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**DOI**

[10.3390/atmos10030151](https://doi.org/10.3390/atmos10030151)

**Publication date**

2019

**Document Version**

Final published version

**Published in**

Atmosphere

**Citation (APA)**

Maheng, D., Ducton, I., Lauwaet, D., Zevenbergen, C., & Pathirana, A. (2019). The sensitivity of urban heat island to urban green space-A model-based study of City of Colombo, Sri Lanka. *Atmosphere*, 10(3), Article 151. <https://doi.org/10.3390/atmos10030151>

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Article

# The Sensitivity of Urban Heat Island to Urban Green Space—A Model-Based Study of City of Colombo, Sri Lanka

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Received: 7 February 2019; Accepted: 18 March 2019; Published: 21 March 2019



**Abstract:** Urbanization continues to trigger massive land-use land-cover change that transforms natural green environments to impermeable paved surfaces. Fast-growing cities in Asia experience increased urban temperature indicating the development of urban heat islands (UHIs) because of decreased urban green space, particularly in recent decades. This paper investigates the existence of UHIs and the impact of green areas to mitigate the impacts of UHIs in Colombo, Sri Lanka, using UrbClim, a boundary climate model that runs two classes of simulations, namely urbanization impact simulations, and greening simulations. The urbanization impact simulation results show that UHIs spread spatially with the reduction of vegetation cover, and increases the average UHI intensity. The greening simulations show that increasing green space up to 30% in urban areas can decrease the average air temperature by 0.1 °C. On the other hand, converting entire green areas into urban areas in suburban areas increases the average temperature from 27.75 °C to 27.78 °C in Colombo. This demonstrates the sensitivity of UHI to vegetation cover in both urban and suburban areas. These seemingly small changes are average grid values and may indicate much higher impacts at sub-grid levels.

**Keywords:** green space; urban heat island; UrbClim

## 1. Introduction

Urban heat islands (UHIs) are meteorological impacts of urbanization that cause the air temperature in urban areas to be higher compared to their surrounding non-urban areas. Increasing urban temperature due to urbanization has been observed and studied in cities around the world such as Atlanta [1], Dhaka [2], Ho Chi Minh City [3], Karachi [4], Jakarta [5], Colombo [6], and Tokyo [7]. UHIs may adversely affect physical and mental health [8–10], as well as promote cardiovascular disease and chronic kidney disease [11]. They also have significant effects on energy consumption for cooling of urban buildings [12,13]. Urbanization is the main driver of UHIs, as it leads to massive land-use land-cover (LULC) change, transforming natural urban landscapes from green into grey areas to accommodate housing and public infrastructure. Land transformation has influenced local hydro-climatological conditions, leading to increasing temperature, extreme rainfall events,

and more flood events due to increased runoff [14–19]. As cities grow due to urbanization, natural elements such as urban green space (UGS) are replaced by high thermal admittance materials which enable the storage of more solar energy, leading to an increase of the surrounding air temperature once it is re-emitted. In case of low vegetation and/or water body in urban areas, solar energy is directly converted into sensible heat instead of latent energy for evapotranspiration and chemical energy in photosynthesis [20,21]. This will increase the air temperature, resulting in higher urban temperatures during the evenings and nights compared to those in surrounding non-urban areas with high vegetation covers [22]. Increasing the air temperature in urban areas is also impacted by the geometry of urban areas. Whether urbanization has resulted from expansion or densification, it alters the urban geometry, which potentially impedes the release of longwave radiation or changes the wind direction and increases shortwave energy absorption due to the bouncing around of sunlight in the urban canopy. This condition might result in higher temperatures when the sky view factor (SVF), which is a measure of the openness of the sky to radiative transport, is low [23,24]. Furthermore, the variation of urban temperature can also be influenced by the interaction between urban temperature and air pollution in urban areas where aerosol particles can minimize the incoming shortwave radiation that changes the surface energy budget [25].

Green space is a very subjective concept and has many interpretations [26]. Presently, most cities in the world are greening their cities. For example, the city of Rotterdam in the Netherlands implements the greening concept in city planning and development [27]. Cities can reduce the heat island effect by using green space that provides shadings and open wind-flow paths, which can eliminate the accumulation of heat [28]. This can be practically done by increasing the percentage of green space in urban areas. For example, cities can introduce some of interventions collectively known as sustainable drainage systems, which include green roofs, vegetated swales, and rain gardens [29].

Many studies have looked at the relationship between the intensity of UHIs and UGS with regard to its composition and configuration [14,30–33]. Composition refers to vegetation density and variety of land-cover types, green space size, as well as spatial distribution. Some studies show that the composition of UGS can be more significant to cooling effects, as opposed to its configuration. In Hanoi, Vietnam, the transformation of agricultural land into the impervious (built-up) surface due to urbanization and industrialization between 2003 and 2015 has increased the mean land-surface temperature (MLST). For example, the MLST in urban built-up areas was 43 °C in 2003, and increased to 46 °C in 2015. On the other hand, the MLST increase was lower in rural open land where vegetation cover was dominant and water bodies are present. In those areas, the MLST was 36 °C in 2003 and 38 °C in 2015, which showed how the vegetation and water contribute to lower surface temperature [32]. Sun and Chen (2017) revealed that 108.86 km<sup>2</sup> of the green space in Beijing was lost, which increased LST between 1.6 °C and 2.2 °C, while 92.5 km<sup>2</sup> of the green space expansion had reduced the LST within the range of −1.1 °C to −0.67 °C. These results indicate that changing the levels of green space influence air temperature changes and generate various temperature patterns.

