrisi Kilimanjaro software (Eastman, 2004).

There were no vector layers available for the localities in Greater Puntarenas previous to this study. Therefore, polygon topology was built using CartaLinx software (ClarkLabs, 1999) by manually digitizing each of the 30 health localities from the boundaries provided by the Ministry of Health's Regional Directorate and both ASTER and QuickBird imagery (Figure 1). The resulting layer provided the areas for each locality as well as the polygons required to extract data from the satellite imagery and derived maps. All image processing and GIS operations, unless otherwise stated, were performed using Idrisi Kilimanjaro (Eastman, 2004).

Two cloud-free QuickBird scenes available for March 2002 and October 2003 were mosaicked to produce one single high-resolution image (2.4 m and 0.6 m spatial resolution in the multispectral and panchromatic bands respectively), which included all the 10 localities of Puntarenas City. There were no single scenes available from very high-resolution sensors that included the total area and had acceptable image quality. Most of the localities are limited by natural barriers including open water and mangroves, so changes in urbanization during 2002–03 are assumed to be minimal. The scenes obtained were individually georeferenced to increase their spatial accuracy (RMS=2.9 m and 3.1 m for the 2002 and 2003 scenes, respectively) by using 38 ground control points obtained with a hand held global positioning system (GPS; Garmin GPSmap 76S). Accuracy of each ground control point was improved further by taking the mean of three GPS readings acquired at least 5 hours apart and at a series of road intersections readily visible in the QuickBird panchromatic and multispectral bands.

Semiautomated land cover maps were produced from the QuickBird scenes by applying supervised image classifiers to each QuickBird image, and the resultant classified images were mosaicked. Classification algorithms included the maximum likelihood (MLC) and backpropagation artificial neural network (BPANN) implemented in Idrisi Kilimanjaro software (Eastman, 2004). GIS operators were applied to the final classified products to extract data at the locality level. The panchromatic image provided a set of mutually exclusive training and validation points for the automated image classifiers. Once the land use/cover maps were obtained, accuracy was assessed by visual interpretation of points selected at random from the original panchromatic QuickBird scene. The proportion of built area and tree cover was extracted for the 10 localities of the Greater Puntarenas area included in the QuickBird imagery and FRAGSTATS software (McGarigal *et al.*, 2002) was used to extract several spatial metrics of the classified built and tree cover areas. Specific metrics were selected to assess the spatial dispersion and clustering of various urban features: total class area, number of patches, patch density, percentage of landscape, percentage of like adjacencies, patch cohesion index, clumpiness index and connectance index.

The QuickBird images were also classified using the object-oriented classification of eCognition software (Baatz *et al.*, 2004), which generally improves the classification of image objects in built environments relative to pixel-based classifiers (Tarantino, 2004; Carleer & Wolff, 2006). Segmentation for each image was performed for level 1 at scale parameter=20, shape factor=0.3 and compactness=0.7; a level 2 segmentation was performed at the same scale parameter but using the spectral difference mode. The level 1 scale parameter determined the size of the objects (corresponds to the maximum allowed heterogeneity) (Baatz *et al.*, 2004), while the relatively low shape and high compactness factors (scaled 0–1) favoured segmentation of the many small and diverse structures in this urban setting. The level 2 segmentation using spectral difference merged contiguous objects that differed in less than the specified scale parameter (Baatz *et al.*, 2004), allowing for the formation of larger objects but maintaining the smaller ones if the spectral difference was large. Samples for different objects were selected from the level 2 segmentation of the scenes for a hierarchical classification scheme and the resulting final maps included the same classes as those obtained with the neural network classification: ‘water’, ‘built’, ‘tree’, ‘grass/bare soil’ and ‘paved’. Because of the simplicity of manual correction in e-Cognition software, this was performed on some of the objects, especially small ‘tree’ patches included within approximately 10 large areas covered by grass (such as soccer fields) that were evidently misclassified. Once the final land use/cover maps were obtained, they were imported into Idrisi Kilimanjaro to assess accuracy, produce mosaics and extract the proportion of built area and tree cover for the 10 localities included in the QuickBird imagery (in the same manner stated previously).

