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Comparing spatial interpolation techniques of local urban temperature for heat-related health risk estimation in a subtropical city

S. Hsu[a*], A. Mavrogianni[b], I. Hamilton[a]

[a]*UCL Energy Institute, Central House 14 Upper Woburn Place, London WC1H 0NN, UK*
[b]*UCL Institute for Environmental Design and Engineering, Central House 14 Upper Woburn Place, London WC1H 0NN, UK*

Abstract

Introduction: The threat of elevated temperatures and more intense and prolonged heat waves coupled with urban heat islands presents a significant risk to human health. City planners and policymakers need tools that predict how overheating risk varies within a city under different climate change and mitigation scenarios. A key driver of determining overheating risk is exposure to local urban temperatures and the extent to which such exposure may be modified by built environments where the majority of people spend their time. Due to the dispersion of monitoring stations, techniques are needed to extrapolate from single point measurements and their modifying determinants. This research aims to compare nine GIS spatial interpolation techniques of estimating street-level temperature in a subtropical city. **Methods:** Taipei city, Taiwan, is located in a subtropical zone with one of the highest population densities in the world. Taipei experienced warmer winters and hotter summers in recent 10 years with average temperature from 16.4 to 30.1°C, and expected to rise from 0.8(RCP2.6) to 3.2(RCP8.5)°C in 2081-2100. In this study, data from the Taiwan Central Weather Bureau weather stations and the Taiwan Environmental Protection Administration air monitoring sites were used. Nine interpolation techniques were applied. These were validated by using records from two sources to cross-validate by comparing Standardised mean error and Standardised Root-Mean-Square error. **Results:** Kriging techniques have better prediction performance than four non-geostatistical interpolation techniques. The performance of OCK techniques indicated the built environment, such as the nearby village park area or home density, can be important modifiers of external temperature in cities. **Discussion:** Local urban climates are complex systems; selecting a robust interpolation technique that accounts for underlying drivers is essential for policymakers. This research provides the basis to further estimate overheating risk by estimating local outdoor street-level temperature and the modifying effects of the built environment.

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* Corresponding author. Tel.: +44-207-679-9242
E-mail address: shih-che.hsu.15@ucl.ac.uk

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Keywords: Geographic Information System; Spatial interpolation; Urban heat island; Local urban temperature; Subtropical city

1. Introduction

The Fifth Assessment Report (AR5) published by the Intergovernmental Panel on Climate Change (IPCC) indicated that the average temperature of the earth increased by 0.85°C (0.69-1.08°C) from 1880 to 2012, and it is extremely likely (> 95%) that this is related to greenhouse gas emissions from human activities [1]. Rising temperatures may lead to an increasing probability of extreme weather events, changes in precipitation patterns, sea level rise, etc. These changes will lead to substantial impacts on ecosystem functions and thereby threaten the survival of organisms and the safety of human health [2]. Climate change can have direct and indirect impacts on public health in numerous ways. Direct effects include increases in heat-related mortality and morbidity due to extreme heat events; indirect effects include potential changes in the levels of air pollution, infectious diseases, food security, and mental health [3,4].

Urban heat island (UHI) is the phenomenon of inadvertent local climate modification arising from human habitation [5,6,7] resulting in a warmer urban centre than its surrounding environment [8]. Due to the characteristics of artificial urban surface materials and higher blockage effects by adjacent buildings in cities, a larger proportion of anthropogenic heat and solar radiation are captured by and emitted within the built environment [9]. Within the urban environment, the UHI will affect the health and thermal comfort of people [10,11]. The elevated temperatures due to the UHI will exacerbate the adverse heat-related health effects caused by global climate change in cities, such as heat stroke, heat exhaustion, cardiovascular and respiratory problems from rising temperatures [12]. It can also increase the city-scale energy demand for cooling which would also result in a vicious circle from the waste heat exhausted by air conditioners, thus further increasing outdoor temperatures [9]. Rapid urbanisation replaces green spaces with artificial impervious surfaces and is, thus, a key factor that could exacerbate the UHI effect [13,14,15].

Overheating risk is influenced not only by changes in the external climate but also by human factors. The personal susceptibility refers to the physical condition of individuals and the interaction of social, economic, behavioural and political characteristics. Both will influence heat exposure directly or vulnerability to heat indirectly [16]. When determining indoor overheating risk, the key driver is exposure to local urban temperatures and the extent to which such exposure may be modified by the buildings where the majority of people spend their time [17,18].

In summary, the threat of elevated temperatures and more intense and prolonged heat waves due to anthropogenic climate change coupled with the UHI effect present a significant risk to human health in urban environments [19]. City planners and policymakers need tools that predict how outdoor and indoor overheating risk varies spatiotemporally within a city under different climate change scenarios and associated mitigation and adaptation pathways. Due to the limited number of external temperature monitoring stations in most cities, prediction methods are commonly used to obtain a more comprehensive distribution of urban temperature. Various techniques can interpolate the temperatures within a region from single point measurements. Satellite images, sophisticated local urban climate modelling, and Geographic Information System (GIS) spatial interpolation are the three main methods used to predict and map the whole-city external temperature distribution.

