M. Salim Ferwati

Exploring the Spatial and Temporal Variation of Air Temperature in the Extreme Desert Climate of Doha, Qatar

Yasuyo Makido[1], Vivek Shandas[2*], M. Salim Ferwati ,[3] and David J. Sailor[4]
1 Portland State University, 1825 SW Broadway, Portland, OR, USA, *ymakido@pdx.edu*
2 Corresponding Author, Portland State University, 1825 SW Broadway, Portland, OR*, USA, *vshandas@pdx.edu*
3 Qatar University, Al Tarfa, Doha 2713, Qatar, sferwati@qu.edu.qa
4 Portland State University, 1825 SW Broadway, Portland, OR, USA, *sailor@pdx.edu*

1. Introduction

The question of mitigating extreme urban heat takes on a new dimension and challenge in a desert climate such as Doha, Qatar. Throughout much of the year the daytime air temperatures remain unbearable, limiting outdoor activities to late evenings. Urban heat mitigation in such a climate will have little effect on the tolerability of daytime extreme temperatures, but may have the potential to increase accessibility to moderate outdoor conditions in the early morning and late evening hours. A first step in estimating the potential for mitigating heat in such an extreme desert climate is to understand the spatial and temporal variation of air temperature throughout the city. Once we understand intra-urban variability and those landscape factors that help to explain thermal differences across the city, we can develop predictive models that relate physical characteristics to the corresponding variations in near-surface air temperatures. In this study we assess the extent to which the built environment, including vegetation, affect intra-urban variability of temperature in Doha, Qatar. Based on empirically derived temperature readings, we address three research questions: (1) to what extent does the air temperature vary during the day? (2) what landscape factors best explain how the temperature varies? And (3) how do analytical techniques for estimating intra-urban temperature affect the accuracy of predictions? By addressing these questions, we develop a spatially-explicit description of urban heat islands within the study region. Below we describe our methods and results, and conclude with a brief description about the implication of our results for urban and regional planning.

2. Methods

The city of Doha is capital and the largest city in the state of Qatar, and it has been one of the fastest growing populations in the Arabic world (UN, 2012). We conducted several vehicle temperature traverses to determine spatial differences in summertime air temperature across the city. The traverse covered all parts of the city of Doha (Figure 1), and occurred on Sept 8 and 9 in 2014. We followed an established protocol (Hart and Sailor, 2009), consisting of a Type T fine (30 gauge) thermocouple mounted within a 12cm long, 2.5 cm diameter white plastic shade tube. The tube was supported on the passenger-side window approximately 25 cm above the vehicle roof. The temperature sensors were connected to data logging temperature recorders with an estimated system accuracy of +/-0.5C and a 90% response time of less than 60 s in 1m/s airflow.). A time synchronous GPS system was also attached to each car so that each temperature measurement could be paired with a GPS location, with a sampling frequency of 5s. Data for vehicle speeds less than 5 km/h were discarded as the temperature sensors were aspirated by the movement of the vehicle, and we wanted to avoid oversampling when vehicles were stopped (e.g. in traffic or at traffic lights). Each day's traverse involved four cars and lasted one hour at three time periods: 6:00-7:00, 13:00-14:00, and 19:00-20:00.

Fig. 1 Coverage of Sept 8 and 9, 2014 vehicle temperature traverse across the study area, Doha

We subsequently computed Land Cover/Land Use (LCLU) characteristics that can be attributable to local urban temperatures. Landsat OLI imagery (acquisition date = 9/12/2014) was used to classify the study area into four categories: urban/built-up, vegetation, soil, and water. We employed the hybrid classification method, which is a combinations of supervised classification and unsupervised classification (Shandas et.al., under review). For this study, we derived four variables at each pixel (30m): urban/non-urban, vegetation/non-vegetation, albedo and distance to coastal line.