On the other hand, the configuration of UGS is related to spatial pattern as well as the layout of UGS including aggregation, shape, and cohesion of patches [34]. In a particular configuration, UHI intensity can be significantly increased or decreased by different spatial arrangements of UGS [35]. The configuration or spatial distribution of urban green space can influence the flow of energy or the energy exchange among different land-cover features. For example, distribution of green space comprising large tree canopies within a certain distance provides a large cooling effect, while green space with grass should be concentrated to maximize the cooling effect [34]. Hence, the configuration of green space should consider spatial distribution (concentrated or dispersed), the distance between each green space, and shape complexity. Even though there is no significant relationship between the degree of aggregation of green space and mean temperature, it has been found that in a particular space, dispersed configuration or evenly distributed UGS has led to a decrease of the mean temperature [14]. Moreover, available UHI studies are intended to evaluate the impact of existing land-use change on increasing temperature [36–41]. However, the research on mitigation of the existing UHI impacts,

and in particular projections of increasing temperature due to urban growth and urban planning, are still limited [19,42–49].

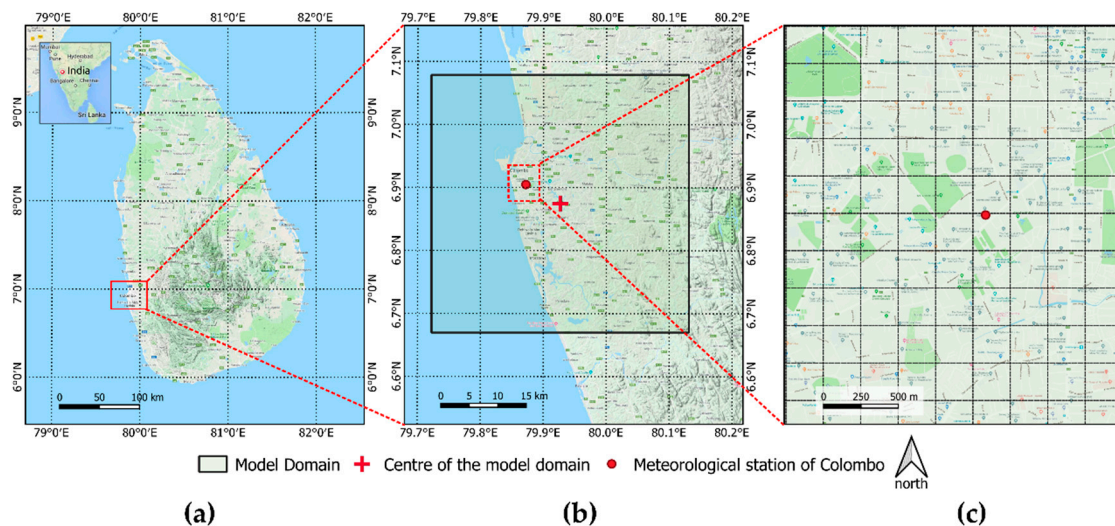
UHI studies can be performed using several methods, including field observations, remote sensing [50], and numerical modelling [51]. Field observations are normally made by comparing records from meteorological stations inside and outside of the urban area or using mobile monitoring cars moving between rural fringe and the city center [20]. In addition, advanced computer technology along with high spatial and temporal resolution of satellite imagery has been used to measure UHIs in more detail [52,53]. The UHI phenomenon can also be studied by using numerical atmospheric simulation (climate) models [54–60]. The latter approach provides a unique ability to study the response of various land-cover change scenarios on UHI.

In this paper, we present the results of a series of numerical experiments using the urban boundary climate model UrbClim [54] in order to understand the sensitivity of UHIs to UGS in Colombo, Sri Lanka. This study starts with the hypothesis that changes in the quantity and distribution of green space have significant impacts on the spatial and temporal temperature distribution in urban areas. Two groups of green area conditions that represent decreasing and increasing green areas are simulated, and the results are compared with the reference year.

## 2. Methodology

### 2.1. Study Area

Colombo, the capital city of Sri Lanka, is one of the emerging cities in Asia. It has a total city area of 37 km<sup>2</sup> and has about 2.4 million inhabitants (Figure 1). The city of Colombo has seen a rapid increase in urbanization in recent decades. It adopted new development programs around a decade ago, triggered by the end of the civil war in the country. According to World Health Organisation (WHO), 9.5 m<sup>2</sup> of green area per capita is the minimum requirement for healthy living [61].



**Figure 1.** The location of the study. (a) Sri Lanka (Source: Google maps <https://goo.gl/9WypnH>); (b) model domain covered with 181 × 181 grid cells of 250 m × 250 m size (grid cells are two dense to show on the figure); (c) The actual grid cells (250 m × 250 m) around the location of the meteorological station.

