Characterize the Spatial-temporal Variations of Urban Heat Island Intensity using a Land Use Regression Approach

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KEY WORDS: Urban Heat Island Effects (UHIE), Intensity, Air Temperature, Spatial-temporal Variations, Land-use Regression (LUR).

ABSTRACT: Human activity is one of the dominated driving forces for global warming, in particularly in the urban areas. The temperature within the urban areas is higher than that of the surrounding rural area, this phenomenon is known as Urban Heat Island Effects (UHIE). In this study, a Land-use Regression (LUR) approach was applied to estimate air temperature based on ambient land-use/land cover allocations, and then to assess the spatial-temporal variability of UHIE intensity in six metropolises of Taiwan. The study materials included in-situ observations of air temperature from 2000 to 2016, landmark database, digital road network data, National land use inventory, MODIS NDVI datasets and thermal power plant distribution database. The Spearman correlation coefficient and stepwise regression were employed to develop the prediction model. Variables with the erroneous direction of correlation, high collinearity (VIF>3) and p-value>0.1 were eliminated out during the variable selection procedures. Model robustness was verified by 10-fold validation and external data verification. The results showed that, with the adjusted R^2 of 0.87, a 10-fold cross validated R^2 of 0.87, and an external data validated R^2 of 0.92, the high explanatory power of the resultant model was confirmed. 19 variables related to green spaces, culture activities, road, traffic and transportation, and industry were selected as important predictors variables in the developed model. Finally, UHI intensity calculated from the resultant model showed that, Taichung City had the highest level of UHI intensity (4.6℃) among the six cities, and then followed by Kaohsiung City (1.8℃), Taoyuan City (3.3℃), New Taipei City (2.6℃), Tainan City (1.3℃), and the level of Taipei City (0.9℃) was the lowest. Regardless the location, only minor variations were observed among the studied 17 years, indicates more efforts were needed for heat mitigation.

1. INTRODUCTION

The global warming have a great impact for environmental health(Hansen *et al*., 2008; Berry *et al*., 2010; Vida *et al*., 2012; Williams *et al*., 2012; Wang, *et al*., 2014; Ding *et al*., 2016).From 1880 to 2012, the global average temperature has increased by 0.85 ℃(IPCC, 2014). In most areas, people will experience more high temperature environment and affect health (Basu and Samet, 2002; Basu, 2009; Ye *et al*., 2012). Human's activity will promote global warming, in particularly in the urban areas. This in turn creates an urban heat island effect(UHIE).UHIE refers to the situation where the average temperature of the atmosphere and the surface of the metropolitan area is higher than that of the neighboring suburbs or natural covered land

(Smoyer-Tomic *et al*.,2013, Lu *et al*., 2016).

Land-use Regression (LUR) can better serve small spatial variability of long-term outdoor air pollution (Pan *et al.*, 2016; Wu, *et al.*, 2017; Hsu *et al.*, 2018; Hsu *et al*., 2019), so it is often used to simulate pollution concentrations. Remote sensing can provide large-scale and multi-temporal surface information for various purposes like forest greenness assessment (Wu *et al.*, 2014). But besides examining UHI effects, they were rarely used to predict temperature (Chen *et al.*, 2006; Tomlinson *et al.*, 2011; Wu *et al.*, 2013; Singh *et al.*,2017). Because the remotely adapted data does not represent the atmospheric temperature, it can only represent the surface temperature. Moreover, the application of remote sensing methods to estimate the nationwide UHI effect will also face the problem of missing data. Therefore, by coupling LUR to remote sensing technology, this combination can be used to better estimate spatiotemporal temperatures.

Geographic Information System (GIS) technologies can provide flexible environments for collecting, storing, displaying, and analyzing the distribution of variables (Demers, 2005; Wu *et al.*, 2018)to develop LUR models, such as artificial cement facilities that cause elevated temperatures (Liu and Zhang, 2011) or Green space that reduces temperature and UHI effects (Yuan and Bauer,2007; Corburn, 2009; Ahmed *et al.*, 2015).

The Taiwan Central Meteorological Bureau has established more than 300 weather stations, but it is still not enough to study the spatial and temporal resolution of high temperatures, such as the UHI effect. Therefore, this paper aims to develop a model that can estimate the temporal and spatial variation of temperature. Based on 18 years of temperature observations at 377 stations in Taiwan, we used the LUR model to study high temperature resolution. In addition, in order to improve the accuracy of this modeling, we further use the number of temples and crematoriums and the Normalized Difference Vegetation Index (NDVI) as variables to assess whether plant growth vegetation cover or incense paper and incense burning Will affect the temperature. This article will show how to apply remote sensing to temporal and spatial variations in temperature and further UHI effects.