- Land surface temperature (LST) from satellite data is widely used to map the urban surface temperature and monitor the surface heat island [20]. Although satellite data offer measured values comprehensively, they are costly, with lower spatial resolution and asynchronous (except for the geostationary meteorological satellite) in general. It is also not easy for nonprofessionals or general users to downscale the data to get high resolution interpolation data. Further, satellite measurements are not a measure of the experienced air temperature and therefore may not give a good indication of the relationship with health.
- Sophisticated local urban climate models, such as the ADMS-Urban model and the Reading Urban Model that were used in the 'development of a Local Urban Climate model and its application to the Intelligent Development of cities' (LUCID) project [7,21,22], offer a comprehensive system for modeling the urban microclimates in large urban areas, cities and towns. The advantage is that detailed street-level air temperature forecasts can be obtained, but the disadvantage is that these models are usually complex and comprising complicated input factors, including shadowing and reflection by buildings on the radiative fluxes, storage of heat in the building fabric and

transport of heat into the atmospheric boundary layer and surface features on the airflow and local fluxes of heat and moisture. It is often not easy to collect such detailed input data or adjust input factors to represent the conditions in different cities [21].
- GIS spatial interpolation can assess the spatial autocorrelation and spatial dependence by measuring the relationship and dependence between near and distant objects [23] and be easily implemented and adjusted in using GIS software. Most studies agree that climate prediction at regional and local scales is important [24], but the common problem of ignoring the spatial heterogeneity in models may decrease model accuracy [25]. GIS is, therefore, a useful and increasingly common method for investigating the potential impacts of climate change on people and infrastructure in cities [26].

This paper aims to compare GIS spatial interpolation techniques of estimating street level air temperature in a subtropical city. Modifying factors which may affect the local temperature, such as green spaces, proximity to water, population and building characteristics, were also considered in order to factor in the potential effects of environmental characteristics on the spatial variability of temperature.

2. Materials and Methods

Taipei city, Taiwan is located in a subtropical zone with one of the highest population densities in the world, 9,945 people per km^2 [27]. In the last 10 years, Taipei experienced warmer winters and hotter summers with average temperature from 16.2°C to 30.1°C compared to the 1981-2010 baseline from 16.1°C to 29.6°C [28]. Average temperatures are expected to rise from 0.8°C under the Representative Concentration Pathway 2.6 (RCP2.6) to 3.2°C of RCP8.5 by 2081-2100 [29].

According to the existing meteorological statistics of Taipei city (Figure 1), July is the hottest month with a maximum monthly average temperature of 29°C and a maximum daily temperature of 33°C; February is the coldest month with a minimum monthly average temperature of 15°C and a minimum daily temperature of 12°C since 1995 on average [30].

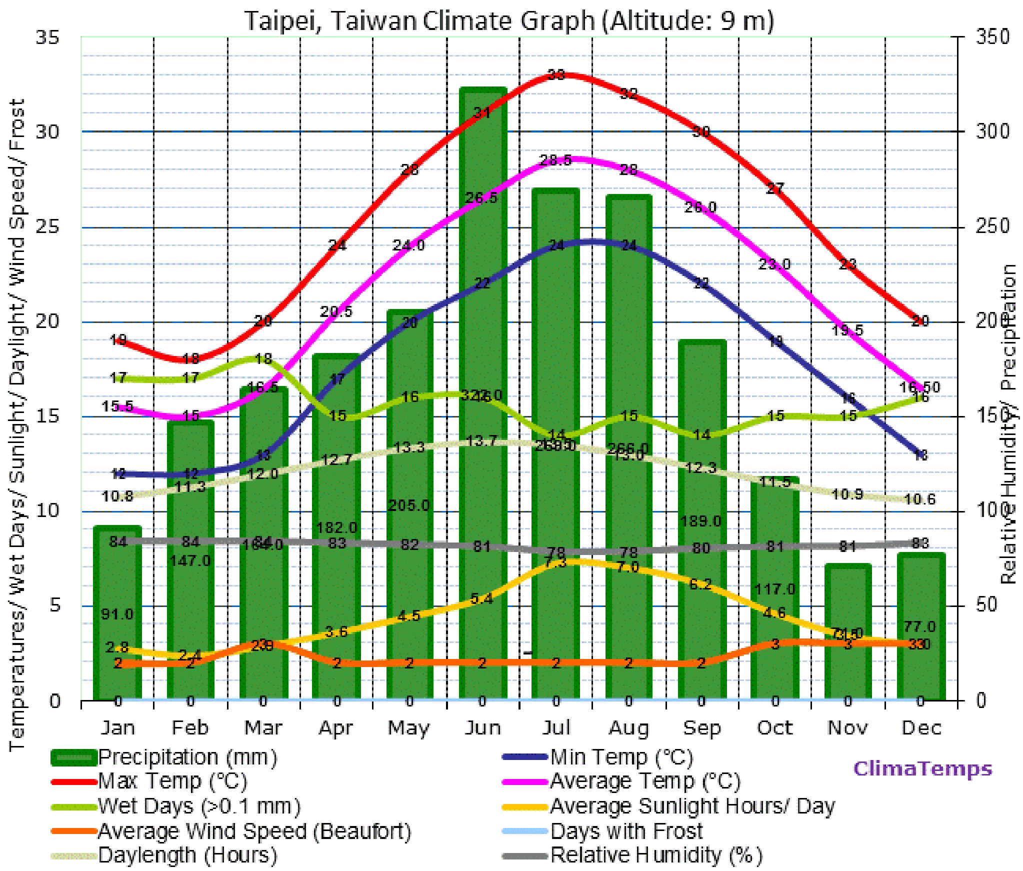

Figure 1. Taipei climate graph [30]

In this study, the most recent monthly average temperature data of February 2016 retrieved from the online archives of the Taiwan Central Weather Bureau weather stations [31] and the Taiwan Environmental Protection Administration air quality monitoring sites [32] were used for temperature prediction and validation. There are 10 weather stations and 25 air quality monitoring sites in total in northern Taiwan across two counties and five cities including Hsinchu, Ilan counties and Taipei, New Taipei, Keelung, Taoyuan, Hsinchu cities. Weather stations are mainly used to measure hourly meteorological conditions including temperature, humidity, wind, atmospheric pressure and precipitation. Air quality monitoring sites are used to monitor hourly air pollutants, such as $PM_{2.5}$, PM_{10}, O_3, CO, NO_2, SO_2, etc., and hourly basic weather conditions including temperature, humidity, wind and precipitation. The precision of temperature measurement in both datasets is within one decimal.

Nine GIS spatial interpolation techniques were applied in this paper to predict external air temperatures across the city. The tested techniques were divided into two categories and briefly described below [23,33]:

- Non-geostatistical techniques and
- Geostatistical techniques.