In order to reveal the area of influence for each discrete temperature measurement, we plotted the linear regression correlation coefficient between temperature and three variables within a certain distance (urban density, vegetation density, and mean Albedo). In this study, we tested from 50m to 1000m buffer distance with 50m increment. Based on the plot, we selected the most influential buffer sizes for each date/time by determining the buffer distances which have the largest positive or negative correlation coefficient or less than 600m (Table 1). Maximum buffer size of 600m was selected based on previous studies, which commonly employed several hundred meters as buffer distances (Kruger 2007 etc), and also our understanding of the influence of land surface characteristics on local temperatures.

Table. 1 Buffer sizes for each variable (meter)

Buffer sizes	9/8/2014			9/9/2014		
	6am	1pm	7pm	6am	1pm	7pm
Urban	600	600	600	600	600	600
Vegetation	100	400	150	600	350	150
Albedo	50	600	50	50	600	50

We employed tree-structures regression model to determine the importance of various land use and land cover characteristics. Regression tree offers a robust tool for handling nonlinear relationships between the dependent variable and predictive variables (Yuan 2008). The algorithm uses a set of independent variables to recursively split a dependent variables into subsets which maximize the reduction in the residual sum of squares (Hansen 2002). For each subset, a multiple linear regression model is constructed to predict the temperature of each cell.

In order to examine the accuracy of model, we employed a holdout method, which partitions the data into two mutually exclusive subsets called a training set and a test set (holdout set). It is common to select 2/3 of the data as the training set and the remaining 1/3 as the test set (Kohabi 1995). For this study, we used randomly selected 70 % of traverse data as the training set and the remaining 30% of the data as the test set. Thus, randomly selected 70 % of traverse points were used to construct the regression tree model. As a comparison to tree-structured regression model, we also employed a linear regression model to examine the accuracy of model predictions.

3. Results and Discussion

We describe results in three parts since they directly correspond to our research questions. To start we describe the results of our tree regression, and due to space limitations, describe only the sample result for Sept 8 and Sept 9 at 7pm (Figure 2). Based on conditional probabilities, the regression tree contains left and right nodes, and in our case, the left node indicates a condition that is true, and the right node indicates a false. The study area is divided into four or five categories based on the node criteria. The values at each end node is the mean temperature for that terminating node, and a multiple linear regression model is constructed to predict the temperature of each pixel. For both models, the first terminating node is the urban density, and it suggests that the percent urban area within 600m radius is the most important factor in the surface temperature in the evening.

The results indicate that urban areas, distance to the coast line are significant and that the temperature vary between 34.3 and 38.6 ^{o}C at 7pm for both days. While the difference may seem small (<2.0 ^{o}C) they are statistically significant and indicate that these two factors provide the most explanatory power for determining the landscape features that create urban heat islands. The difference between two days (35.7 high on Sept 8th versus 38.6 high on Sept 9th), while expected, creates some difficulty in establishing one UHI model for Doha, as we will describe below. Also notable, is that we examined multiple distances from sampling points to determine those distances that provide the highest predictive power for each of the locations. Urban areas within 600m, distance to coast ranging from 1 – 8km, and albedo within 50 meters from sampling locations proved to provide the greatest explanatory power for our regression model.

