The effects of lateral boundary conditions resolution for heat island studies in tropical urban of Kuala Lumpur

N A Isa, S A Salleh, W M N Wan Mohd, M C G Ooi, A Chan and M A Islam
1Centre of Studies of Surveying Science and Geomatics, Faculty of Architecture, Planning and Surveying, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia
2Applied Remote Sensing and Geospatial Research Group, Faculty of Architecture, Planning and Surveying, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia
3Department of Atmospheric Sciences, National Central University, 32001 Chung-Li, Taiwan
4Department of Civil Engineering, Faculty of Engineering, University of Nottingham, Malaysia Campus, Jalan Broga, 43500 Semenyih, Selangor, Malaysia

Email: aekbal@salam.uitm.edu.my (S A Salleh)

Abstract. Lateral boundary condition (LBC) is one of the key features included in the Weather Research and Forecasting (WRF) simulation model. Nowadays, numerous LBCs were developed with various spatial (grid) and temporal resolutions for a wide range of applications. Choosing the most suitable LBCs to ensure appropriate representation of climates should be properly conducted. Thus, this paper analysed the effects of the LBC resolutions on the regional climate downscaling for heat island studies. The comparisons were made on the performance of respective LBCs to regenerate the near-surface temperature distributions within the Kuala Lumpur city. NCEP GDAS/FNL 0.25 Degree Global Tropospheric Analyses dataset with higher spatial and temporal resolution was found to perform better than the other LBC during intermonsoon season. However, both datasets were determined to give reliable representations of urban climate condition within the city as both datasets depicted close results in determining the impact of urbanization on the thermal environment.

1. Background

Studying climate has many challenges and one of them is obtaining the climate datasets. As for today, general circulation models (GCM) are the most common tool used for climate simulation and assessments [1]. Abundant GCMs are developed in order to cater the needs in climate studies around the world to ensemble the main characteristics of the general circulation pattern for high simulation performances. However, the applications of the GCMs for regional climate studies are very disappointing due to typically poor spatial resolutions (1° to 3°). The GCMs only sufficient to resolve large-scale forcings but fail to resemble the local impacts [2]. Therefore, the regional climate models (RCM) are employed to downscale the GCMs into finer resolutions which are able to account the local impacts by nesting a higher resolution into limited area model (child domain) over the area of interest [3]. To achieve this, lateral boundary conditions (LBC) are employed for boundary condition initialization in the parent domain.

Lateral boundary condition (LBC) represents the boundary condition of the Earth surfaces which is required for dynamical downscaling from mesoscale model into regional model. In nested domains, the LBC is provided by parent domains for its nest(s). Previous studies have disputed the errors
resulted by the LBCs, however, several recommendations were made to minimize these errors [2], [4]–[6] including spatial and temporal resolution selections. Recent study by Davies [7] has determined that, the errors resulted by the LBCs can be controlled and only consists of a tiny part of the overall errors. Even though the previous studies have enlightened the performance of LBCs, these studies were conducted in the middle to high latitude regions with very little information regarding this matter within the tropical regions [2], [4]–[7]. Due to this, site-specific study is essential in choosing the best LBCs for the particular region especially Malaysia.

The present study analysed the impact of two different global LBC datasets and their performance in determining the urbanization impacts towards thermal environment. These LBCs are freely available in the National Centre of Atmospheric Research (NCAR) archive, developed with different spatial and temporal resolutions. The comparisons made can be used for future research with a similar climate background. New research within this region are urged to bring the uncertainty of LBCs issues to light especially when very high resolution simulations are needed.

Historically, the climate was naturally changing over a long period of time, ranging from decades to centuries. Back then, natural phenomena such as solar output variations and volcanic eruptions were the sole cause of the climate changes [8]. However, after the Industrial Revolution in 1700s, urbanization was one of the significant causes that contributes to the changes in global climate and the change rate was rapidly increasing in the 21st century due to the explosive of human population [8], [9]. Therefore, it can be concluded that the urbanization is significantly affecting the climate as documented previously. Thus, this study also investigated the effects of urbanization towards the thermal variation in determining any supporting evidence on the issues within the tropical context.