Non-geostatistical techniques we used in this paper were mainly deterministic methods having no assessment of errors with the predicted values, while geostatistical techniques are stochastic methods providing an assessment of the errors. Geostatistical techniques include a family of kriging algorithms which use generalised least-squares regression for estimating continuous attributes.

The non-geostatistical techniques include:

- Splines, which use mathematical polynomials passing through all input points to estimate values, are the best techniques for representing phenomena fitted on a smooth surface.
- Trend Surface Analysis (TSA) is a statistical technique that fits the samples in a regression model and predicts the values by geographical coordinates. TSA is a stochastic interpolator, but it can detect the trend in sample data.
- Inverse Distance Weighting (IDW) is a weighted-average technique generally for dense points to interpolate cell values by a combination of sample points and the weighting function of inverse distance.
- Natural Neighbor (NaN), generally working well with clustered scatter points, is another weighted-average technique with the identical equation of IDW but using unique triangulation of the data.

The geostatistical techniques include:

- Ordinary Kriging (OK),
- Universal Kriging (UK) and
- Simple Kriging (SK), three types of classic kriging.
- Empirical Bayesian Kriging (EBK), which differs from other kriging methods by accounting for the error in estimating the underlying semivariogram through repeated simulations, automates parameters to receive accurate results when building a prediction model. EBK are especially suitable for small datasets [34].
- Original CoKriging (OCK) uses the autocorrelation which depends on the distance and direction between sample points for each variable as well as the cross-correlations between main variable and other variables to help make predictions. Theoretically, the prediction performance would be better than kriging in which there is no cross-correlation. However, there is more variability as well because the more unknown autocorrelation parameters are included [35].

The three most frequently used or cited techniques based on the review of 51 studies [33] are OK, IDW and OCK. Built-in tools in ArcGIS 10.3.1 were used to apply all of the above techniques. Krigings are powerful sophisticated weighted-average techniques considering the spatial correlation of distance and direction between sample points, which are most appropriate when a spatially correlated distance or directional bias in the data is known.

When applying the OCK interpolation technique to predict local temperature, in addition to the spatial autocorrelation of monitoring sites, modifying variables were included for weighting in the prediction model of the whole-city outdoor air temperature, including the following datasets:

- Data on the altitude level of the monitoring sites was derived from ASTER Global Digital Elevation Model (GDEM) Version 2 released by the Ministry of Economy, Trade, and Industry (METI) of Japan and the United States National Aeronautics and Space Administration (NASA). The resolution of GDEM is 30 m x 30 m (ASTER 2011). Altitude is also the only variable which used to estimate external temperature in the cokriging studies, mainly in mountainous areas [36,37,38,39].
- Data on population and home density in a Basic Statistical Area[1] was provided by the Department of Statistics, Minister of the Interior, Taiwan [40].
- Data on nearby village park area and nearby river area (dimensions) were provided by the Taipei city government open data website [41,42].

Cross-validation was used to quantify the prediction model accuracy. The measured value from one location at a time was removed and the rest of the measured values were used to create a prediction model to predict the value in this location. The predicted value was then compared to the measured value. The performance metrics of spatial interpolation included five indicators:

[1] The Basic Statistical Area is defined as the smallest spatial unit available which archives population or socioeconomic data. Different datasets will have their own Basic Statistical Area size and the population in the Basic Statistical Area is usually less than 450 people.

- Mean error,
- Standardised mean error,
- Root mean square error
- Average standard error and,
- Standardised root mean square error.

A better performing model would have the following features. If the predicted value is close to the measured value, the mean error and standardised mean error should be near zero. If the standardised root mean square error is close to one, which means the average standard error is close to the root mean square error, the average standard error is valid to assess the variability correctly. By comparing the mean error, standardised mean errors and standardised root mean square errors between different interpolation techniques, the quality of interpolation can be assessed.

3. Results

Among the four non-geostatistical interpolation techniques tested in this paper, the Splines technique had the worst prediction performance, because all monitoring sites are located in the same spatiotemporal temperature section of predicted surface and some predicted sections are wrongly ranged as well. For example, the ranges of lower than 0°C and higher than 38°C in figure 2 are unreasonable. The predicted surface of TSA technique includes only three sections across Taipei, so it is also poor to locate all monitoring sites in the correct temperature section accordingly. For example, the monitoring site of 11.2°C was located in the wrong section from 16.0°C to 16.7°C in figure 3. The IDW technique had the lowest mean error among all interpolation techniques and both of IDW (Figure 4) and NaN (Figure 5) techniques have better predicted temperature surfaces across Taipei, nine sections of IDW and eight sections of NaN respectively, compared to the Splines and TSA techniques. The eight predicted temperature sections of NaN technique are mainly centered in northern Taipei and there are only three sections across most part of Taipei (Figure 5), so the prediction of local temperatures across Taipei would not be accurate and detailed enough. Although a low mean error of was obtained for the IDW technique, it would be problematic to assess the variability correctly, since IDW is a deterministic method having no assessment of errors with the predicted values in ArcGIS. Therefore, it is hard for us to compare the prediction performance of IDW technique with other spatial interpolation techniques by the same standard.