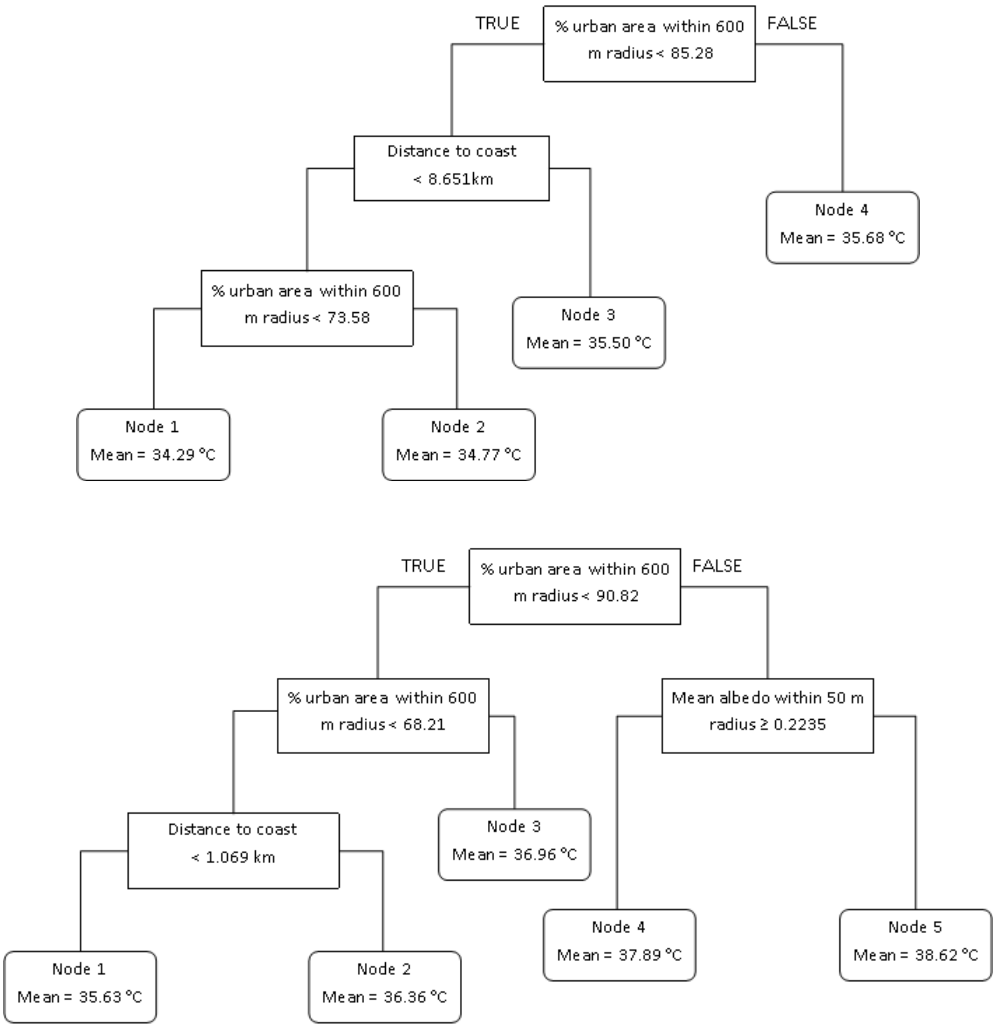

Fig. 2 Tree-structured regression model for 8th of Sept, 2014 7pm (upper) and 9th of Sept, 2014 7pm (lower)

Using the results of the regression tree analysis, we developed two spatial description of temperature variability for 8th and 9th of Sept at 7pm (Figures 3 and 4).