2. METHODS

2.1 Study Area and Material

Taiwan is located in South East Asia with a total population of 23 million (Central Intelligence Agency, 2018). 78.2% of the population lives in urban areas, and the urbanization rate increases by 0.8% annually. In addition to traffic emissions (Liu and Zhang, 2011), the unique temple culture caused by incense paper and incense and fast-fried restaurants is also one of the reasons (Kuo *et al*., 2015; Yu *et al.*, 2015).

Our research on UHI intensity (UHII) focuses on the six most populous areas in Taiwan (local government law, 2016), such as Taipei City with a population of 2.6 million, New Taipei City with a population of 3.9 million, and population of 2.8 million in Taoyuan City. The population of Taichung City is 2.2 million, the population of Tainan City is 1.9 million, and the population of Kaohsiung City is 2.8 million. The highest population density in Taipei is the six major cities (9791 people/km2), followed by New Taipei City, Taoyuan City, Taichung City, Kaohsiung City and Tainan City. We use the township with the smallest proportion of artificial cement facilities as a reference to calculate the UHI of each city.

2.2 Weather database

Taiwan's Central Weather Bureau established 377 weather stations until 2017 to systematically monitor meteorological data throughout the island. We calculated the annual average of the temperature data collected by the weather station and developed the LUR model with 3467 measurements as the dependent variable. The data from 2000 to 2016 was used for model development and the 2017 data was used for external validation. As the number of stations increases every year, the total number of stations per year is not equal. We included data for each station from 2000 to 2016 each year in the model.

2.3 Geo-Spatial database

We build LUR models with information on land-use or land-cover related information from different GIS layers and spatial databases. In the study we calculated the density of various roads around the station with the spatial distribution of the road network provided by the Transportation of the Ministry of Transportation. We also used the 2010 database in Industrial Development Bureau. to measure the distance from the weather station to the nearest industrial park. The study further combines national land use survey databases with land-use information such as residential areas, farms and mountains, parks and green spaces. The spatial distribution of temples and Chinese restaurants with the Point of Interest (POI) landmark database and the crematorium from the Taiwan EPA environmental database present Taiwan's unique cultural sources. A digital terrain model (DTM) with a resolution of 20 m * 20 m is applied to obtain the altitude of the measurement location. Due to the large amount of external heat generated by the thermal power plant, we collected the locations of all thermal power plants in Taiwan from Google Maps and calculated the distance from the weather station to the nearest thermal power plant.

In addition to the GIS database discussed above, we also considered the greening around the station during the study period by using NASA's MODIS Normalized Difference Vegetation Index (NDVI). We collected NDVI images with a spatial resolution of 250 m * 250 m and summarized them into annual averages for analysis.

To represent the distribution of land use/land cover around each meteorological station, these geospatial predictive variables are abstracted from a circular buffer between 25m and 5000m.

2.4 LUR model development and validation

We will establish a land-use regression model using the method described in our previous paper (Wu *et al.*, 2017; Hsu *et al*., 2018; Hsu *et al*., 2019). First, we used a supervised stepwise procedure to maximize the percentage of explained variability (R^2).. To determine which predictors to include, we chose the a priori direction of temperature (for example, green space is negative and road is positive (Liu and Zhang, 2011; Ahmed *et al.*, 2015). The model starts with the variable with the highest interpretation variance and has the regression slope of the expected direction in the univariate analysis. Other variables are then separately added to the model by evaluating whether the variance expansion factor (VIF) is <3 and the p value is <0.1. Repeat this process until all variables do not meet the above criteria. Finally, we used R^2 and adjusted R^2 to evaluate model performance. We then used 10x cross-validation (90% data for model development and 10% data for verification) to verify the reliability and robustness of the model. In addition, data from 2000 to 2016 was used for model development and data for 2017 was used for external validation.

3. EXPERIMENTAL RESULTS

3.1 Descriptive statistics of atmospheric temperature

The temperature did change statistically during the 17-year period (p value <0.05). The annual average temperature in Taiwan is 21.5 ± 3.6 ° C (median: 22.6 ° C), which is linearly related to the highest temperature (R2 = 0.87). The statistical results show that the temperature in the south is the highest, and there is no significant difference in temperature between the north and the east (p value > 0.05).