The rapid urban development in Colombo has altered the urban landscape by decreasing green areas, resulting in an uneven spatial green area distribution resulting in 34 out of 55 administrative divisions not complying with the WHO standards for the city [62]. Recent observational studies in Colombo reveal that the metropolitan area is experiencing a UHI as there is a significant urban–rural temperature difference, which has not been observed in recent decades [40,41,63]. However, it is a

huge challenge to protect the existing green spaces in the metropolitan area of Colombo from human activities, which can influence the Colombo urban climate.

Colombo is situated in the tropical monsoon climate and experiences average maximum temperatures of about 31 °C from March to April. The south-western monsoon season that produces large quantities of rainfall is expected from May to September. Average minimum temperatures drop to 22 °C during the drier months of December to February.

## 2.2. UrbClim

UrbClim is an urban boundary climate model developed by using a land-surface scheme that includes simplified urban physics, coupled with a 3-D atmospheric boundary layer module [54]. The model is designed to simulate the temperature and heat-stress fields using high spatial resolution up to 100 m. UrbClim comprises two main modules, namely surface module and atmospheric module. In the land-surface scheme of UrbClim, an impermeable slab with proper values of emissivity, albedo, and aerodynamic and thermal roughness length is used to represent the urban terrain. The model also takes into account anthropogenic heat fluxes. The surface module simulates the relevant physical interactions between soil, vegetation, and atmosphere following the scheme developed to investigate the interactions between the land-surface and regional atmospheric circulations and climate [64]. UrbClim model makes some major simplifications in the atmospheric model compared to a “standard” mesoscale model such as the weather research and forecast (WRF) model [57], to achieve fast simulations.

The UrbClim performance has been validated by simulating UHI in Toulouse (France), Ghent (Belgium), Antwerp (Belgium), and Bilbao (Spain) [54]. Moreover, UrbClim model performed at an acceptable accuracy with the root mean square error (RMSE) values ranging from 1.6 °C to 1.9 °C when the model’s outputs are validated with data from 11 ground stations, and has lower computational costs compared to the WRF model when simulating the UHI in Barcelona (Spain) [55]. UrbClim has been implemented to define a new method to assess the UHI in Amsterdam based on the UHI simulation over some cities in Europe [56] and to investigate future UHIs in Delhi, India [65].

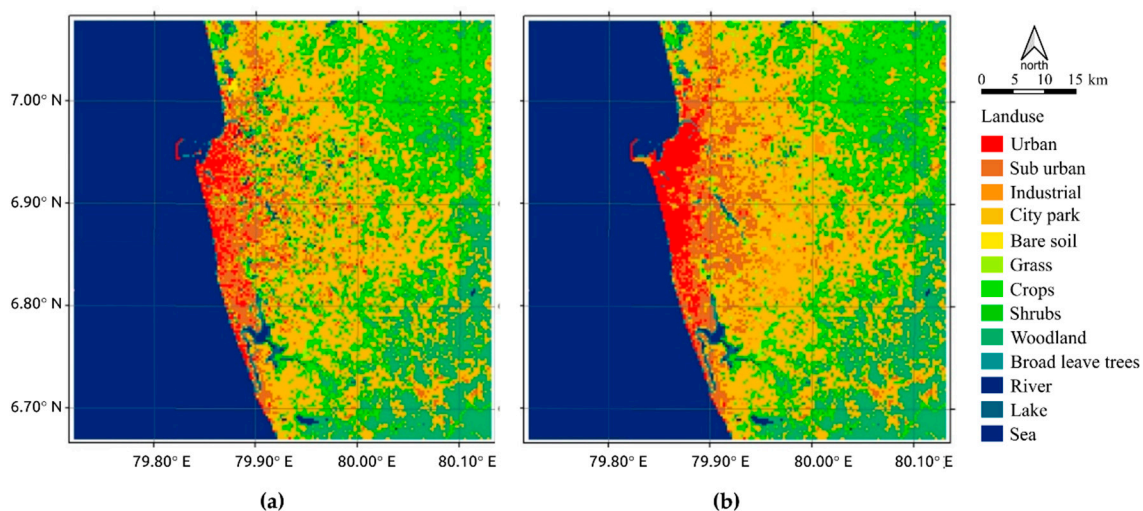
## 2.3. Model Setup

Like many limited-area atmospheric models, UrbClim requires two types of data: the geographical data consisting of land cover and topography, and meteorological data which can be obtained from historical re-analyses or large-scale (e.g., global) models. Landsat satellite images for the years 1997 and 2015 were used as the basis for land-cover data. Both geographical (e.g., land use, topography) and meteorological data (initial and lateral boundary conditions) input data sets should have an identical model grid configuration. For this study, a 250 m spatial resolution as grid spacing for the model was selected. Given the grid spacing, the area of interests was covered by a model domain of 181 × 181 square grid that consists of 32,761 grid cells with the center point at 79.9268° E, 6.8745° N.