Once the land use/cover maps were obtained from QuickBird, accuracy was assessed by using points selected at random from the original panchromatic QuickBird scene. The proportion of built area and tree cover was extracted for the 10 individual localities included in the QuickBird imagery and FRAGSTATS software was used to extract several spatial metrics of the classified built and tree cover areas in the same manner as was stated previously.

Data analyses

Data on daily rainfall, as well as minimum, maximum and mean temperatures were aggregated weekly to match weekly reporting of dengue case data obtained by the Ministry of Health. The weekly number reported for the 30 localities in the Greater Puntarenas area were plotted with the corresponding rainfall and temperature data, and an analysis of cross correlations was performed to determine significant lags between the weather variables and dengue cases. A comparison was also conducted for the monthly EVI data from MODIS and dengue cases. The correlation (Pearson) was analyzed using Statistix software between the mean NDVI data from dry and wet seasons of 2002 and the corresponding incidence data, as well as dengue case data. Correlations between NDVI and house density were also evaluated.

The accuracies of the classification maps were compared and Pearson correlations (Statistix software) were determined between dengue incidence and proportional tree cover and built area extracted from the best QuickBird land use/cover maps. Considering that the small number of localities included in the QuickBird imagery (n=10) limited the application of a multivariate approach, correlation matrices were created to evaluate linear relationships between metrics of spatial dispersion and clustering of tree cover and built area (extracted with FRAGSTATS). All the statistical analyses were evaluated at α of 0.05.

Results

Meteorological influences on timing of dengue incidence

The Ministry of Health's Regional Directorate provided data on dengue cases in Greater Puntarenas for both dry and wet seasons for all the years analyzed (2002–04). Specifically, in 2002, 1434 cases of dengue fever were reported, 2017 in 2003 and 442 in 2004. Over these three years, the number of cases peaked during the wet season as rainfall increased (Figure 2). The data obtained from the National Meteorological Institute contained missing values, which made the time series analysis of cross correlations difficult for the entire period 2002–04. However, an analysis of cross correlations for three specific subperiods where the time series was continuous revealed a significant correlation of 0.73 ($p<0.05$) between rainfall and reported dengue cases, with lag of −5 weeks detected during the period of weeks 8–31 in 2003.

Ambient temperatures were also significantly correlated with the number of cases of dengue fever reported, and the use of mean, maximum or minimum temperatures provided similar results. Overall, the analyses of reported cases and cross correlations for weekly mean, maximum or minimum temperatures for available sections of 2002–04 resulted in significant negative correlations (values ranged from −0.49 to −0.64; $p<0.05$ in each case) with lags ranging from −1 to 2 weeks; where high correlations were commonly present when there were no lags.

Seasonal dynamics of vegetation indices

During 2002, the monthly EVI obtained from MODIS for the Greater Puntarenas area was lower for the first and last months of the year (dry season), and, as expected, increased in the wet season. Reported cases of dengue also increased but several weeks after the initial increase in EVI, consistent with the lag effect with rainfall (Figure 3).

The mean NDVI calculated from the ASTER multispectral bands for all four scenes was generally higher in the localities with lower incidence of dengue fever during 2002. This was evident for total reported cases during the year, as well as wet and dry seasons individually. However, the correlation was statistically significant only in the dry season (Pearson $r=-0.40$; $p=0.03$). In addition, the NDVI for both seasons was negatively correlated with house density, and this correlation was stronger and more significant during the wet season (Pearson $r=-0.75$; $p<0.0001$).

Image classification and correlations with dengue incidence

Classification of urban areas from very high resolution imagery commonly results in accuracies close to 80 per cent (Sugumaran *et al.*, 2002; Shackelford & Davis, 2003), but spectral separation of some features such as turbid water and asphalt, bare soils and concrete can be difficult (Sawaya *et al.*, 2003; Herold *et al.*, 2003). The most accurate land use/cover map resulting from BPANN classification of the 2002/2003 QuickBird image possessed overall accuracy of 80 per cent and Kappa of 0.74 (Figure 4). Individual class errors for the built class were 24 per cent errors of omission and 20 per cent errors of commission, while the tree class had 7 per cent errors of omission and 10 per cent errors of commission. Changes in urbanization during 2002–03 were assumed to be minimal in this area; therefore, the mosaicked imagery was considered adequate for analyses of dengue case data for both of these years.