3.2 LUR model development and validation

Table 1 showed the LUR model. The overall model R^2 is 0.88, the average 10-fold cross-validation R^2 is 0.87, and the external data verification R^2 is 0.92. Indicates that this new model exhibits a high level of predictive performance. The main variables selected for the model include altitude, forests within 5,000 meters, distance from thermal power plants, tourist botanical gardens within 5,000 meters, crematoriums within 75 meters, mountains within 5,000 meters, forests within 25 meters, 250 The NDIV in Mian, the scenic spot is less than 500 meters away and the temple is less than 50 meters away. Except for thermal power plants, crematoriums and temples, these variables are mostly negatively correlated with atmospheric temperatures. In our model, height first enters the model and is the most important factor for part R^2 = 0.84. Arnfield (2003) reported that things like asphalt, concrete, stone, steel and other hard surfaces may destroy the cooling effect of the vegetation (and then raise the temperature). But similar variables (such as roads, residential areas, and industrial parks) were filtered out in the models we developed. Therefore, we conclude that lowering the temperature by increasing the altitude plays a very powerful role, masking other factors that affect the temperature of the atmosphere.

Table 1. Land-use regression model for annual average temperature (℃).

Variable	Regression Coefficient	VIF	Partial R^2
Intercept	23.607		
Altitude	-0.005	1.573	0.840
Forest_5000 m	-9.594×10^{-9}	2.207	0.014
Thermal power plant	1.503×10^{-5}	1.184	0.008
Tourism botanical garden_5000 m	-0.153	1.042	0.002
Crematorium _75 m	0.071	1.129	0.002
Mountain_5000 m	-0.053	1.301	0.002
Forest_25 m	-1.852×10^{-4}	1.317	0.001
NDVI_250 m	-0.500	1.316	0.001
Scenic area_500 m	-0.464	1.043	0.001
Temple_50 m	4.805	1.002	0.001

Model Performance:
Overall Model R^2 = 0.875; Adjusted R^2=0.874; 10-fold Cross-Validation R^2 = 0.870; External validated R^2 = 0.917

3.3 Spatiotemporal variations of atmospheric temperature

The model of this study simulates the annual average temperature in Taiwan. Further calculations of UHII in six metropolitan areas during the study period, Taichung City has the highest UHII value (4.60 ℃), followed by Taoyuan City (3.27 ℃), New Taipei City (2.64 ℃), Kaohsiung City (1.75 ◦C) , Tainan city (1.34 ◦C) and Taipei City (0.87 ◦C). Although Taipei is the most densely populated city in the six major cities, it has the lowest UHII. This may be because the township that is the reference point for calculating Taipei UHII is also very urbanized, and the proportion of artificial cement facilities is much higher than the reference points of the other five metropolises (8 to 24 times). In other words, metropolitan urbanization is broader than other metropolitan areas, and the city's reference point may not be so meaningful. In addition, the UHII level in Taipei is estimated to be very different from the previous one in this study (Wu *et al.*,2013), indicating that Taipei's highest surface UHII is 10.2 ℃). This is because Wu et al. Only the surface temperature of UHII in the short term (daily) is estimated, rather than the long-term calculation of the atmospheric temperature (annually) of UHII.

4. DISCUSSION

This paper combines the LUR model with GIS and remote sensing data to estimate the temperature in Taiwan and successfully combines the LUR model with the data from the weather station established by the Central Weather Bureau to estimate the temperature in Taiwan. This paper successfully applied remote sensing to the spatiotemporal variation of temperature, further expanding the UHI effect.

Although atmospheric temperature reflects the same trend as surface temperature, relying solely on surface temperature will tend to overestimate UHII and may therefore be less reliable than atmospheric UHII. In addition, atmospheric temperatures may be related to human health (Basu, 2009; Ye *et al.*, 2012; Guo *et al.*, 2016). Therefore, this paper uses remote sensing images to develop a LUR model to predict atmospheric temperature, which is more beneficial for health applications than just estimating surface temperature. In addition, by using LUR, it can cover the deficiencies of missing data and the number of sites for the kriging method in the cloudy weather of the satellite method.

Taiwan's cars have the highest density in Asia, with 378 cars per square kilometer, so traffic is one of the most important variables when developing the LUR model. However, there is currently no data on traffic intensity in Taiwan. The NOx concentration that can express the density of a motor vehicle is also unacceptable because the number of monitoring stations is too small (76 stations). Therefore, there is no flow variable in this LUR model. For other variables, although thermal power plants generate considerable external heat, Asia must also include resources with specific cultural resources. For example, in Asia, fragrant paper and incense are of religious importance (Lui *et al*., 2016), so we use the number of temples and crematoriums across Taiwan to reflect this partial emissions. In fact, in our newly developed LUR model, incense paper and incense burning is an important predictor. Therefore, we recommend that other scholars use this unique source of emissions as a predictor to develop LUR models to estimate atmospheric temperatures in other Asian regions.