For the surface module, land-use data were prepared by using Landsat satellite images from the year 1997 and 2015 selected with the cloud cover less than 10% and daytime as the main selection criteria. Land-use classification was made by following the local climate zone classification (LCZC) framework developed by the world urban database and access portal tools (WUDAPT) [66]. In the LCZC framework, land-use land cover is classified by considering land definitions from the local climate zone (LCZ) classification designed for urban climate studies. The LCZ framework is based on universal knowledge of built forms and land-cover types, and it is not based on local characteristics such as local topography and climatology of individual cities [67]. Originally, the LCZ framework consists of 17 standard classes divided into ten built types and seven land-cover types. The built type represents urban and non-urban forms identified by height and density of roughness features such as compact high-rise, compact mid-rise, compact low-rise or open low-rise as well as typical urban materials such as paved surface, and low plants or scattered trees in open areas. Moreover, the land-cover type is a classification of surface covers around the roughness which are influenced

by various factors such as anthropogenic activities and weather patterns [67]. The first application of the LCZ framework for the city of Colombo has been made in a previous study [68] in which a set of sub-classification is developed for the LCZ to adapt the local features, for instance, the compact low-rise zone has mid-rise sub-classification that combines the compact mid-rise and open mid-rise zone, which are some typical land-cover patterns in Colombo.

In this study, the LCZ classes have been re-arranged to accommodate the 15 land-use classes of UrbClim by considering building density and arrangement, the permeability of areas, and building materials. For instance, three compact land uses from the LCZ were classified into urban land-use class in UrbClim. Having established the land-use classes, the LCZC classification tool in SAGA GIS [69] was used to generate two land-use maps from the Landsat satellite images to understand land-use change from 1997 to 2015 in Colombo. The SAGA GIS is a free open source GIS application that provides some plugins for land classification purposes including the LCZC. In SAGA GIS, the LCZC needs training areas that can be prepared in Google Earth (GE). Before running the land classification, Landsat image was resampled from 30 m to 250 m by using the nearest neighbor method to meet the UrbClim spatial resolution. In addition, some corrections have been made related to the actual land use and land cover by conducting the field survey and referring to the city development information. Two land-use maps corresponding to 1997 and 2015 (Figure 2) were created, which were based on the UrbClim land-use classes. Other parameter values for the surface module such as albedo and emissivity are specified by following the standard values prepared by the UrbClim development team [54].



**Figure 2.** Land-cover map of (a) 1997; and (b) 2015.

The land-use map of 1997 was considered as the reference land use to calculate the relevant percentage changes by 2015 (see Table 1). Analysis of the land-use change shows that during the 19-year period, urban areas have been increased by approximately 51% while suburban areas have been decreased by 15%. It is evident that increased urbanization results in new industrial areas and that a lot of marshes and wetlands located around the city of Colombo have been lost. On the other hand, the proportion of open water bodies decreased with almost 9%, by reclaiming the small lakes located in the vicinity of these marshes/wetlands as urban areas.

Initial and lateral boundary condition data for the atmospheric module were obtained from the ERA-Interim reanalysis of the European center for medium-range weather forecasts (ECMWF) from 1996 to 2015 totally covering a period of 20 years. Such an extended period is needed to obtain statistically valid results. The reanalysis data is obtained by using temporal and spatial resolution parameters. The temporal resolution of data from the ERA-Interim is 3 h, while the spatial resolution is  $0.75 \times 0.75$  degree. In this study, the observed air temperature was obtained from the only one

weather station from the department of meteorological (DoM) located within the area of interest. The station has hourly observations of 2 m air temperature for 1997 and 2015.

**Table 1.** Land-use change between 1997 and 2015.

Land-Use Classes	Land-Use Change (%)
Urban	50.90
Suburban	−15.50
Industrial	32.39
City Park	2.01
Green Areas (Grass, Crops, Shrubs, Woodland, Broadleaf Trees)	−8.94
Open Water (River, Sea, Lake)	−8.97

#### 2.4. Numerical Simulations

All numerical experiments were performed for 20 years (1996 through 2015) of reanalysis data as model boundary conditions, changing only the land-use data for each experiment. Further use of the same forcing data would allow us to understand the isolated impact of UHIs because impacts such as global warming had equally affected all numerical experiments. To investigate the sensitivity of the UHI to green area in the city of Colombo, this study was conducted by using two groups of numerical simulations, namely “urbanization impact simulations” and “greening simulations”. The urbanization-related simulations were conducted in two parts. The first urbanization impact simulation was performed to identify the existence of the UHI due to land-use change from 1997 to 2015, while the second simulation was intended to investigate the extension of the UHI by expanding urbanization to suburban areas. This is actually a realistic circumstance, as the city of Colombo is expanding over the time and most of the existing suburban areas are converted into urban areas. For instance, the built-up area in Colombo from 1997 to 2017 was expanded beyond the metropolitan area as indicated by an increase in the normalized difference built-up index (NDBI) of suburban areas [40], which was seen to deliver an impact on the UHI in Colombo. Urban expansion was included by assuming a reduction of green space in suburban areas. In this study, the land use of 2015 was used as the baseline for the urban expansion simulation in which the green area in the suburbs was assumed to drop to 0%, which indicated a conversion of entire suburban areas into urban areas. The simulation was performed by providing 10% green area in suburban areas and comparing the results with the average temperature due to the actual land-use change in 2015. Following similar steps, the simulations were proceeded by providing 5% and 0% of green areas in suburban areas.