The correlation analyses for the incidence of dengue fever using the proportion of built area or tree cover for 2002 at the locality level did not reveal statistical significance (Pearson $r=-0.16$; $p=0.66$ and $r=-0.27$; $p=0.45$ respectively). However, a similar analysis for the BPANN land use/cover map with the 2003 dengue case data showed a significant negative relationship with built area (Pearson $r=-0.74$; $p=0.01$) and a positive relationship with tree cover (Pearson $r=0.75$; $p=0.01$), in spite of the small number of localities included in the analyses ($n=10$). In addition, the built class metrics obtained using FRAGSTATS did not show correlations with dengue incidence (Table 1), but the clumpiness index, patch cohesion index and percentage of like adjacencies from the tree class did correlate with dengue fever in 2003 (Table 2). These metrics also correlated significantly with the proportion of tree cover.

The object-oriented classification applied to the QuickBird multispectral bands using eCognition software resulted in a more accurate land use/cover map for the Puntarenas City area of Greater Puntarenas, where the individual classes were more uniform and better defined, most of the speckle within patches was reduced and improvement was evident in the classification of built areas (Figure 4). This map had an overall accuracy of 86 per cent and Kappa of 0.81. The built class had 20 per cent errors of omission and 11 per cent errors of commission, while tree class had 14 per cent errors of omission and 8 per cent errors of commission. The correlations between the incidence of dengue fever during 2002 and the proportion of built area or tree cover obtained with eCognition for the 10 localities were not statistically significant (Pearson $r=0.23$; $p=0.52$ and $r=-0.46$; $p=0.19$ respectively). Although tree cover from this map was not significantly correlated (at 95 per cent level) with dengue incidence for 2003 (Pearson $r=0.54$; $p=0.10$), a moderate positive relationship was still observed. Furthermore, the correlation of dengue incidence in 2003 with the proportion of built area was significant (Pearson $r=-0.73$; $p=0.02$), confirming a negative relationship between both variables. Of the FRAGSTATS metrics, the clumpiness index and percentage of like adjacencies for built (Table 3), and the patch cohesion index for tree (Table 4) showed the strongest significant correlations with dengue incidence in 2003. These metrics also correlated significantly with the proportion of tree or built areas.

Discussion

Dengue cases in the Greater Puntarenas area varied between 2002, 2003 and 2004, but also showed clear seasonality each year (Figure 2). Interannual variation may be explained by an earlier start of the rainy season and increased rainfall in 2003 (Ministerio de Salud, n.d.), which increased reported cases. In addition, decreased rainfall, herd immunity to the circulating serotype (DEN-1) and improved vector control may explain the decrease in dengue cases during 2004, which was a countrywide phenomenon (Troyo *et al.*, 2006).

Seasonality of infection and associations of dengue with rainfall are common findings in urban areas and suggest that *Ae. aegypti* larvae are found mostly in outdoor containers that collect rainwater (Focks & Chadee, 1997; Morrison *et al.*, 2004). Moreover, the lag of −5 weeks observed in 2003 suggests an increase in virus transmission following rainfall in Greater Puntarenas. Previous studies have reported a similar lag between rainfall and dengue cases (Nakhapakorn & Tripathy, 2005), which may be explained as a sequence of events that begins with increased mosquito larval habitats and mosquito densities, followed by mosquito infection, extrinsic virus replication (i.e. within mosquitoes), transmission to humans and onset of symptoms.

Monthly data from MODIS showed that increases in EVI were also followed by increases in dengue fever cases (Figure 3). Rainfall is associated with increased leaf production and increases in vegetation indices (Thomson *et al.*, 1996) and EVI results were consistent with weekly rainfall data. Temporal variations in NDVI, analyzed at low spatial resolution, were reported as predictive for cases of dengue in Mexico (Peterson *et al.*, 2005) and have been studied in more detail for other mosquito-borne diseases such as malaria (Hay *et al.*, 1998;Liu & Chen, 2006). With these types of temporal relationships, health authorities may be able to predict peaks of dengue cases to efficiently redirect resources for dengue prevention and management of expected patients.