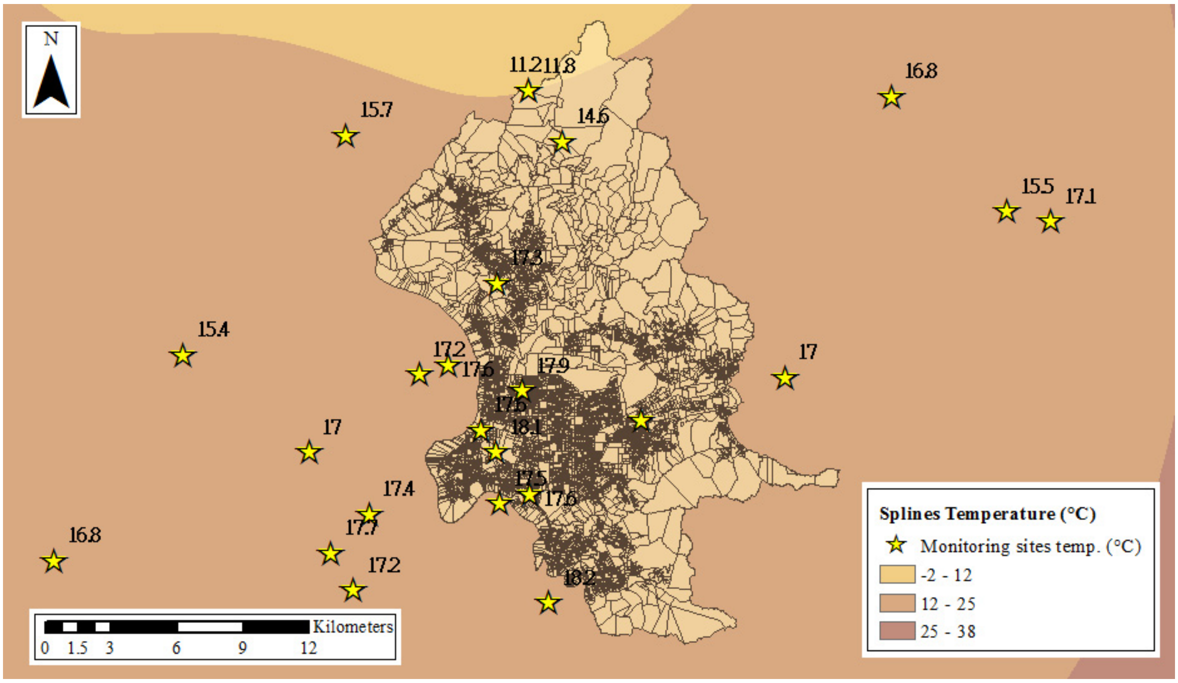

Figure 2. The predicted temperature (°C) surface of the Splines technique.

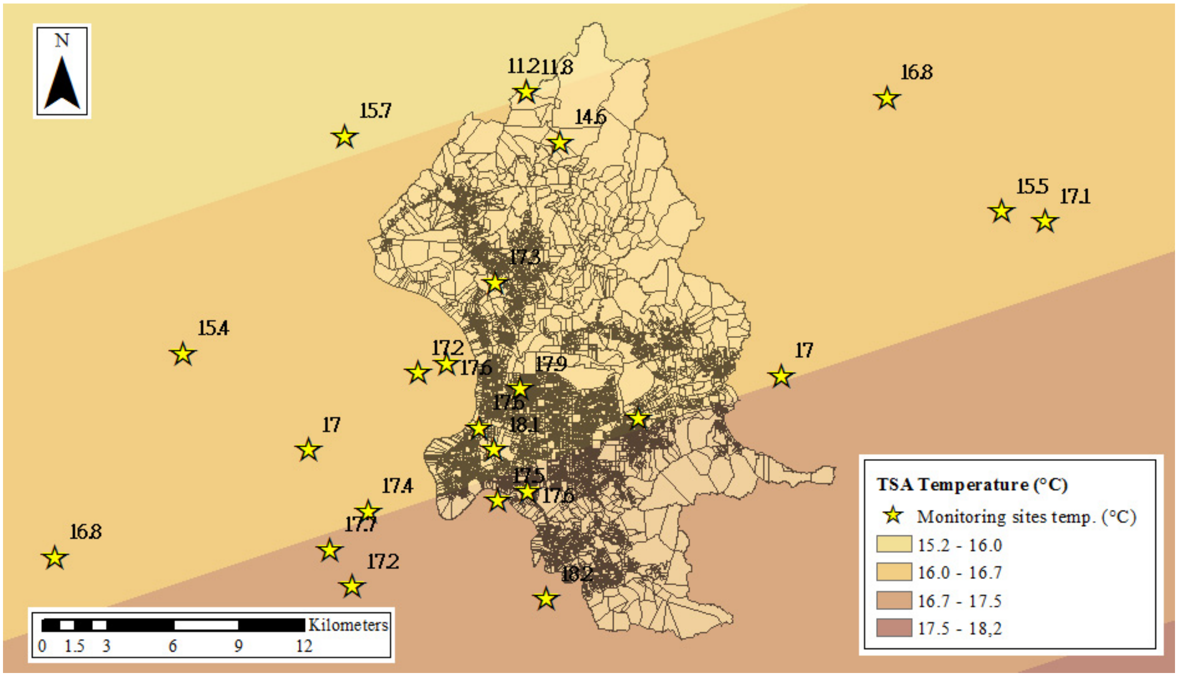

Figure 3. The predicted temperature (°C) surface of the TSA technique.