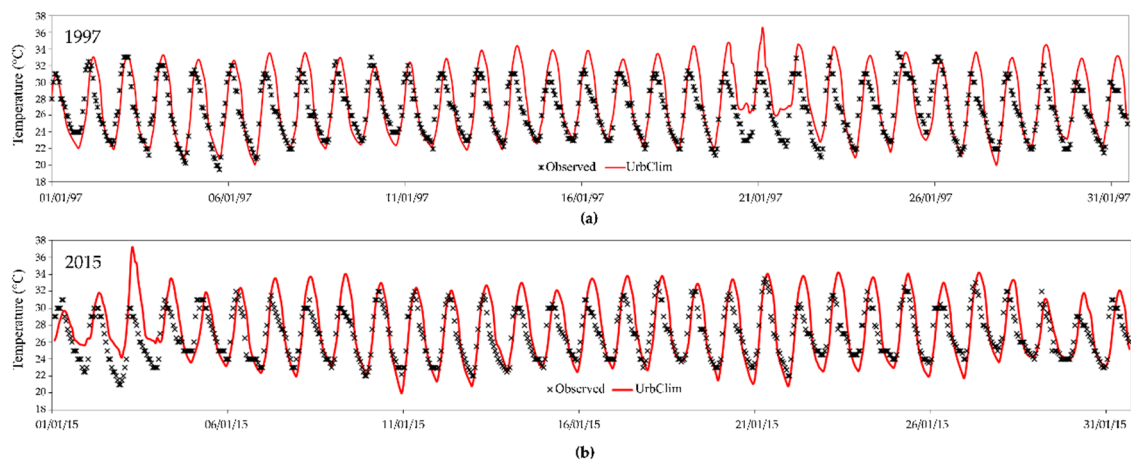
The greening simulations in this study are assuming various urban greening such as parks, grass, and urban forest. Increasing green areas were made by incrementally increasing the amount of green space in urban areas by 10%, 20%, and 30%. The maximum increment of 30% green area is a practical approach for a city in a developing country such as Sri Lanka. The greening simulations were started by increasing green cover in urban areas by 10%, and comparing the result with the existing condition in 2015. The similar procedure was applied when green areas increased by 20% and 30%.

The model’s performance has been evaluated by comparing 2 m air temperature from the model’s output with observational data from a meteorological station. The difference between both data has been investigated by using the RMSE, the mean absolute error (MAE), and the Pearson correlation coefficient, which have been generally used to evaluate the performance of climate models [70,71] including modelling the UHI in Barcelona [55].

### 3. Results

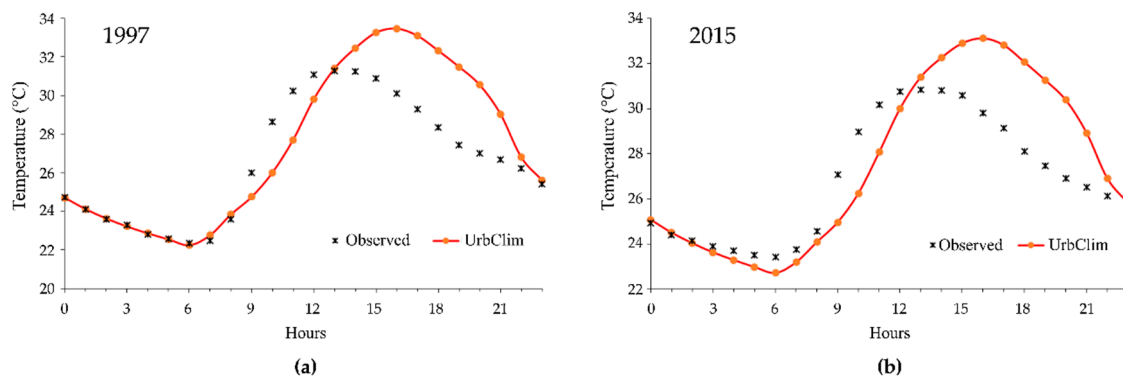
#### 3.1. Model Validation

The statistical tests were made to evaluate the model’s performance by comparing simulated values from the model and observed data from the meteorological station. The simulated values were extracted from a grid point situated about 100 m from the measurement station. This is the nearest grid point to the coordinate of the Colombo meteorological station located approximately at latitude 6.9047° N and longitude 79.8725° E where the air measurement device is positioned at 2 m above the grass. The nearest grid point was selected since the grid point values are indicating the climate condition of the cell area of 250 × 250 m, which covers the location of the point measurement. The time series plots for the simulated and observed data is given in Figure 3 that shows 2 m air temperature values in January 1997 and 2015, respectively. It can be seen that the simulated air temperature is overestimated as confirmed by the RMSE value that is higher than 2 °C.



**Figure 3.** Simulated and observed daily time series 2 m air temperature of January (a) 1997; (b) 2015.

The overestimate in the simulation is observed at the daytime and earlier at the night time as shown in Figure 4. UrbClim tends to overestimate temperatures after 13:00 with the highest value of 4.06 °C and 3.96 °C in 1997 and 2015, respectively. It clearly shows that the temperature at the grid point at the daytime is higher than at the point measurement. Furthermore, the temperature is well simulated by UrbClim at the night time when the high intensity of UHIs is generally observed. The maximum bias values for the nighttime temperature are 0.58 °C in 1997 and 0.79 °C in 2015.