The spatial relationship between dengue incidence and NDVI was not clear in Greater Puntarenas. Vector densities and disease are usually higher in areas with high NDVI for diseases like yellow fever and malaria where common vectors and vector habitats are present in forest, rural, or crop areas (Sithiprasasna *et al.*, 2003; Rogers *et al.*, 2006). For dengue, an inverse relationship would be expected seeing as NDVI and house density are inversely correlated (Eisele *et al.*, 2003). However, recent mapping suggests that variables related to temperature may be more important than vegetation indices in determining dengue distributions at a global scale (Rogers *et al.*, 2006), but more studies are needed at a finer scale.

The only significant negative correlation between NDVI and dengue fever incidence during the dry season of 2002 may reflect seasonal differences regarding the most productive types of larval habitats in the Greater Puntarenas area. It is possible that localities with low NDVI and high house densities presented more dengue cases due to crowding and because the most relevant mosquito larval habitats may have been containers that are manually filled with water (flowerpots, vases, laundry washtubs and water storage containers). These habitats are common during the dry season in other urban areas of Latin America and Costa Rica, especially where water service is frequently interrupted (Pontes *et al.*, 2000; Calderon-Arguedas *et al.*, 2004). In contrast, the spatial distribution of dengue fever during the wet season may have been more affected by other factors related to human activity, as well as the effects of rainfall and vegetation on the most relevant mosquito larval habitats.

Compared to the NDVI obtained from ASTER, the image classification of QuickBird scenes evidenced more detailed relationships between the incidence of dengue fever and urban structure in Puntarenas City, in spite of the smaller sample size. NDVI usually results in high values (e.g. > 0.5) for photosynthetically active vegetation (trees, grasses, small shrubs), while other surfaces (concrete, tin roofs, soils, impervious surfaces) display low values (e.g. <0.3). Therefore, a mean NDVI may have captured only a small portion of detailed differences for each type of surface in a locality, while QuickBird imagery permitted an acceptable separation of built and tree classes from areas where *Ae. aegypti* rarely would be present such as roads, large water bodies and sections of grass or bare soil.

In Puntarenas City, localities with less built area and more tree cover seemed to have more virus transmission during 2003. However, the relationships were not significant in 2002, which may be an effect of the small sample size, low incidence, different distribution and/or types of mosquito larval habitats and different vector control activities. In general, previous studies that have employed satellite imagery have shown that dengue is related to built up areas as opposed to forested areas (Nakhapakorn & Tripathy, 2005), but tree cover may play a different role within cities. The situation in Puntarenas City may be similar to what has been suggested for urban areas of Kenya, where the number of anopheline larval sites first increases with household density but then decreases when density is very high (Keating, 2003). Even though results from Puntarenas City should be viewed with caution because of the small sample size and imperfect accuracies of the land use/cover maps, increased mosquito densities and availability of larval habitats outside built areas and in locations exposed to rainfall could explain these findings.

Although more people may be present in densely built up areas within cities, there may be less dengue fever reported in such areas due to better housing types, smaller back yards, less tree cover, and the presence of more commercial and business buildings. Houses in economically advantaged zones may have windows, screens and possibly air conditioning, which provide an initial barrier for mosquito and host contact. In addition, water storage for personal use may be less prevalent in these areas, and limited space may mean fewer outdoor containers. Moreover, several studies have shown that outdoor habitats protected from direct sunlight are more likely to contain larvae of *Ae. aegypti* and that tree cover is associated with more suitable larval habitats (Bisset-Lazcano *et al.*, 2006; Barrera *et al.*, 2006). Therefore, shade provided by trees in larger backyards and open areas like parks may protect mosquito habitats from heating and direct sunlight, which can result in higher vector densities in localities with more tree cover.

The correlation matrices (Table 1– Table 4) showed that some characteristics of tree cover and built areas obtained with FRAGSTATS (McGarigal *et al.*, 2002) may be useful for determining relationships between urban structure and the spatial distribution of dengue fever within cities. Even though some variables were correlated significantly with dengue incidence in 2003, most of these were also strongly correlated with the proportion of tree cover or built area. The effect of each of these variables individually on dengue incidence may be similar because of their correlation, which may confuse the interpretation of results. Once the proportion of tree cover or built area is considered, it is possible that FRAGSTATS variables would not explain further variance in dengue incidence. Thus, the utilization of FRAGSTATS variables such as clumpiness index, patch cohesion index and percentage of like adjacencies warrants further evaluation using a larger number of observations and multivariate approaches, which would help identify the most useful variables and their possible relationships with dengue fever.