2. Methods
The methods employed during this study are explained as follows:

2.1. WRF-ARW Simulation

| Data Type | NCEP FNL Operational Model Global Tropospheric Analyses, continuing from July 1999 | NCEP GDAS/FNL Global Tropospheric Analyses and Forecast Grids |
|-----------|----------------------------------------------------------------------------------|---------------------------------------------------------------|
| Data Format | WMO_GRIB1                                                                        | WMO_GRIB2                                                     |
| Temporal Resolution | 6 hours                                                                          | 3 hours                                                       |
| Spatial (Grid) Resolution | 1° × 1°                                                                         | 0.25° × 0.25°                                                  |
| Data Coverage | From 0E to 359E and 90N to 90S                                                   | From 0E to 359E and 90N to 90S                                |

Two widely used global LBCs were chosen for the comparisons, namely NCEP FNL Operational Model for Global Tropospheric Analyses which provided from 1999 onwards (refers as Simulation 1) and NCEP GDAS/FNL for Global Tropospheric Analyses and Forecast Grids which provided from 2015 onwards (refers as Simulation 2). Table 1 shows the comparisons between the LBCs’ characteristics. The datasets were employed due to their common applications in representing the
urban climate condition within regional context especially in tropical simulation modelling [10]–[14]. The dataset employed were dated 17th April 2017 to coincide the Landsat satellite images utilized in this study. This date was also chosen due to intermonsoon season phase which has less synoptic forcing as compared to monsoon seasons and another intermonsoon season in October [15].

Figure 1. The domains design and setup

| Physic Option                  | Physic Scheme                        |
|--------------------------------|---------------------------------------|
| Microphysics                  | WRF Single-Moment 3-class scheme      |
| Longwave Radiation            | RRTM scheme                           |
| Shortwave Radiation           | Dudhia scheme                         |
| Surface Layer                 | MM5 similarity                        |
| Land Surface                  | Noah Land Surface Model               |
| Planetary Boundary Layer      | Yonsei University                     |
| Cumulus Parameterization      | Kain-Fritsch                          |

The regional dynamic downscaling were performed through Weather Research and Forecasting Model with Advanced Research WRF (WRF-ARW) core solver version 3.8. Using four nested domains with the grid size of 37.5km (40 × 40), 12.5km (88 × 88), 2.5km (201 × 201) and 0.5km (151 × 151), the
near surface temperature were produced. The dimensions in the parentheses are the grid dimensions designed in the easting and northing direction. Based on Figure 1, the centre of all four domains were focused on the location of the Kuala Lumpur city to provide relaxation zone to the edge of each domain, intended to reduce the errors by employing the LBC[16]. The largest domain (D01) covered a part of Southeast Asia region and the smallest domain (D04) was designed to focus on the Klang Valley region where the Kuala Lumpur city is located. Since the WRF-ARW offers a variety of multiple physics options ranging from simple to very sophisticated schemes, a well-tried scheme employed by Isa et al [17] was used to configure the physics options available in the model as shown in Table 2. Similar domain design and physics schemes were employed in both simulations for the two different LBCs.

2.2. Remotely-Sensed Data Extraction

To extract the urbanized area, the present study has utilized the Landsat 8 Operational Land Imager (OLI) satellite image. The image was dated 17th April 2017 and chosen due to the clear sky view which reduce the chance of atmospheric errors to occur [17]. Radiometric calibration were employed to correct the image as suggested by the data provider [18] by converting the pixel values into surface reflectance as shown in Equation 1. Then, sun angle correction was performed using Equation 2.

\[
\rho_{\lambda}' = M_{\rho} \times Q_{\text{CAL}} + A_{\rho}
\]  

(1)

where \( \rho_{\lambda}' \) = surface reflectance without sun angle correction

\( M_{\rho} = \text{band-specific multiplicative rescaling factor from metadata} \)

\( Q_{\text{CAL}} = \text{Quantized and calibrated standard product pixel value} \)

\( A_{\rho} = \text{band-specific additive rescaling factor from metadata} \)

\[
\rho_{\lambda} = \frac{\rho_{\lambda}'}{\cos(\theta_{SZ})} = \frac{\rho_{\lambda}'}{\sin(\theta_{SE})}
\]