However, there are no variables selected in this study that may improve the performance of the model. For example, traffic intensity, number of buildings and population are not included because we cannot find this data in Taiwan. Nonetheless, the model uses data collected from hundreds of weather stations in Taiwan over the past 18 years to represent temporal and spatial changes in atmospheric temperature, although some uncertainty may be caused by site distribution (e.g., fewer sites located in mountain areas). After all, LUR models with culturally specific predictors were developed using integrated weather data collected over the past 18 years, which can be performed at very high prediction levels and can be used to show temperature changes in Asian cities.

Finally, in our LUR model, altitude is the most important factor, accounting for 96% of all model performance. This result indicates that in the future study of atmospheric temperature as an influential condition, altitude can be used as a substitute for Taiwan's atmospheric temperature. Future research will make it easier to estimate the effects of atmospheric temperature by reference to the corresponding height.

5. CONCLUSIONS

In view of the importance of remote sensing data for the development of LUR models, this study builds LUR models from temperature data from 377 weather stations over the past 18 years, combining LUR models with GIS and remote sensing data to estimate spatial variability of long-term atmospheric temperature.In addition, this method can also be used for future research to estimate Taiwan's long-term UHII. It also provides some insights into future epidemiological studies such as the health impact indicators of local residents.

6. REFERENCES

Ahmed, A.;Ossen, D.;Jamei, E.;Manaf, N.;Said, I. and Ahmad, M.,2015. Urban surfacetemperature behaviour and heat island effect in a tropical planned city. Theor. Appl. Climatol, 119, pp. 493 - 514.

Arnfield, A.J., 2003. Two decades of urban climate research: A review of turbulence, exchanges of energy and water, and the urban heat island. International Journal of Climatology, 23(1), pp. 1-26.

Basu, R., 2009. High ambient temperature and mortality: a review of epidemiologic studies from 2001 to 2008. Environmental Health, 8.

Basu, R. and Samet, J.M., 2002. Relation between elevated ambient temperature and mortality: A review of the epidemiologic evidence. Epidemiologic Reviews, 24(2), pp. 190-202.

Chen, X.L.; Zhao, H.M.; Li, P.X. and Yin, Z.Y., 2006. Remote sensing image-based analysis of the relationship between urban heat island and land use/cover changes. Remote Sensing of Environment, 104(2), pp. 133-146.

Corburn, J., 2009. Cities, climate change and urban heat island mitigation:localising global environmental science. Urban Studies, 46(2), pp. 413 - 427.

Demers, M.N., 2005. Fundamentals of Geographic Information Systems. John Wiley&Sons, Inc., Newyork, USA.

Ding, N., H. L. Berry and C. M. Bennett, 2016. The importance of humidity in the relationship between heat and population mental health: evidence from Australia. Public Library Of Science One, 11(10), e0164190.

I.P.o.C.C.,2014. Climate Change 2014 Synthesis Report Summary for Policymakers.

Guo, Y.M.;Gasparrini, A.;Armstrong, B.;Tawatsupa, B.;Tobias, A.;Lavigne, E.;Coelho, M.D.Z.S.;Pan, X.C.;Kim, H.;Hashizume, M.;Honda, Y.;Guo, Y.L.;Wu, C.F.;Zanobetti, A.;Schwartz, J.D.;Bell, M.L.;Overcenco, A.;Punnasiri, K.;Li, S.S.;Tian, L.W.;Saldiva, P.;Williams, G. and Tong, S.L.,2016. Temperature Variability and Mortality: A Multi-Country Study. Environmental Health Perspectives, 124(10), pp. 1554 - 1559.

Hansen, A., P. Bi, M. Nitschke, P. Ryan, D. Pisaniello and G. Tucker, 2008. The effect of heat waves on mental health in a temperate Australian city. Environmental Medicine, 116(10), pp. 1369-1375.

Hsu, C.Y.;Wu, C.D.;Hsiao, Y.P.;Chen, Y.C.;Chen, M.J. and Lung, S.C.C.,2018. Developing Land-Use Regression Models to Estimate $PM_{2.5}$-Bound Compound Concentrations. Remote Sensing, 10(12).

Hsu, C.Y.;Wu, J.Y.;Chen, Y.C.;Chen, N.T.;Chen, M.J.;Pan, W.C.;Lung, S.C.C.;Guo, Y.L. and Wu, C.D.,2019. Asian Culturally Specific Predictors in a Large-Scale Land Use Regression Model to Predict Spatial-Temporal Variability of Ozone Concentration. International Journal of Environmental Research and Public Health, 16(7).