The overall classification accuracy of QuickBird imagery using BPANN was acceptable and image segmentation increased accuracy in agreement with previous reports (Carleer & Wolff, 2006). However, it is possible that better relationships and different relevant variables may be revealed by further improving classification accuracy through inclusion of detailed information on texture, shape and relationship to neighbours and subobjects (Shackelford & Davis, 2003; Tarantino, 2004), as well as additional spectral information and increase in sample size (Roessner *et al.*, 2001).

Although bivariate linear regression and multiple regression models have been used previously (Eisele *et al.*, 2003; Nakhapakorn & Tripathy, 2005), the small number of observations (only 10 localities for QuickBird and FRAGSTATS data) is a limitation of our study that could be addressed in future analyses by using subpixel classifiers applied to medium resolution imagery, which typically cover larger areas per scene than QuickBird. Furthermore, regression requires independence for one of the variables (e.g. each locality) and even though independence was assumed, most of the boundaries between localities cannot be considered barriers to mosquito or human dispersal. However, vector dispersal may be somewhat limited since some studies suggest that *Ae. aegypti* females frequently do not travel more than 100 to 200 metres (Harrington *et al.*, 2005; Russel *et al.*, 2005) and that busy roads may act as barriers to their movement (Russel *et al.*, 2005). Since one of the purposes of this study was to identify relationships that may explain variation in dengue incidence, spatial autocorrelation was not considered, although tests for autocorrelation may reveal that it should be accounted for in developing statistical and deterministic spatial models for prediction of dengue fever or vector distributions.

It is important to mention that the relationships discussed above between tree cover, built areas, and incidence of dengue fever assume that virus transmission took place within the health locality of residence, and that the disease was associated with vector densities and *Ae. aegypti* larval habitats. Also, differences in human behaviour, education and control activities, which affect mosquito densities and/or virus transmission (Kuno, 1995), may have been coincidently associated to dengue fever and thus provide additional explanations for the relationships obtained. It should be noted that transmission and productive mosquito habitats are frequently clustered at fine scale levels such as specific houses or neighbourhoods (Strickman & Kittayapong, 2002; Chadee, 2004). Therefore, aggregation of cases and structural characteristics at the locality level may result in bias. Nevertheless, the locality level served as an initial exploration into the possible relationships between dengue fever and aspects of the urban environment that are observable using very high-resolution satellite imagery.

These results should be of interest to local scale health agencies and urban planners respectively who seek improved spatial information for dengue prevention and control, and knowledge of how tree cover and other forms of shade-producing vegetation may affect vector habitats. In addition, these approaches may serve to develop city scale risk maps and identify locations for enhanced prevention and control activities, or used to make rapid predictions and locate priority zones, especially in areas where prompt action is required and limited or no epidemiological and entomological data available. In this sense, remotely sensed imagery provide a means to guide precision vector control similar to its use in precision agriculture (Beeri & Peled, 2006) to target areas within agricultural zones that require specific inputs (e.g. fertilizers, pesticides, herbicides and so on) at critical times of the growing cycle.

Conclusions

In the urban environment of Greater Puntarenas, it was possible to discern relationships between dengue incidence and local weather data, as well as remotely sensed information extracted from various sources. Although dengue fever has been inversely related to vegetation and directly associated to built areas at coarse spatial scales (Nakhapakorn & Tripathy, 2005), the opposite seems true when analyzing dengue fever distribution at a local scale within the urban environment.