(2)

where \( \theta_{SZ} \) = Local sun elevation angle

\( \theta_{SE} \) = Local solar zenith angle

This study employed a combined algorithm conducted by Bhatti and Tripati [19] to extract the built-up areas (urbanized areas) since both study areas share the same tropical climate characteristics. [19] has suggested that the original NDBI algorithm by [20] should be calibrated. This is supported by [21]–[24] which suggested that the confusion to separate the built-up areas from green cover and water features can be eliminated or at very least reduced using Normalized Difference Vegetation Index (NDVI) and Modified Normalized Difference Water Index (MNDWI). [19] also suggested that, the NDBI layer should be enhanced using Principal Component Analysis (PCA) technique to assign the best pixel values for the MIR wavelength. Equation 4, Equation 5 and Equation 6 show the algorithm of NDBI, NDVI and MNDWI respectively.
2.3. Model Validation
The performance of both simulations which utilized the two different LBCs was evaluated and presented using statistical error indices, including mean absolute error (MAE), root mean square error (RMSE) and linear agreement ($R^2$). The performance of both simulations in reproducing the near-surface temperature were tested against the ground observations provided by the Malaysian Meteorological Department (MMD). Three ground stations were involved and located around the Kuala Lumpur city (in red line), namely MARDI Serdang, FRIM Kepong and Subang as shown in Figure 2.

![Figure 2. Location of MMD ground stations](image)

2.4. Data Sampling and Inferential Statistics
The original raw data has been filtered to ensure it is free from outliers. The exclusion of data outliers was performed using quartiles and boxplots as suggested by [25], [26]. Then, descriptive data examination were performed prior to analyses for determining the data distribution nature. In this study, the whole population was used as data samples. Since the data nature was found to be approximately normally distributed; indicated by the ratio of kurtosis and skewness value against the standard error, a series of parametric statistical analyses was chosen to analyze the data samples. Therefore, the interactions of the urbanized area towards the thermal environment were examined using inferential statistics including the Pearson’s correlation test to identify their relationships and one-way Analysis of Variance (ANOVA) with the control of Welch’s and Brown-Forsythe’s tests to determine whether or not the impact is significant.

3. Result and analysis
The findings and discoveries of the present study are discussed and presented as follows:

3.1. Simulations Performance
Table 3 shows the MAE, RMSE and $R^2$ values for the two simulations. Based on the results, it can be concluded that Simulation 2 excels in regenerating the actual near-surface temperature profile with the MAE of $\pm 1.9^\circ$C, RMSE of $\pm 1.4^\circ$C and $R^2$ of 0.881 as compared to Simulation 1 which has the MAE of $\pm 1.5^\circ$C, RMSE of $\pm 1.8^\circ$C and $R^2$ of 0.763. The diurnal pattern of air surface temperature in the three ground stations are shown in Figure 3. In both simulations, similar patterns were identified. In both simulations, the models tend to underestimate the near-surface temperature in two stations which are MARDI and Subang despite some overestimations during night time, whereas, in FRIM Kepong, the
near-surface temperature was overestimated except during the highest peak. Comparing both simulations, large residuals were identified in Simulation 1 during day time when the temperature was increasing rapidly.

**Table 3.** MAE, RMSE and R² of Simulation 1 and Simulation 2

|                      | NCEP FNL Operational Model Global Tropospheric Analyses, continuing from July 1999 (Simulation 1) | NCEP GDAS/FNL Global Tropospheric Analyses and Forecast Grids (Simulation 2) |
|----------------------|-------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------|
| MAE                  | ±1.5°C                                                                                          | ±1.0°C                                                                   |
| RMSE                 | ±1.8°C                                                                                          | ±1.4°C                                                                   |
| R²                   | 0.763                                                                                           | 0.881                                                                    |

**Figure 3.** Hourly profiles of near-surface temperature for both simulations in three different stations

3.2. **Urbanization Effects**

In this study, the urbanization effects towards the thermal environment were also investigated and the results are discussed as follows:

3.2.1. **Spatial distribution of urbanized areas and near-surface temperature profile.** Based on Figure 4, the Kuala Lumpur city was dominated more than half by built-up areas which covers approximately 85% of the city. The highest built-up area percentage is 99.5%, which indicates that the surface area is almost impervious whereas the lowest built-up percentage is 0%, which indicates that there are no man-made features constructed in this area. The highest built-up area percentage was found in Sentul which compacted with residential areas. The lowest built-up percentage was found in forest reserves in the city such as Bukit Tabur, Bukit Gasing and Bukit Besi. By examining the spatial distribution of the built-up areas, the study has found that the higher built-up area percentages were found in the northern, southern and central region of the city. The higher built-up area percentages often found within developed areas such as Sentul (residential), Kepong (industries), Central of Kuala Lumpur (business) and Bukit Bintang (business). These areas are expected to have higher thermal variation as compared to other areas. Lower built-up percentages were found in western and eastern regions of the city such as Bukit Tunku and Mont Kiara and are expected to have lower thermal variation.
Figure 4. Spatial distribution of built-up areas in the Kuala Lumpur city