Kuo, S.C.;Tsai, Y.I. and Sopajaree, K.,2015. Emission identification and health risk potential of allergy-causing fragrant substances in $PM_{2.5}$ from incense burning. Build. Environ, 87, pp. 23 - 33.

Liu, L. and Zhang, Y.Z.,2011. Urban Heat Island Analysis Using the Landsat TM Data and ASTER Data: A Case Study in Hong Kong. Remote Sensing, 3(7), pp. 1535 - 1552.

Lui, K.H.;Bandowe, B.A.;Ho, S.S.;Chuang, H.C.;Cao, J.J.;Chuang, K.J.;Lee, S.C.;Hu, D. and

Ho, K.F.,2016. Characterization of chemical components and bioreactivity of fine particulate matter ($PM_{2.5}$) during incense burning. Environ. Pollut, 213, pp. 524 - 532.
Pan, W.C.;Wu, C.D.;Chen, M.J.;Huang, Y.T.;Chen, C.J.;Su, H.J. and Yang, H.I.,2016. Fine particle pollution, alanine transaminase, and liver cancer: A Taiwanese prospective cohort study (REVEAL - HBV). J. Natl. Cancer Inst, 108.
Singh, P.;Kikon, N. and Verma, P.,2017. Impact of land use change and urbanization on urban heat island in Lucknow city, Central India. A remote sensing based estimate. Sustainable Cities and Society, 32, pp. 100 - 114.
Smoyer-Tomic, K.E.;Kuhn, R. and Hudson, A.,2003. Heat wave hazards: An overview of heat wave impacts in Canada. Natural Hazards,28(2-3), pp. 463 - 485.
Tomlinson, C.J.;Chapman, L.;Thornes, J.E. and Baker, C.,2001. Remote sensing land surface temperature for meteorology and climatology: a review. Meteorological Applications, 18(3), pp. 296 - 306.
Vida, S., M. Durocher, T. B. M. J. Ouarda and P. Gosselin, 2012. Relationship between ambient temperature and humidity and visits to mental health emergency departments in Québec. Psychiatric Services, 63(11), pp. 1150 - 1153.
Wang, X., E. Lavigne, H. Ouellette-kuntz and B. E. Chen, 2014. Acute impacts of extreme temperature exposure on emergency room admissions related to mental and behavior disorders in Toronto, Canada. Journal of Affective Disorders, 155, pp. 154 - 161.
Williams, S., M. Nitschke, T. Sullivan, G. R. Tucker, P. Weinstein, D. L. Pisaniello, K. A. Parton and P. Bi, 2012. Heat and health in Adelaide, South Australia: assessment of heat thresholds and temperature relationships. Science of the Total Environment, 414, pp. 126 - 133.
Wu, C.D.;Chen, Y.C.;Pan, W.C.;Zeng, Y.T.;Chen, M.J.;Guo, Y.L. and Lung, S.C.,2017. Land-use regression with long-term satellite-based greenness index and culture-specific sources to model PM2.5 spatial–temporal variability. Environ. Pollut, 224, pp. 148 - 157.
Wu, C.D.;Lung, S.C.C. and Jan, J.F.,2013. Development of a 3-D urbanization index using digital terrain models for surface urban heat island effects. Isprs Journal of Photogrammetry and Remote Sensing, 81, pp. 1 - 11.
Wu, C.D.;McNeely, E.;Cedeno-Laurent, J.G.;Pan, W.C.;Adamkiewicz, G.;Dominici, F.;Lung, S.C.C.;Su, H.J. and Spengler, J.D.,2014. Linking Student Performance in Massachusetts Elementary Schools with the "Greenness" of School Surroundings Using Remote Sensing. Plos One, 9(10).
Ye, X.F.;Wolff, R.;Yu, W.W.;Vaneckova, P.;Pan, X.C. and Tong, S.L.,2012. Ambient Temperature and Morbidity: A Review of Epidemiological Evidence. Environmental Health Perspectives, 120(1), pp. 19 – 28.
Yu, K.P.;Yang, K.R.;Chen, Y.C.;Gong, J.Y.;Chen, Y.P.;Shih, H.C. and Lung, S.-C.C.,2015. Indoor air pollution from gas cooking in five Taiwanese families, 93, pp. 258 - 266.
Yuan, F. and Bauer, M.E., 2007. Comparison of impervious surface area andnormalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. Remote Sensing of Environment, 106(3), pp. 375 - 386.