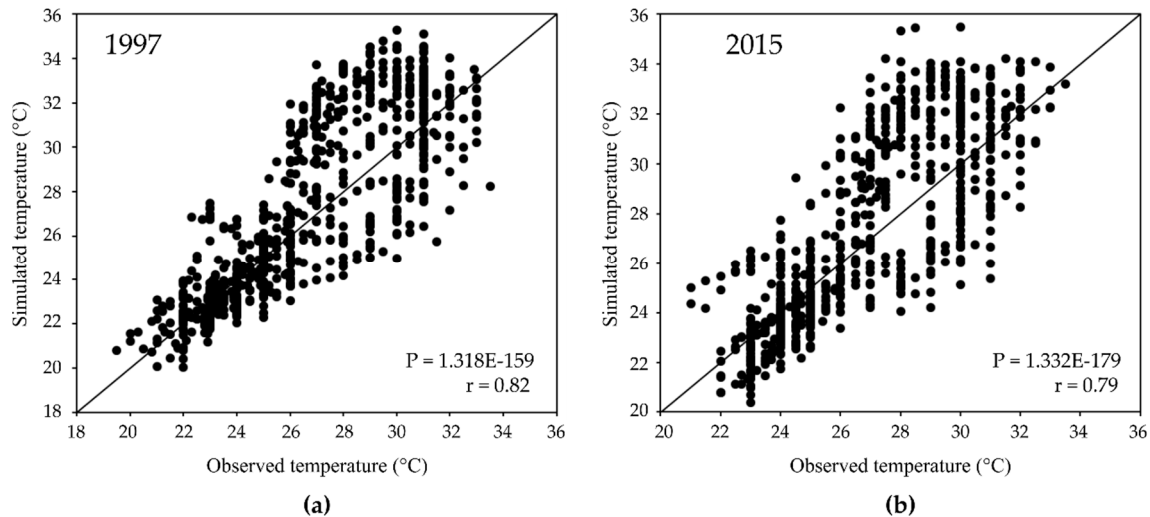


**Figure 4.** Mean diurnal variation of 2 m air temperature of January (a) 1997; (b) 2015.

The statistical test showed that the RMSE of the two data sets for 1997 and 2015 were 2.43 °C and 2.39 °C, respectively. In addition, the MAE test showed that the absolute error values for 1997



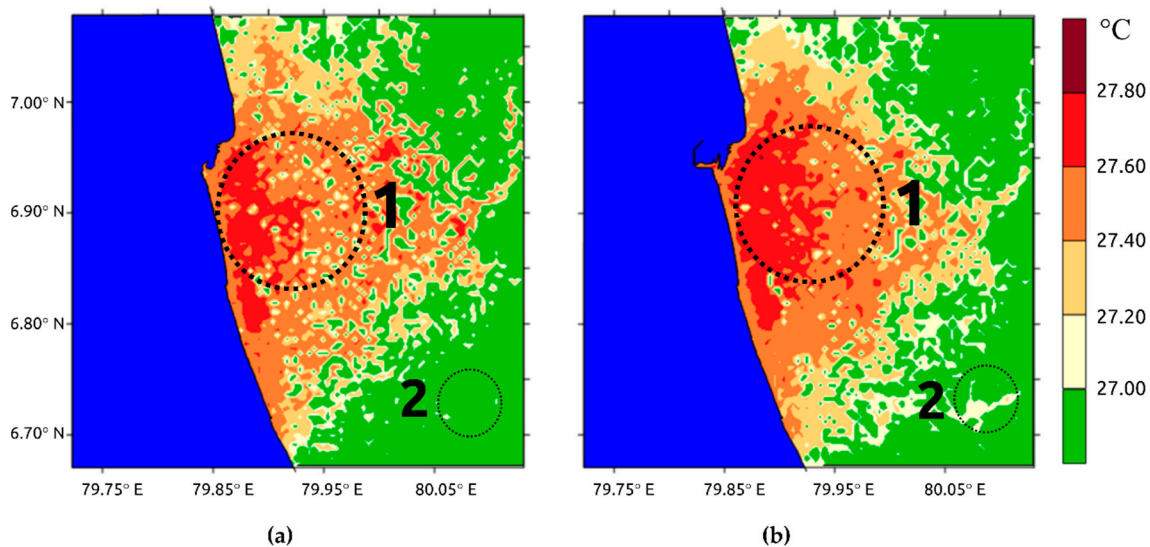
and 2015 were 1.86 °C and 1.89 °C, respectively. The MAE, which is less than 2 °C, is considered to be acceptable for 2 m temperature simulations [72]. Furthermore, the Pearson correlation coefficient between simulated and observed data for 1997 and 2015 were 0.82 and 0.79, respectively as given in Figure 5. Since these values are within the range of 0.5 and +1, the correlation check is fairly acceptable compared to the similar test using more than one meteorological stations from the UHI studies with UrbClim in Europe [54].



**Figure 5.** The Pearson correlation coefficient between simulated and observed 2 m air temperature in January (a) 1997; (b) 2015.

### 3.2. Impact of Land-Use Change on UHIs

The first simulation was conducted to investigate the contribution of the land-use change from 1997 to 2015 on increasing air temperature and development of UHIs. At this step, 2 m air temperature variations were simulated in relation to the land-use change which showed that decreased green areas from 1997 to 2015 resulted in increased temperatures (see Figure 6).



**Figure 6.** Spatial 2 m air temperature distribution in Colombo in (a) 1997; (b) 2015. Area 1: The urban land cover and Area 2: non-urban land cover was used for temperature comparisons.

