Conclusions

The summer of 2009 was cooler than average in Detroit, but it was not devoid of the either warm spells or spatial variability in temperature across the metropolitan region. While the spatial variability observed was statistically significant for both daily lows and daily highs, they behaved quite differently. The mean spatial variability was twice as large during the daily lows as daily highs, but the variability about that mean was also twice as large. The daytime spatial variability is most likely noise while the nighttime spatial variability is due to the urban landscape. In turn, the affect of the urban landscape on the temperature pattern strongly varies depending on the large-scale weather conditions. There was significantly more consistency of the spatial pattern during the daily lows than the daily highs.

Initial results indicated that the temporal variability in each station's anomalies was so large that it seemed to drown out the relevant differences between the station's (i.e. a relevant spatial variability), but bootstrapping results suggested that this large temporal variability (e.g. some days all stations are roughly the same temperature and other days there is a large difference between the stations) does not imply similarly large uncertainty in each station's mean anomaly (i.e. the stations still have relevant differences in their mean anomaly). Thus the daily low mean spatial pattern was significant (relative to the uncertainty), but this was not true during the daily highs. The spatial pattern of temperature was also spatially different between the daily lows (warm downtown) and highs (warm west side of region). Visually the spatial pattern indicated that the water bodies bordering the east, northeast and southeast side of the city played as significant a role as the distribution of urban landscape. The stability of the daily low spatial pattern was greatly more stable than the daily high spatial pattern. In light of these results, health officials and civil engineers concerned with spatial variability of temperature should be aware that while the spatial variability is significant during both daily extremes it is also highly different between daily extremes.

During hot weather, results implied that spatial variability exists even if the sample size was often too small to determine statistical significance. While warmer weather classifications, during both days and nights, did not seem the have more spatial variability; the average spatial variability of the oppressive air masses was on par with the other air masses. The small sample size likely prohibited establishment of statistical significance during oppressive air masses. Additionally, this method indicated that during drier weather classifications (air masses), the daily low spatial variability was larger. Physically this made sense, as radiative heat loss is usually more profound during drier weather. The times during NWS heat advisories also indicated typical amounts of spatial variability. However the sample size was even smaller and statistical significance could not be established. When a heat wave definition was used to classify hot days and heat waves, we saw that one heat wave did occur late in the season. During that heat wave, the average spatial variability during the daily lows was smaller than typical although the daily highs were on par. However when individual days (e.g. as oppose to consecutive days) were examined we saw typical values for both daily extremes, and the number of qualified individual days were more numerous and indicated the spatial variability was statistically significant. Lastly, the relationship between apparent temperature percentiles and spatial variability indicated that spatial variability does not disappear at the highest percentiles. However a significant negative slope was seen in the daily lows; this is expected since daily lows are typically higher when the radiative cooling rates (which are driving the spatial variability) are low. While this observational study had difficulty obtaining statistically significant results, the results seem to suggest health officials should be conscious of spatial variability during hot weather - regardless of the definition of hot.

Linking across scales, the temporal variability of the small-scale metropolitan region spatial variability was seemingly controlled by temporal variability of the large-scale weather conditions. Large-scale wind speed and cloud cover observations correlated well with the spatial variability in both daily extremes (except afternoon cloud cover). Results indicated that the daily low spatial variability could be modeled effectively (explained > 50%, RMSE less than half the mean value) using three such variables. Overnight cloud cover was the strongest part of that equation, being roughly twice as strong of a predictor as the next strongest variable (previous afternoon cloud cover). This is straightforward because less overnight cloud cover allows radiative cooling rates to strongly vary by location because local intrinsic factors that retains heat well (nearby water, urban canyon effect, imperviousness, etc.) will be significantly warmer. The daily high spatial variability was not well linked to the large-scale weather conditions because it was being driven mostly by noise (e.g. synoptic wind direction) and lake effects. Lake effects tend to be highly variable because not only does each lake breeze affect the high with a different spatial pattern, but also sometimes the lakes impact the entire urban region, rather than just near the water. Since the observations proved linked to the daily low, reanalysis values were tested and showed similar worth as predictors. The results were similar in that all three variables were deemed appropriate to predict the daily low, and the goodness of that model was only slightly less. The results indicated that health officials concerned with spatial variability should be able to approximate (either from in-situ observations or forecast products) the amount of spatial variability during the daily low.

Ultimately public health officials would like to predict which parts of the city are warmer; thus we investigated the ability to predict the observed temporally averaged anomalies at each location. Here the choice to use the three spatial variables (D2CC, PIS and D2H2O) arose because of their relative ease of creation, but there are many more and better variables (e.g. locally averaged sky view factor, urban surface (broadband) albedo, normalized difference vegetation index). The variables correlated fairly well and objective tests indicated multiple variable regression models were appropriate to model both the daily low's and high's 110DM anomalies at each station. The equation for the daily low, the only equation that included the PIS variable, passed the initial inspection of goodness. The equation indicated the PIS variable was notably more influential than the other 2 variables. Further testing of the utility of the equation backed up our initial results and instilled confidence in the model. Lastly a bootstrapping technique indicated we could have confidence in the coefficients while also providing a better estimation of the coefficients. Thus, health officials in Detroit should be aware that the average overnight relative temperatures could be estimated fairly confidently from just three spatial variables.

It may be more useful to predict the anomalies during times with large spatial variability since the temporal averaging likely diminished the signal created by the urban landscape and it is the time in which the spatial variability is most pertinent to health officials (our results indicate confidence in the ability to predict the high spatial variability times). The nights were sub selected with a bootstrapped version of the equation discussed earlier for predicting the UHI magnitude, and the afternoons with wind speed values. The recalculated values indicated a much clearer and robust spatial pattern than that in the 110DM values, as well as larger mean spatial variability. The predicative equation derived from multiple variable regression performed similarly but explained slightly less variability. This is because while the conducive weather conditions allowed an increased number of factors to be relevant to the overall spatial variability, we held constant the number of variables used to explain that variability. Further testing did not indicate a large drop off in performance; however the confidence in the regression coefficients did decrease likely as a result of the smaller (half) sample size. In general, the results indicated that when the spatial variability is large the mean anomalies can be similarly predicted, with spatial variables, although not with increased success.