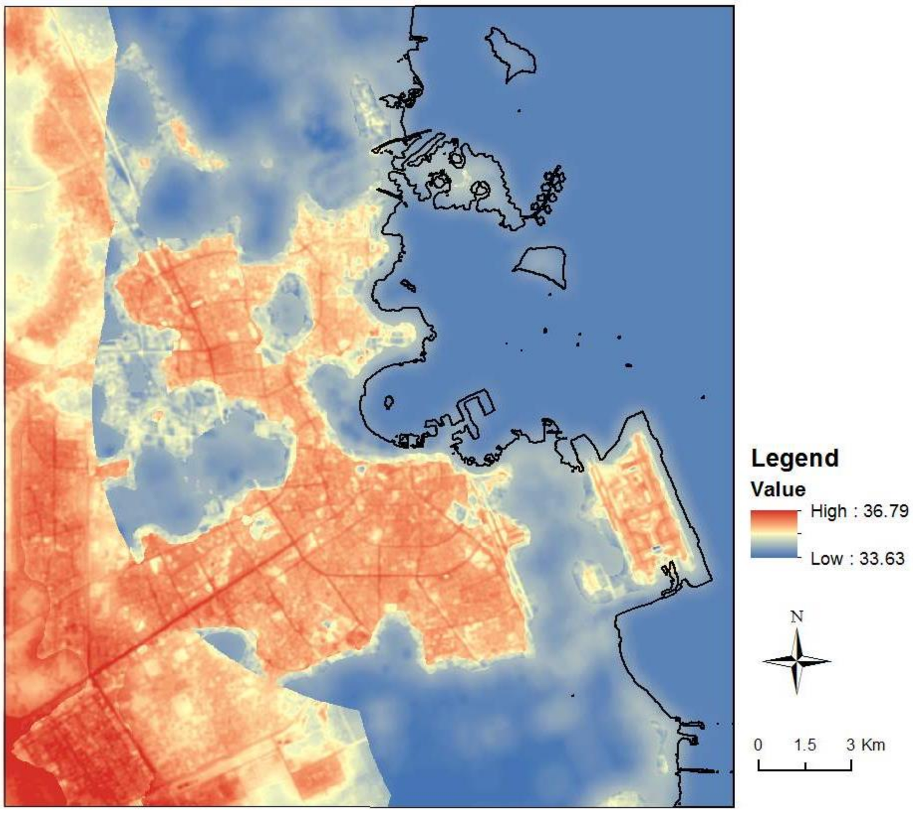

Fig. 3 Predicted surface map using tree-regression models (unit is in °C) for 9/8/2014 7pm

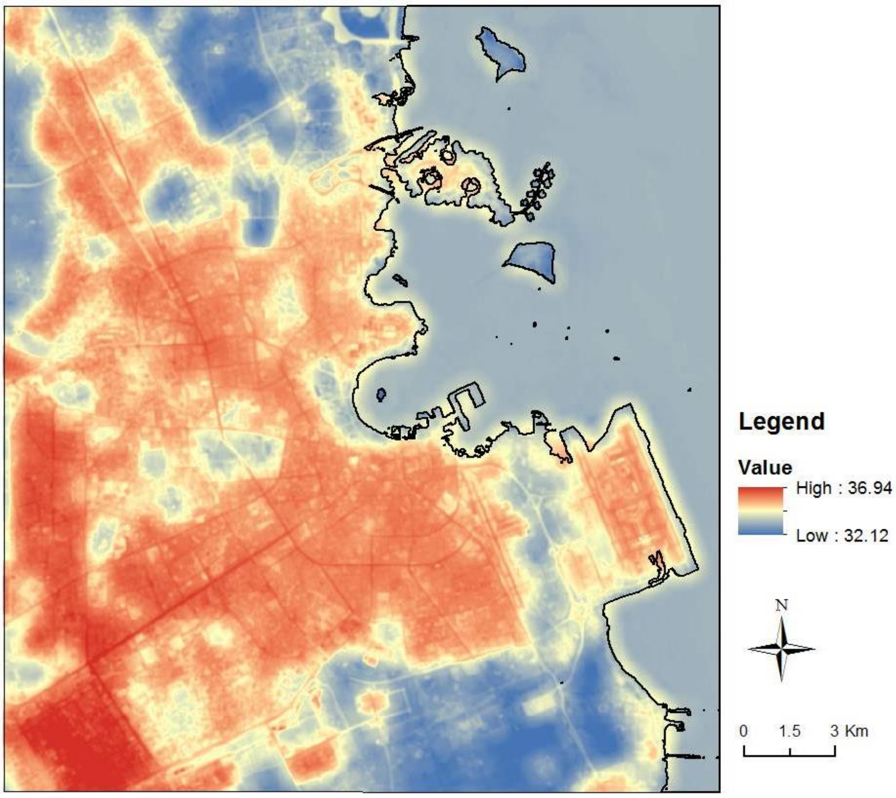

Fig. 4 Predicted surface map using linear regression models (unit is in °C) for 9/8/2014 7pm

To validate the prediction of the UHI models, we conducted a Pearson's correlational analysis between estimated surface temperatures using 70 % of traverse data and true surface temperatures at remaining 30 % of traverse data. In all cases, the correlation coefficient is higher for using tree-structures regression models as opposed to the standard linear regression model. The Pearson's analysis suggests that the tree regression model more accurately predicts the surface temperatures than the linear regression model.