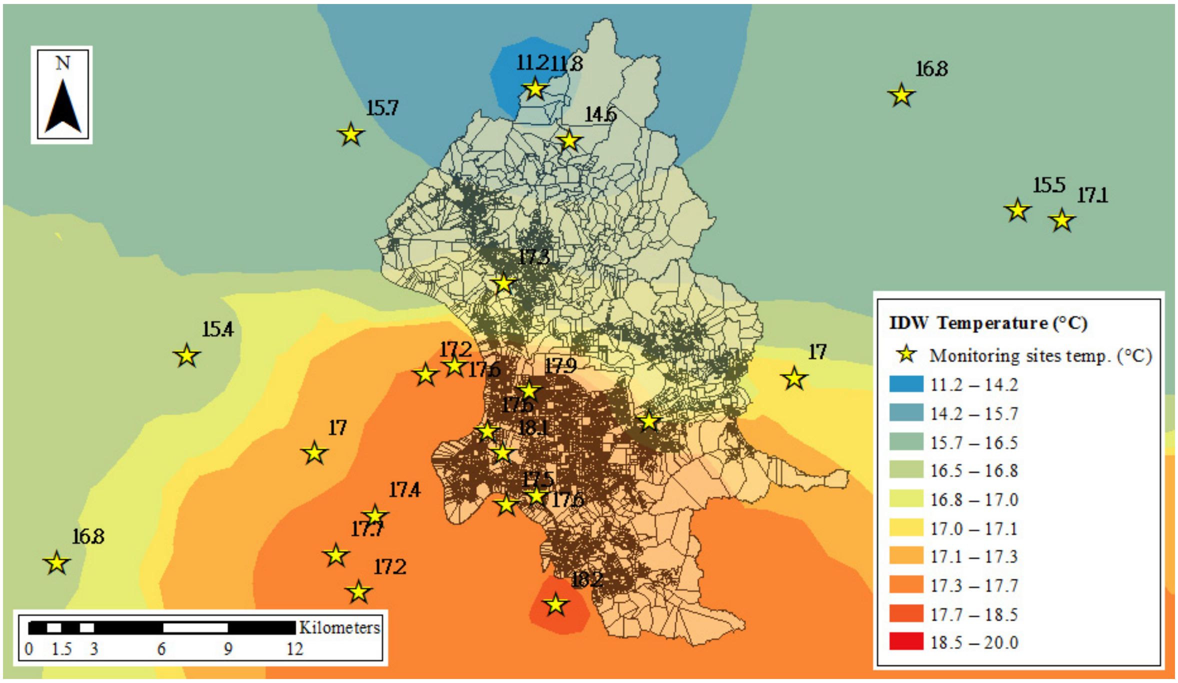

Figure 4. The predicted temperature (°C) surface of the IDW technique.

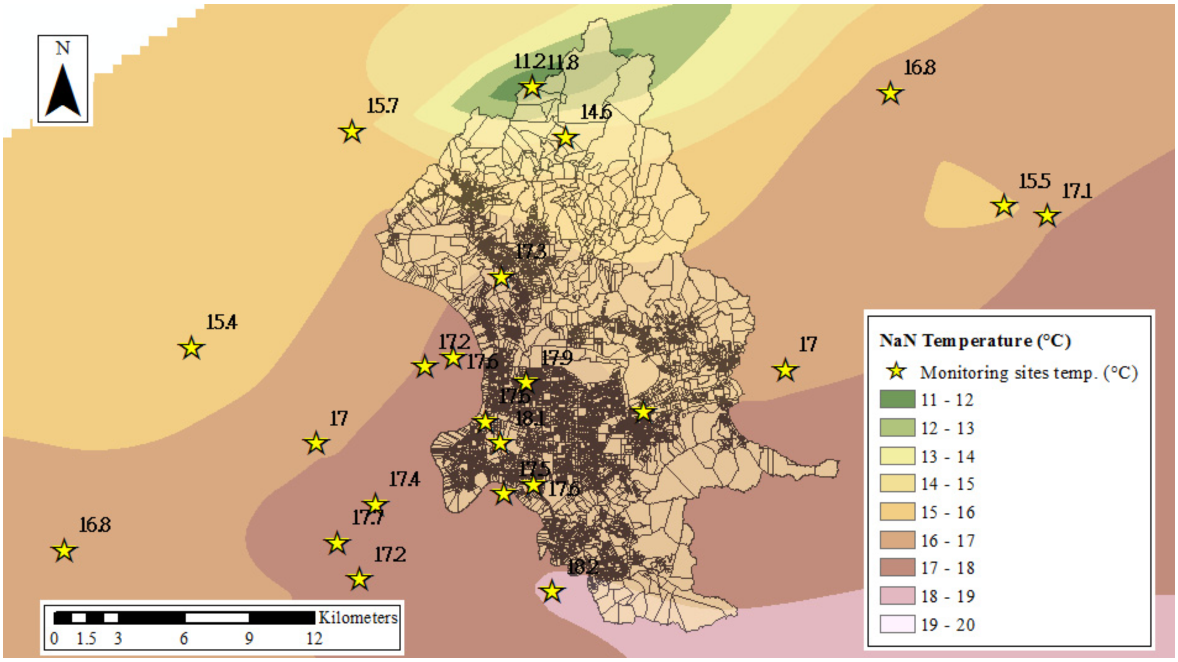

Figure 5. The predicted temperature (°C) surface of the NaN technique.

Comparing five geostatistical interpolation techniques (Table 1), the OCK_1 technique with three weighting factors, the autocorrelation value of monitoring temperatures and two cross-correlations between monitoring sites and nearby village park area, home density, had the best prediction performance, of which the standardised mean error is closest to zero and the standardised root mean square error is closest to one. OCK_1 was found to be the best performing technique with a standardised mean error of 0.034, followed by EBK (-0.060), SK (-0.071), OK (-0.091) and UK (0.092). With regard to variability, OCK_1 is also the best performing technique with a standardised root mean square error of 0.984, followed by OK (0.893), EBK (0.841), SK (0.692) and UK (2.682).

Table 1. Prediction errors of five geostatistical interpolation techniques

Prediction Errors	OK	UK	SK	EBK	[1]**OCK_1**	[2]OCK_2
Sample (N)	35	35	35	35	35	35
Mean	-0.134	0.040	-0.050	-0.093	**0.040**	-0.116
Root-Mean-Square	0.898	1.227	0.915	0.950	1.227	0.864
Mean Standardised	-0.090	0.092	-0.071	-0.060	**0.034**	-0.079
Root-Mean-Square Standardised	0.890	2.682	0.692	0.841	**0.984**	0.896
Average Standard Error	1.035	0.454	1.483	1.168	1.236	1.089

[1] OCK_1 technique with three weighting factors, monitoring temperatures, nearby village park area and home density
[2] OCK_2 technique with three weighting factors, monitoring temperatures, nearby village park area and population density

When applying different modifying factors in the OCK interpolation technique (Table 2), the suitability is also accessed by comprising the standardised mean errors and standardised root mean square errors for comparing accuracy and variability (Figure 6). Because of the upper limitation of the dataset numbers in ArcGIS 10.3.1, temperature and any additional three variables were chosen each time as the four weighting datasets out of the five modifying factors: altitude level, nearby village park area, nearby river dimensions, home density or population density in the Basic Statistical Area. The cross-validation performance of each OCK interpolation combination was subsequently compared. Home density (OCK_1) was shown to have better interpolation performance than population density (OCK_2), and the nearby village park area (OCK_1) had better interpolation performance than the nearby river dimensions (OCK_3).