Advanced classification algorithms applied to high-resolution satellite imagery provided useful information for the analysis of dengue fever within Puntarenas City . Although remotely sensed data may not be useful to directly detect water collecting container habitats for *Ae. aegypti* larvae (Moloney *et al.*, 1998), the information on built environment and tree cover used in this study offered variables that may capture certain properties of urban structures that favour mosquito habitats and disease transmission. Furthermore, information extracted from imagery may be used to drive spatial models and create maps that predict dengue incidence and guide control strategies. Many of the limitations of remote sensing in the epidemiology of urban vector borne diseases may be overcome in part through use of very high-resolution imagery, although the limited availability of these data in some tropical areas, low temporal resolution and classification errors continue to pose challenges for understanding the spatiotemporal dynamics of this emerging pantropical urban disease.

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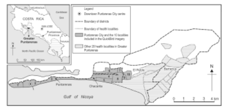

Figure 1.
Map showing the location of the 30 health localities – 10 in Puntarenas City included in the QuickBird imagery and analyses, the remaining 20 included in ASTER and MODIS images and analyses – in the Greater Puntarenas study area, Puntarenas Province, Costa Rica.

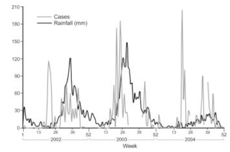

Figure 2.
Weekly number of dengue cases reported and rainfall in the Greater Puntarenas area, Puntarenas Province, Costa Rica, 2002–4.