Table. 2 Pearson's correlation coefficient between estimated surface temperatures using 70 % of traverse data and true surface temperatures at remaining 30 % of traverse data

	9/8/2014			9/9/2014		
	6am	1pm	7pm	6am	1pm	7pm
Tree Regression Model	0.394	0.697	0.724	0.633	0.809	0.750
Linear Regression Model	0.330	0.638	0.676	0.397	0.789	0.688

4. Conclusions

The creation of impervious surfaces is central to creation of cities. In areas where temperatures can cause major health impacts, understanding the role of landscape features is an essential part of developing mitigation strategies. Our analysis provides insight into the role of local land cover in temperature variations across the city, leading to the development of specific recommendations for future development in the region. In the case of Doha, urban areas, distance to coastline, and albedo are three landscape features affecting local temperatures. If planning agencies are considering options for mediating temperature for greater access to outdoor spaces, then reducing the amount of impervious surfaces may be a first step. While changing land cover may not be cost effective or a feasible option in places containing large amount of impervious surface, covering the concrete with trees may be a reasonable alternative. Despite the arid climate, given the abundant amount of water from desalination in Doha, water resources may be readily available for expanding the urban canopy. Alternatively, increasing the albedo of surfaces is a common practice, which in this case can reduce the absorption of solar radiation. Finally, the distance from coastline indicates that the mediating influence of coastal waters can significantly impact inland air temperatures. If, however, coastal winds are blocked by high rise buildings along the coastline, then the inland areas will not benefit from this mediating influence. Restricting the development along the coast, especially those buildings that prevent coastal processes from meditating inland temperatures, is a policy that has traction in scholarly research (Wong, et al., 2011), and may be a policy option that can improve short and long term quality of life for Doha residents.

Acknowledgment

This paper was made possible by NPRP grant # NPRP 5-074-5-5015 from the Qatar National Research Fund (a member of Qatar Foundation). The statements made herein are solely the responsibility of the authors

References

Hansen, M. C., DeFries, R. S., Townshend, J. R. G., Sohlberg, R., Dimiceli, C., & Carroll, M. 2002: Towards an operational MODIS continuous field of percent tree cover algorithm: examples using AVHRR and MODIS data. Remote Sensing of Environment, 83(1), 303-319.

Hart MA., and DJ Sailor, 2009: Quantifying the Influence of Land-Use and Surface Characteristics on Spatial Variability in the Urban Heat Island. Theoretical and Applied Climatology 95.3-4: 397-406.

Kohavi, R., 1995: A study of cross-validation and bootstrap for accuracy estimation and model selection. Ijcai, Vol. 14, No. 2, pp. 1137-1145.

Krüger, E., & Givoni, B. 2007: Outdoor measurements and temperature comparisons of seven monitoring stations: Preliminary studies in Curitiba, Brazil. Building and environment, 42(4), 1685-1698.

Shandas, V., Y Makido, C Hong, S Ferwati, and D Sailor (under review). Rapid urban growth and development patterns in the Middle East: The Case of Doha, Qatar. Computers, Enviornment, and Urban Systems.

Wong, M.S., Nicho, J., and Ng, E..2011: A study of the 'wall effect' caused by proliferation of high-rise buildings using GIS techniques, Landscape and Urban Planning 102 (4), 245-253

Yuan, F., Wu, C., & Bauer, M. E. 2008: Comparison of spectral analysis techniques for impervious surface estimation using Landsat imagery. Photogrammetric Engineering & Remote Sensing, 74(8), 1045-1055.