Table 2. Prediction errors of OCK geostatistical interpolation techniques

Prediction Errors	[1]**OCK_1**	[2]OCK_2	[3]OCK_3	[4]OCK_4	[5]OCK_5	[6]**OCK_6**
Sample (N)	35	35	35	35	35	35
Mean	**0.040**	-0.116	-0.122	-0.058	-0.119	**0.040**
Root-Mean-Square	1.227	0.864	0.893	1.432	0.972	1.227
Mean Standardized	**0.034**	-0.079	-0.083	-0.031	-0.056	**0.034**
Root-Mean-Square Standardized	**0.984**	0.896	0.902	0.802	0.817	**0.984**
Average Standard Error	1.236	1.089	1.019	1.785	1.331	1.236

[1] OCK_1 technique with three weighting factors, monitoring temperatures, nearby village park area and home density
[2] OCK_2 technique with three weighting factors, monitoring temperatures, nearby village park area and population density
[3] OCK_3 technique with three weighting factors, monitoring temperatures, nearby river dimensions and home density
[4] OCK_3 technique with two weighting factors, monitoring temperatures, home density
5 OCK_3 technique with two weighting factors, monitoring temperatures, nearby village park area
[6] OCK_3 technique with four weighting factors, monitoring temperatures, nearby river dimensions and home density, altitude of monitoring sites

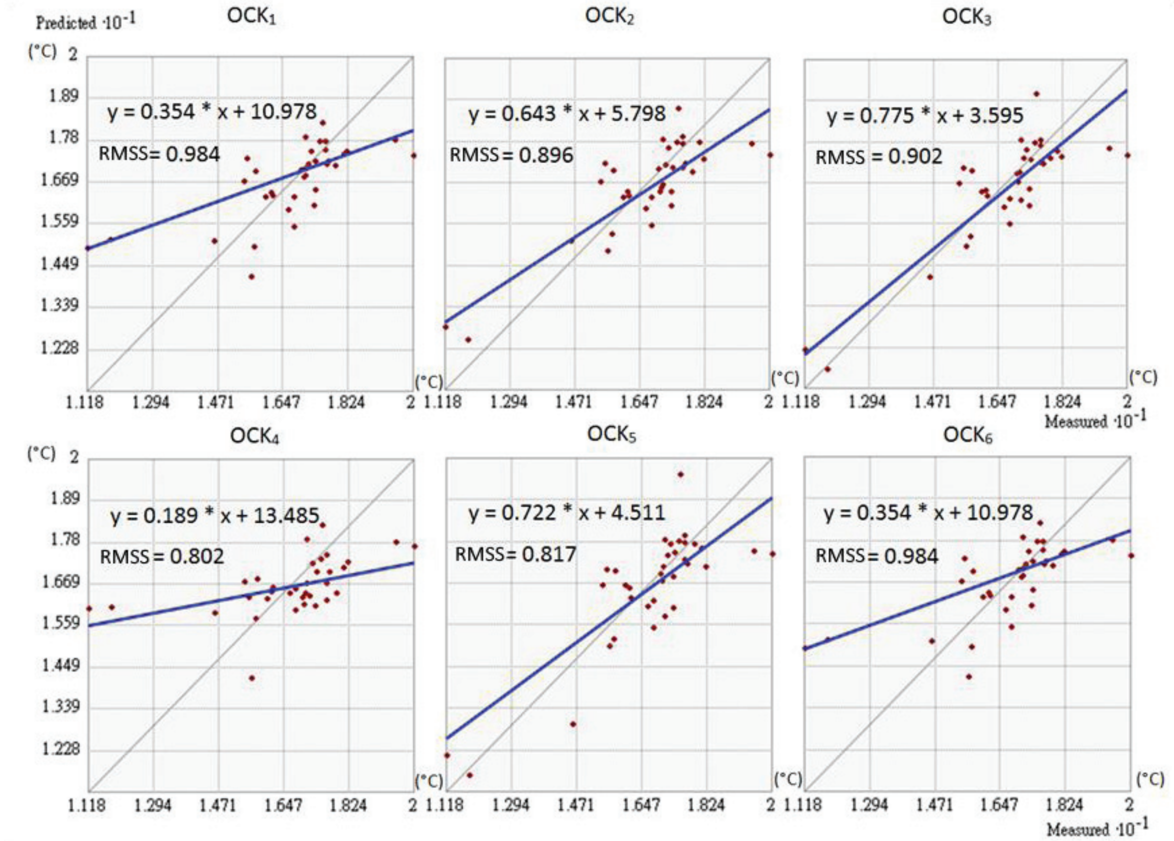

Figure 6. The prediction plots of OCK geostatistical interpolation techniques

When comparing the prediction performance of the OCK technique with different numbers of weighting datasets, it was found that with only one additional modifying factor, the prediction performance of the OCK technique with only home density (OCK_4) weighting was better than the interpolation with only nearby village park area weighting (OCK_5); OCK_6 prediction performance with three additional modifying factors (altitude level, home density, and nearby village park area) was equal to OCK_1 when only two additional modifying factors (home density and nearby village park area) were used, so considering the altitude level of monitoring sites did not appear to influence the results considerably. The best factors for estimating the local outdoor air temperature across the whole city were home density and nearby village park area as shown in Table 2.