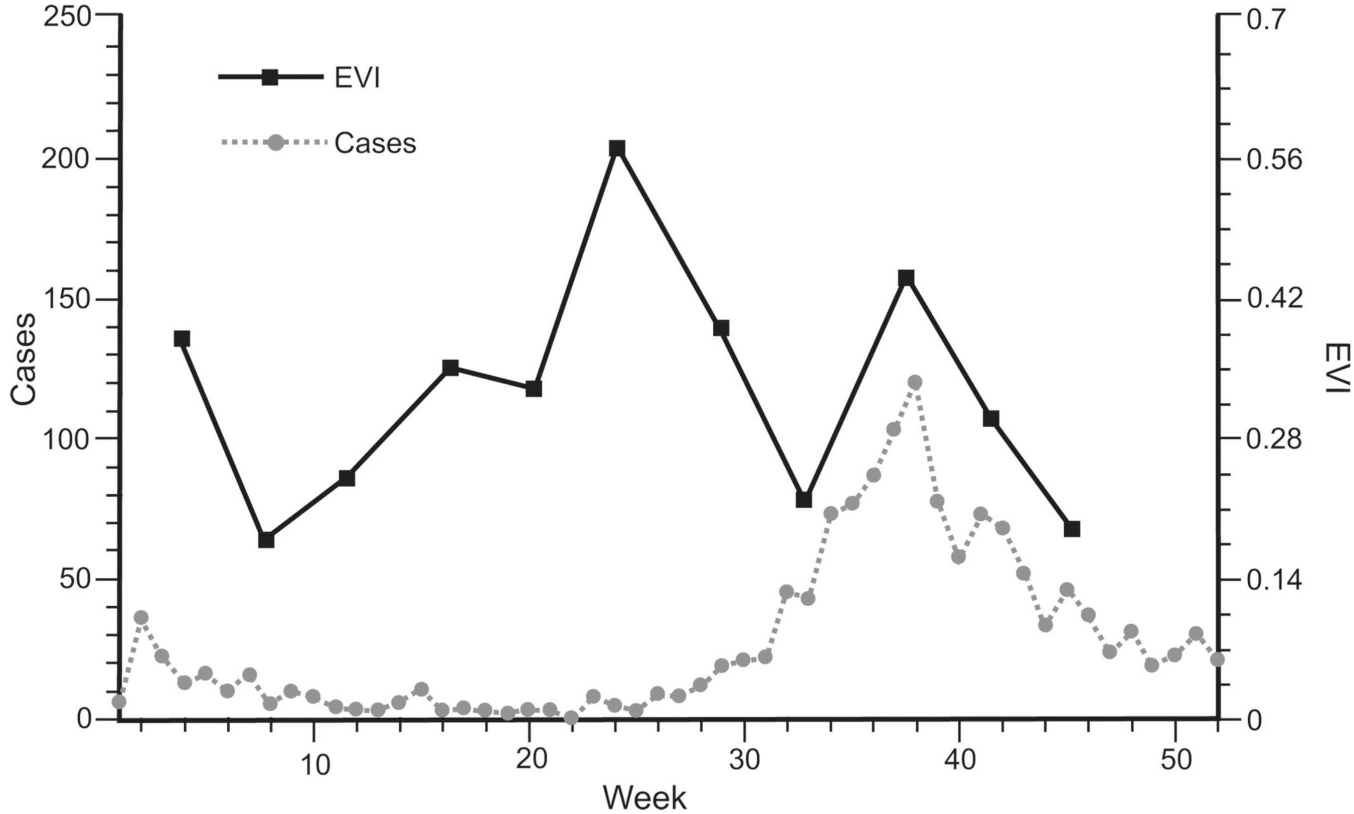

Figure 3.
Monthly enhanced vegetation index (EVI) and reported dengue cases in the Greater Puntarenas area, Puntarenas Province, Costa Rica, 2002.

Figure 4.
Masked sections of the back-propagation artificial neural network (A) and object-oriented classification (B) land use/cover maps of downtown Puntarenas, Costa Rica

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Table 1

Correlation matrix of dengue incidence in 2002 (DI 02) and 2003 (DI 03), proportional built area, and FRAGTATS metrics extracted for the 'built' class of the BPANN map.

	DI 02	DI 03*	CAb	CPYb	COHb	CONb	NPb	PLAb	PLNb
DI 03	0.19								
p-value	0.60								
CAb	0.25	−0.44							
p-value	0.49	0.21							
CPYb	0.47	−0.46	0.54						
p-value	0.17	0.18	0.11						
COHb	0.08	0.49	0.05	0.28					
p-value	0.82	0.15	0.88	0.44					
CONb	−0.50	0.04	−0.78	−0.16	0.11				
p-value	0.14	0.92	0.01	0.67	0.76				
NPb	0.20	−0.25	0.84	0.07	−0.19	−0.91			
p-value	0.58	0.48	<0.01	0.86	0.59	<0.01			
PLAb	0.48	−0.47	0.595	1.00	0.27	−0.22	0.13		
p-value	0.16	0.17	0.07	0.0	0.44	0.54	0.72		
PLNb	0.25	−0.44	1.00	0.54	0.05	−0.78	0.84	0.60	
p-value	0.49	0.21	0.0	0.11	0.88	0.01	<0.01	0.07	
PB	−0.16	−0.74	0.63	0.63	−0.08	−0.18	0.29	0.64	0.627
p-value	0.66	<u>0.01</u>	0.05	0.05	0.82	0.61	0.42	0.04	0.05

*Note:*DI: dengue incidence, CAb: class area, CPYb: clumpiness index, COHb: patch cohesion index, COb: connectance index, NPb: number of patches, PLAb: percentage of like adjacencies, percentage of landscape, PB: proportion of built area.

*Statistically significant p-values for correlations of dengue incidence with other variables are underlined.

Table 2

Correlation matrix of dengue incidence in 2002 (DI 02) and 2003 (DI 03), proportional tree area, and FRAGTATS metrics extracted for the ‘tree’ class of the BPANN map.

	DI 02	DI 03*	CAt	CPYt	COHt	CONt	NPt	PLAt	PLNt
DI 03	0.19								
p-value	0.60								
CAt	0.33	0.59							
p-value	0.35	0.07							
CPYt	−0.09	0.70	0.37						
p-value	0.81	<u>0.02</u>	0.29						
COHt	−0.21	0.72	0.45	0.96					
p-value	0.56	<u>0.02</u>	0.19	<0.01					
CONt	−0.51	0.24	−0.38	0.66	0.618				
p-value	0.13	0.50	0.27	0.04	0.056				
NPt	0.39	−0.41	0.27	−0.75	−0.70	−0.93			
p-value	0.26	0.24	0.45	0.01	0.02	<0.01			
PLAt	−0.08	0.72	0.40	1.00	0.96	0.64	−0.73		
p-value	0.83	<u>0.02</u>	0.25	0.0	<0.01	0.048	0.02		
PLNt	0.33	0.59	1.00	0.37	0.45	−0.38	0.27	0.40	
p-value	0.35	0.07	0.0	0.29	0.188	0.27	0.45	0.25	
TC	−0.27	0.75	0.29	0.94	0.95	0.75	−0.80	0.94	0.28
p-value	0.45	<u>0.01</u>	0.42	<0.01	<0.01	0.01	0.01	<0.01	0.42

*Note*DI: dengue incidence, CAt: class area, CPYt: clumpiness index, COHt: patch cohesion index, CONt: connectance index, NPt: number of patches, PLAt: percentage of like adjacencies, PLNt percentage of landscape, TC: proportion of tree cover.