Figure 5. Spatial distribution of mean near-surface temperature for Simulation 1 and Simulation 2

Figure 5 shows the spatial distribution of the daily mean of near-surface temperature within the Kuala Lumpur city produced by Simulation 1 and Simulation 2. In Simulation 1, the lowest mean temperature was 27.1°C and the highest mean temperature was 29.9°C. A close resemblance was also determined in Simulation 2 with the lowest mean temperature was 27.0°C and the highest mean temperature was 29.9°C. Based on the figure, the spatial distribution and pattern of the mean near-surface temperature in both simulations were similar to each other where the eastern regions possess lower mean temperature as compared to other regions across the city.

By delving deeper into Figure 5, it was found that the lowest near-surface temperature was identified in the mountainous region of Bukit Tabur which located in the north-eastern region of the Kuala Lumpur city. Other than Bukit Tabur, several areas were also identified to have lower near-surface temperature distributions which are Bukit Kiara, Bukit Tunku and Bukit Besi. The highest near-
surface temperature was identified in Sri Petaling which located in the southwestern region. Higher near-surface temperatures were also found in other areas as well, namely Kepong, Danau Kota, Bukit Bintang, Chow Kit, Kampung Baru and Segambut. Based on this, it can be said that the areas which are more urbanized contribute to the increase in the near-surface temperature.

3.2.2. Pearson’s correlation test result. By comparing both simulations, it was identified that Simulation 1 obtained a close result as Simulation 2. The correlation between the near-surface temperature and the urbanized area were 0.662 and 0.648 for Simulation 1 and Simulation 2 respectively. Portrayed in Figure 6, the relationships were indicated in increasing trendline. The trendline in Simulation 1 slanted more as compared in Simulation 2 which explained a slightly higher correlation result obtained. To conclude, in presenting the correlation, both simulations gave reliable performances. In other words, both LBCs can be employed for similar studies in tropical regions for regional downscaling.

![Figure 6. Relationships between near-surface temperature and urbanized area for Simulation 1 and Simulation 2](image)

Supporting the previous studies, it was identified that the urbanization was affecting the thermal environment with a positive correlation. This advocates that urbanization is indeed responsible in the increase of the ambient temperature within the city based on the fact that the increase of built-up area coverage will increase the near-surface temperature.

3.2.3. One-way ANOVA test result. In investigating the performance of both LBCs employed, both simulation results undergo the same one-way ANOVA procedures. By utilizing the datasets produced by both simulations, the investigation of the effects of urbanization towards the thermal environment returned similar results for the one-way ANOVA test performed where every test was rejecting the null hypothesis, suggesting the same conclusion. The variations of the means within the samples studied revealed the effects of urbanization towards the thermal environment was significant as the p-value rejected the null hypothesis of the one-way ANOVA. The test has confirmed that there was at least one significant difference in the comparison between the group means suggesting the changes in urbanized area coverage will significantly affect the thermal variation within the Kuala Lumpur city.

4. Conclusion
This study analysed the performance of two different LBCs in initializing the boundary conditions during WRF-ARW simulations to regenerate the near-surface temperature profile. It has been determined that the LBC with higher spatial and temporal resolution offer better performance of regional climate downscaling. Even though this is the case, both LBCs were capable to offer reasonable results pertaining to interactions of the urbanized area on the thermal environment within the Kuala Lumpur city. Thus, it is suggested that both of the LBCs can be employed in simulating the
regional climate. Future studies can be conducted to examine the spatial and temporal resolution impacts on regional climate downscaling separately for detailed investigation.

Acknowledgements
The authors would like to express their gratitude to the Universiti Teknologi MARA (UiTM) for funding this project under Geran Bestari Perdana 600-IRMI/DANA 5/3 BESTARI (P) (074/2018).