4. Discussion

Local urban climates are complex systems; tools that simulate local urban climate variables at a fine spatial resolution are essential for policymakers, especially when the monitoring sites are scattered and scarce in a given area. Spatial interpolation can be a useful tool towards this goal as they are significantly less computing and resource intensive compared to, for example, sophisticated local urban climate models. GIS-based spatial interpolation techniques are easy to implement for assessing spatial autocorrelation and dependence [23].

People spend 90-95% of their time in indoor environments and 66% of that time in their own homes [17], so the built environment has become an important modifier for predicting the health effect of environmental factors [43]. Climate change trends and UHI effects, combined with building stock transformations driven by energy efficiency are predicted to affect indoor environmental quality and associated health effects as well [11,43,44]. External temperature is an important determinant of indoor temperature and overheating risk. This research provides the basis of a selection method of an appropriate spatial interpolation technique of external temperature that could be used to predict outdoor and indoor overheating risk and thermal discomfort in future researches.

This study suggests the local home density and nearby green land area are two important determinants of the local outdoor temperature in a city. This is in agreement with previous studies which indicated a strong correlation between the increasing of temperature and the disappearance of green areas and increasing urban density in the city [45,46,47,48]. This study also revealed a similar result with previous studies, which is OCK is one of recommended GIS spatial interpolation techniques for predicting environmental characteristics [34].

There are a number of limitations in this study. The spatial interpolation only used average monthly temperatures for February 2016. Future studies could explore whether the prediction performance varies by season, and whether the prediction performance would be better if more weighting factors are included.

5. Conclusions

This paper evaluated the prediction performance of nine frequently adopted GIS spatial interpolation techniques on local urban temperature. It has shown that the five geostatistical interpolation techniques have better overall prediction performance than the four non-geostatistical interpolation techniques. The modifying effects of environmental characteristics on the performance of the OCK technique were also compared with different combinations of weighting factors for predicting the local external temperature; it is indicated that the built environment, such as the nearby village park area or home density, can be important modifiers of external temperature in cities.

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References

[1] IPCC, 2013: Summary for policymakers, in: *Climate Change 2013: The Physical Science Basis, Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, UK, 2013, pp.1-29.
[2] IPCC, *Climate Change 2007: Impacts, Adaptation and Vulnerability, Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, Cambridge, UK, 2007, pp.1-976.
[3] A. Costello, M. Abbas, A. Allen et al., Managing the health effects of climate change, *UCL-Lancet Commission* 373 (2009) 1693-1733.
[4] N. Watts, W N. Adger, P. Agnolucci et al., Health and climate change: policy responses to protect public health. *The Lancet* 386 (2015) 1861-1914.
[5] T. R. Oke, The heat island characteristics of the urban boundary layer: characteristics, causes and effects, in: J. E. Cermak, A. G. Davenport, E. J. Plate et al. (Eds), *Wind Climate in Cities*, Kluwer Academic, Netherlands, 1995, pp.81-107.
[6] C. S. B. Grimmond, M. Blackett, M. J. Best et al., Initial results from Phase 2 of the international urban energy balance model comparison, *International Journal of Climatology* 31(2) (2011) 244-272.
[7] I. Hamilton, J. Stocker, S. Evans et al., The impact of the London Olympic Parkland on the urban heat island, *Journal of Building Performance Simulation* 7(2) (2014) 119-132.
[8] B. Y. Tam, W. A. Gough & T. Mohsin, The impact of urbanization and the urban heat island effect on day to day temperature variation. *Urban Climate* 12 (2015) 1–10.
[9] P. A. Mirzaei, Recent challenges in modeling of urban heat island, *Sustainable Cities and Society* 19 (2015) 200-206.
[10] A. Milojevic, P. Wilkinson, B. Armstrong et al., Impact of London's Urban Heat Island on Heat-related Mortality, *Epidemiology* 22(1) (2011) S182–S183.
[11] A. Mavrogianni, P. Wilkinson, M. Davies et al., Building characteristics as determinants of propensity to high indoor summer temperatures in London dwellings, *Building and Environment* 55 (2013) 117–130.
[12] M. Anderson, C. Carmichael, V. Murray et al., Defining indoor heat thresholds for health in the UK, *Perspectives in public health* 133(3) (2013) 158–164.
[13] T. R. Oke, 1982. The energetic basis of the urban heat island, *Quarterly Journal of the Royal Meteorological Society* 108(455) 1–24.
[14] T. W. Owen, T. N. Carlson & R. R. Gillies, An assessment of satellite remotely-sensed land cover parameters in quantitatively describing the climatic effect of urbanization, *International Journal of Remote Sensing* 19(9) (1998) 1663–1681.
[15] Q. Xie & Z. Zhou, Impact of urbanization on urban heat island effect based on tm imagery in Wuhan, China, *Environmental Engineering and Management Journal* 14(3) (2015) 647–655.
[16] B. Fernandez Milan, & F. Creutzig, Reducing urban heat wave risk in the 21st century, *Current Opinion in Environmental Sustainability* 14 (2015) 221–231.