*Statistically significant p-values for correlations of dengue incidence with other variables are underlined.

Table 3

Correlation matrix of dengue incidence in 2002 (DI 02) and 2003 (DI 03), proportional built area, and FRAGTATS metrics extracted for the 'built' class of the eCognition map.

	DI 02	DI 03*	CAb	CPYb	COHb	CONb	NPb	PLAb	PLNb
DI 03	0.19								
p-value	0.60								
CAb	0.25	−0.63							
p-value	0.48	0.05							
CPYb	0.46	−0.75	0.766						
p-value	0.18	0.01	0.009						
COHb	0.55	−0.58	0.779	0.92					
p-value	0.10	0.08	0.007	<0.01					
CONb	−0.04	−0.33	−0.08	0.30	−0.08				
p-value	0.91	0.35	0.818	0.41	0.84				
NPb	−0.07	0.22	0.199	−0.27	−0.05	−0.80			
p-value	0.86	0.54	0.579	0.44	0.90	0.01			
PLAb	0.48	−0.74	0.79	1.00	0.93	0.24	−0.23		
p-value	0.16	0.02	0.006	0.0	<0.01	0.50	0.53		
PLNb	0.25	−0.63	1.00	0.77	0.78	−0.08	0.20	0.79	
p-value	0.48	0.05	0.0	0.01	0.01	0.82	0.58	0.01	
PB	0.23	−0.73	0.90	0.84	0.80	0.18	−0.10	0.85	0.91
p-value	0.52	0.02	<0.01	<0.01	0.01	0.62	0.78	<0.01	<0.01

*Note*DI: dengue incidence, CAb: class area, CPYb: clumpiness index, COHb: patch cohesion index, CONb: connectance index, NPb: number of patches, PLAb: percentage of like adjacencies, PLNb percentage of landscape, PB: proportion of built area.

* Statistically significant p-values for correlations of dengue incidence with other variables are underlined.

Table 4

Correlation matrix of dengue incidence in 2002 (DI 02) and 2003 (DI 03), proportional tree area and FRAGTATS metrics extracted for the ‘tree’ class of the eCognition map.

	DI 02	DI 03*	CAt	CPYt	COHt	CONt	NPt	PLAt	PLNt
DI 03	0.19								
p-value	0.60								
CAt	0.20	0.45							
p-value	0.57	0.19							
CPYt	−0.40	0.57	0.24						
p-value	0.25	0.08	0.50						
COHt	−0.26	0.64	0.38	0.95					
p-value	0.46	<u>0.05</u>	0.27	<0.01					
CONt	−0.63	0.26	−0.33	0.71	0.54				
p-value	0.05	0.47	0.35	0.02	0.10				
NPt	0.45	−0.50	−0.10	−0.94	−0.93	−0.67			
p-value	0.20	0.14	0.79	<0.01	<0.01	0.03			
PLAt	−0.38	0.59	0.28	1.00	0.96	0.69	−0.93		
p-value	0.27	0.07	0.43	0.0	<0.01	0.03	<0.01		
PLNt	0.20	0.45	1.00	0.24	0.38	−0.33	−0.10	0.28	
p-value	0.57	0.19	0.0	0.50	0.27	0.35	0.79	0.43	
TC	−0.46	0.54	0.18	0.96	0.86	0.79	−0.86	0.95	0.18
p-value	0.19	0.11	0.63	<0.01	<0.01	0.01	<0.01	<0.01	0.63

Note DI: dengue incidence, CAt: class area, CPYt: clumpiness index, COHt: patch cohesion index, CONt: connectance index, NPt: number of patches, PLAt: percentage of like adjacencies, PLNt percentage of landscape, TC: proportion of tree cover.

* Statistically significant p-values for correlations of dengue incidence with other variables are underlined.