The maximum temperature increment was found to be 0.8 °C with the average temperature increment within urban areas recorded to be 0.2 °C. Moreover, the total urban area (observed in

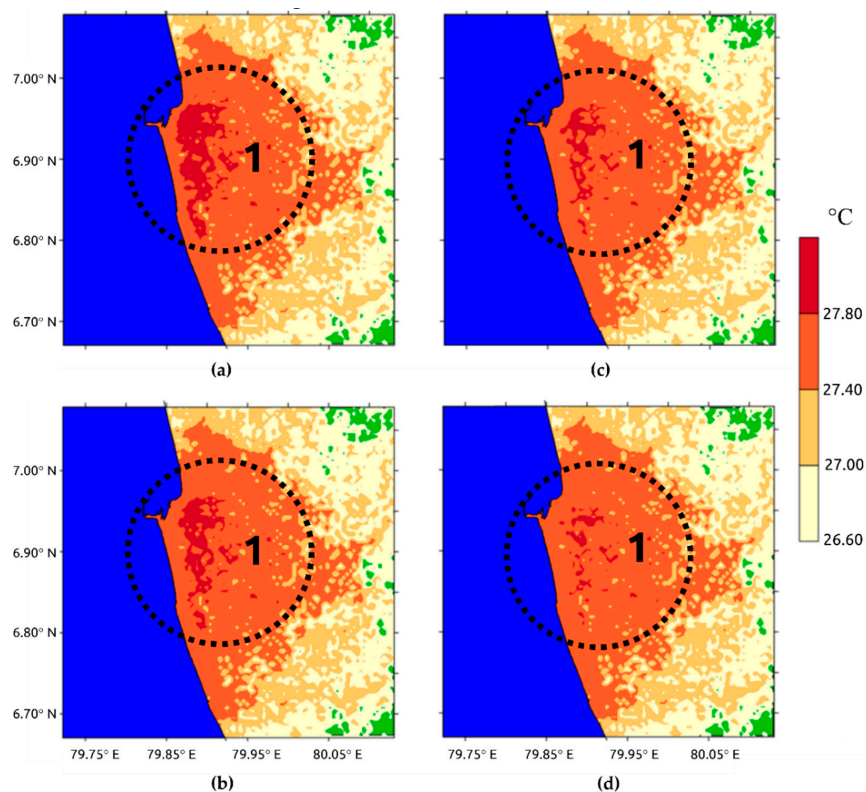
location 1 in Figure 6) with the average temperature of 27.80 °C or above, increased from 114.81 km<sup>2</sup> in 1997 to 344 km<sup>2</sup> in 2015. A significant increase in temperature due to extended urbanization can be seen in the suburban areas indicated in location 2 from Figure 6 the average temperature increased sharply up to 27.20 °C in 2015. Furthermore, the results show an increase in the average UHI from 0.45 °C in 1997 to 0.80 °C in 2015. However, the temperature differences between urban and suburban areas in this study were less than found in the study [63] in which the temperature difference ranged from -0.90 °C to 4.40 °C.

### 3.3. Greening Simulations

The green scenarios for urban areas (scenario 1–3) were developed by increasing the green area of parks by 10%, 20%, and 30%. The spatial distribution of increasing green areas was considering the spatial temperature distribution due to land-use change from 1997 to 2015. This was made by increasing green area in the area where the temperature ranged between 26 °C and 27 °C, which were based on the spatial temperature distribution in 2015.

The greening simulations showed that increasing green areas decreased average temperatures as well as UHIs. In general, the highest intensity of UHI is observed at the nighttime particularly during clear sky and calm wind [22]. In this study, it was observed that increasing green areas reduced the average daily temperature in urban areas from 27.75 °C to 27.67 °C and decreased the average night time UHI from 1.41 °C to 1.25 °C. The average night time UHI in this study was based on the temperature from 18:00 to 06:00, while the average day time was based on the temperature from 06:00 to 18:00.

Moreover, increasing green areas also influenced the spatial distribution of urban temperature. It was observed that there was a decrease in the area affected by high temperature (greater than 27.0 °C) as indicated in location 1 in Figure 7.



**Figure 7.** (a) Average temperature distribution due to land-use change in 2015; (b) Average temperature distribution with 10% greening; (c) 20% greening; (d) 30% greening.