[17] R. Duarte-Davidson, C. Courage, L. Rushton et al., Benzene in the environment: an assessment of the potential risks to the health of the population, *Occupational and environmental medicine* 58(1) (2001) 2–13.
[18] J. Taylora, P. Wilkinson, M. Davies et al., Mapping the effects of urban heat island, housing, and age on excess heat-related mortality in London, *Urban Climate 14 (2015) 517-528*
[19] C. Koppe, S. Kovats, G. Jendritzky et al., Heat-waves: risks and responses, *Health and Global Environmental Health Series*, No.2(2) (2004) 1-124.
[20] R. Mechri, C. Ottlé, O. Pannekoucke et al., Downscaling meteosat land surface temperature over a heterogeneous landscape using a data assimilation approach, *Remote Sensing* 8(7) (2016) 586.
[21] S. Evans, 3D cities and numerical weather prediction models: an overview of the methods used in the LUCID project. *AnalysiUCL Working Papers Seriess* 148, (2009) 1-18.
[22] S. I. Bohnenstengel, S. E. Belcher, P. Clark P et al., The Lucid project: the local urban climate in London, *Urban climate newsletter* 36 (2010) 10.
[23] C. Childs, ESRI Education Services, Interpolating surfaces in arcgls spatial analyst, *ArcUser* (2004).
[24] Y. Bai, I. Kaneko, H. Kobayashi et al., A Geographic Information System (GIS)-based approach to adaptation to regional climate change: a case study of Okutama-machi, Tokyo, Japan. *Mitigation and Adaptation Strategies for Global Change* 19(5) (2014) 589–614.
[25] G. Guo, Z. Wu, R. Xiao et al., Impacts of urban biophysical composition on land surface temperature in urban heat island clusters, *Landscape and Urban Planning* 135 (2015) 1–10.
[26] Y. Wu, T. Hayat, A. Clarens et al., Climate change effects on transportation infrastructure scenario-based risk analysis using geographic information systems. *Transportation Research Record* 2375 (2013) 71–81.
[27] Department of Budget, Accounting and Statistics (DBAS) of Taipei City Government. Population density of Taipei city. (2016). Available at: http://w2.dbas.taipei.gov.tw/statchart/a2.htm [Accessed 29 Jul. 2016].
[28] Taiwan Central Weather Bureau (TWCB). Monthly average temperature. (2016). Available at: http://www.cwb.gov.tw/V7/climate/monthlyMean/Taiwan_tx.htm [Accessed 1 Jul. 2016].
[29] Taiwan Climate Change Projection and Information Platform (TCCIP), National Science and Technology Center for Disaster Reduction (NCDR) of Ministry of Science and Technology, Taiwan. Future climate projection. (2016). Available at: http://tccip.ncdr.nat.gov.tw/v2/future_chart_en.aspx [Accessed 1 Jul. 2016].
[30] Taiwan.climatemps.com. Taipei climate and Taipei temperatures. (2016). Available at: http://www.taiwan.climatemps.com/ [Accessed 29 Jul. 2016].
[31] Taiwan Central Weather Bureau Observation Data Inquire System.. Daily data and monthly data of temperature. (2016). Available at: http://e-service.cwb.gov.tw/HistoryDataQuery/index.jsp [Accessed 1 Jul. 2016].
[32] Taiwan Air Quality Monitoring Network, Taiwan Environmental Protection Administration (TEPA). Air quality monitoring history data. (2016). Available at: http://taqm.epa.gov.tw/taqm/en/YearlyDataDownload.aspx [Accessed 29 Jul. 2016].
[33] J. Li & A. D. Heap, A review of spatial interpolation methods for environmental scientists, *Australian Geological Survey Organisation* 68 (2008) 154.
[34] J. Li & A. D. Heap, Spatial interpolation methods applied in the environmental sciences: A review, *Environmental Modelling and Software* 53 (2014) 173–189.
[35] R. Sluiter, Interpolation methods for climate data: literature review, *KNMI, R&D Information and Observation Technology* (2009) 1–28.
[36] J. S. Yang, Y. Q. Wang & P. V. August, Estimation of land surface temperature using spatial interpolation and satellite-derived surface emissivity, *Journal of Environmental Informatics* 4(1) (2004) 37–44.
[37] S. Park. Integration of satellite-measured LST data into cokriging for temperature estimation on tropical and temperate islands, *International Journal of Climatology* 31(11) (2011) 1653–1664.
[38] T. Ishida & S. Kawashima, Use of cokriging to estimate surface air temperature from elevation, *Theoretical and Applied Climatology* 47(3) (1993) 147–157.
[39] Y. Jantaka, S. Ongsomwang & S. Charungthanakij. Using cokriging technique for surface interpolation of climate data in Thailand, (2011).
[40] Department of Statistics, Minister of the Interior, Taiwan. Data on population and home density in a Basic Statistical Area. (2016). Available at: https://gist.motc.gov.tw/GIS_MetaData/GIS_Metadata?id=TW-05-315000000H-000786 [Accessed 29 Jul. 2016].
[41] Data.taipei. Parks of Taipei city. (2016). Available at: http://data.taipei/opendata/datalist/datasetMeta?oid=a132516d-d2f3-4e23-866e-27e616b3855a [Accessed 1 Jul. 2016].
[42] Data.taipei. Rivers of Taipei city. (2016). Available at: http://data.taipei/opendata/datalist/datasetMeta?oid=c1997f06-b376-4880-865d-57b01d2b15c4 [Accessed 1 Jul. 2016].
[43] J. Taylor, A. Mavrogianni, M. Davies et al., Modelling and mapping air pollution ingress and temperature response of dwellings in Great Britain, *PHE 2015 Annual UK Review Meeting on Outdoor and Indoor Air Pollution* (2015) 1–17.
[44] M. Raatikainen, J-P. Skön,M. Johansson et al., Effects of energy consumption on indoor air quality, *World Academy of Science, Engineering and Technology* 61 (2012) 2093-2099.
[45] A. R. Beer, T. Delshammar & P. Schildwacht, A changing understanding of the role of green space in high-density housing: A European perspective, *Built Environment* 29(2) (2003) 132–143.
[46] N. H. Wong, & C. Yu, Study of green areas and urban heat island in a tropical city, *Habitat International* 29(3) (2005) 547–558.
[47] A. M. Coutts, J. Beringer & N. J. Tapper, Impact of increasing urban density on local climate: Spatial and temporal variations in the surface energy balance in Melbourne, Australia, *Journal of Applied Meteorology and Climatology* 46(4) (2007) 477–493.
[48] S. K. Jusuf, N. H. Wong, E. Hagen et al., The influence of land use on the urban heat island in Singapore, *Habitat International*, 31(2) (2007) 232–242.