References
[1] IPCC 2001 Climate change 2001: synthesis report
[2] Amengual A, Romero R, Homar V, Ramis C and Alonso S 2007 Impact of the lateral boundary conditions resolution on dynamical downscaling of precipitation in Mediterranean Spain Clim. Dyn. 29 487-499
[3] Giorgi F and Mearns L 1999 Introduction to special section: regional climate modelling revisited J. Geophys. Res. 104 6335–52
[4] Warner T, Peterson R and Treadon R 1997 A tutorial on lateral boundary conditions as a basic and potentially serious limitation to regional numerical weather prediction Bulletin of the American Meteorological Society 2599–2617
[5] Denis B, Laprise R and Caya D 2002 Sensitivity of a regional climate model to the resolution of the lateral boundary conditions Clim. Dyn. 20 107–126
[6] Dimitrijevic M and Laprise R Validation of the nesting technique in a regional climate model and sensitivity tests to the resolution of the lateral boundary conditions during summer Clim. Dyn. 25 555–580
[7] Davies T 2014 Lateral boundary conditions for limited area models Q. J. R. Meteorol. Soc. 140 185–196
[8] EPA 2016 Climate change indicators: weather and climate United States Environmental Protection Agency [Online]. Available: https://www.epa.gov/climate-indicators/weather-climate. [Accessed: 05-Nov-2018]
[9] Asimakopoulos D 2011 Climate and climate change Energy and Climate in the Urban Built Environment, 2nd ed., M. Santamouris, Ed. New York, USA: Routledge Taylor and Francis Group 19–32
[10] Morris K 2016 Effect of vegetation and waterbody on the garden city concept : An evaluation study using a newly developed city , Putrajaya , Malaysia Comput. , Environ. Urban Syst. 58 39–51
[11] Trihamdani A, Lee H, Kubota T and Phuong T 2015 Configuration of green spaces for urban heat island mitigation and future building energy conservation in Hanoi Master Plan 2030 Buildings 5 933–947
[12] Isa N, Wan Mohd W and Salleh S 2017 The effects of built-up and green areas on the land surface temperature of the Kuala Lumpur City ISPRS Archives 42 107–112
[13] Lima F, Martins F, Pereira E, Lorenz E and Heinemann D 2016 Forecast for surface solar irradiance at the Brazilian Northeastern region using NWP model and artificial neural networks Renew. Energy 87 807–818
[14] Van Doan Q, Kusaka H, and Ho Q 2016 Impact of future urbanization on temperature and thermal comfort index in a developing tropical city: Ho Chi Minh City Urban Clim. 17 20–31
[15] Ooi et al. 2018 Comparison of WRF local and nonlocal boundary layer physics in Greater Kuala Lumpur, Malaysia in IOP Conference Series: Earth and Environmental Science 1–7
[16] NCAR, Weather Research and Forecasting: ARW version 3 modelling system user’s guide January 2016. 2016.
[17] Isa N, Wan Mohd W, Salleh S and Ooi M 2018 The effects of green areas on air surface temperature of the Kuala Lumpur city using WRF- ARW modelling and Remote Sensing technique IOP Conf. Ser. Earth Environ. Sci. 117 1–8
[18] USGS 2018 Using the USGS Landsat Level-1 Data Product [Online]. Available:
https://landsat.usgs.gov/using-usgs-landsat-8-product. [Accessed: 07-Dec-2018].

[19] Bhatti S and Tripathi N 2014 Built-up area extraction using Landsat 8 OLI imagery,” GIScience Remote Sens. 51 445–467

[20] Zha Y, Gao J, and Ni S 2003 Use of normalized difference built-up index in automatically mapping urban areas from TM imagery Int. J. Remote Sens. 24 583–594

[21] He C, Shi P, Xie D and Zhao Y Improving the normalized difference built-up index to map urban built-up areas using a semiautomatic segmentation approach Remote Sens. Lett. 1 213–221

[22] Lee J, Lee S and Chi K 2010 Development of an urban classification method using a built-up index Sel. Top. power Syst. Remote Sens. 39–43

[23] Varshney A 2013 Improved NDBI differencing algorithm for built-up regions change detection from remote-sensing data: An automated approach Remote Sens. Lett. 4 504–512

[24] Xu H 2008 A new index for delineating built-up land features in satellite imagery Int. J. Remote Sens. 29 4269–76

[25] Tukey J 1977 Exploratory data analysis Biometrical J. 23 413–414

[26] Hoaglin D, Iglewicz B and Tukey J 2012 Performance of some resistant rules for outliers labeling J. Am. Stat. Assoc. 81 991–999