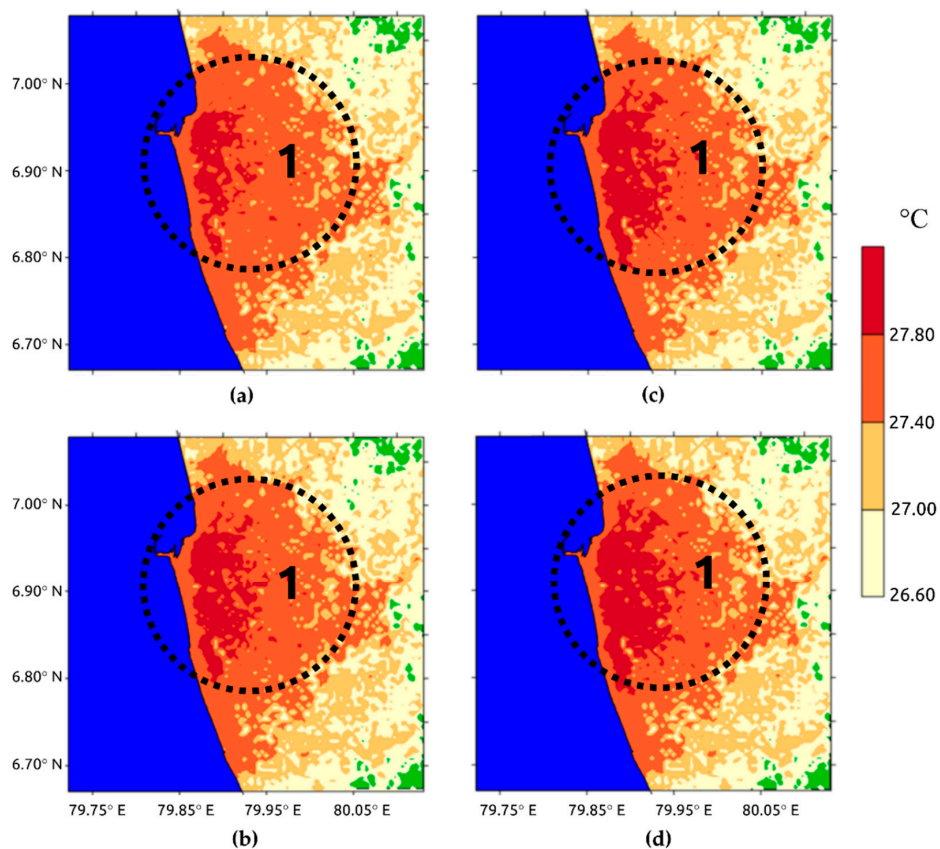
It shows that the extent of the UHI effects can be reduced by 17.62 km<sup>2</sup> (26%), 31.25 km<sup>2</sup> (47%) and 43.31 km<sup>2</sup> (64%) when simulating scenarios 1, 2, and 3, respectively. The summary of model’s outputs from scenario 1, 2, and 3 are provided in Table 2.

**Table 2.** Model’s outputs for greening scenarios.

Simulation	Average Temperature in Urban Areas (°C)	Average Daytime UHI (°C)	Average Nighttime UHI (°C)	The Area Experience More Than 27.8 °C as Avg. Temperature (km <sup>2</sup> )	Area Reduction (km <sup>2</sup> )
Existing situation	27.75	0.26	1.41	67.12	
Scenario 1	27.72	0.25	1.33	49.50	17.62
Scenario 2	27.70	0.24	1.28	35.87	31.25
Scenario 3	27.67	0.22	1.25	23.81	43.31

### 3.4. Urban Expansion Simulations

The second simulation of the impact of urbanization was done by assuming that there is urban expansion towards suburban areas. This was made by decreasing the green areas by 10%, 5%, 0%, in scenario 4, scenario 5, and scenario 6, respectively. The UrbClim’s output showed that decreasing green areas in suburban areas had an impact on increasing temperature and UHI in Colombo. The simulation results of the average temperature distribution from the existing situation, scenario 4, 5, and 6 are mapped and shown in Figure 8. It shows that the average daily temperature in urban areas increased from 27.75 °C to 27.78 °C. As the UHI intensity is higher in the night time, it was observed that urban expansion increased the average nighttime UHI intensity from 1.41 °C to 1.44 °C when the vegetation cover in the suburban region was reduced.



**Figure 8.** (a) Average temperature distribution due to land-use change in 2015; (b) Providing only 10% greening; (c) Providing by 5%; (d) No green areas.

Moreover, an increase in areas affected by high UHI intensity was observed. The areas experiencing average high temperature increased by 35.63 km<sup>2</sup> (53%), 52.01 km<sup>2</sup> (77%), and 75.19 km<sup>2</sup> (112%) when UrbClim simulated air temperatures using scenario 4, 5, and 6, respectively. The summary of model's outputs for urban expansion simulations are given in Table 3.

**Table 3.** Model's outputs for urban expansion scenarios.

Simulation	Average Temperature in Urban Areas (°C)	Average Daytime UHI (°C)	Average Nighttime UHI (°C)	The Area with Avg. Temperature More Than 27.8 °C (km <sup>2</sup> )	Increased Areas (km <sup>2</sup> )
Existing situation	27.75	0.26	1.41	67.12	
Scenario 4	27.76	0.22	1.42	102.75	35.63
Scenario 5	27.77	0.22	1.42	119.13	52.01
Scenario 6	27.78	0.22	1.44	142.31	75.19

#### 4. Discussion

The simulation results above show that changes in the quantity and distribution of UGS in Colombo affect the spatial and temporal temperature distribution. Between 1997 and 2015, urban areas in Colombo increased by 51%. These land-use changes along with global climate change have increased the average temperature by 0.2 °C in urban areas. However, global climate change alone has more contribution in increasing the average temperature in rural areas or new urban areas [49]. Moreover, the average UHI intensity also increased from 0.45 °C in 1997 to 0.80 °C in 2015. The main factor contributing to increasing urban temperature is that the decreased green space resulted in a low evapotranspiration rate while most of the solar energy was converted to sensible heat, or stored and slowly released during the night [51,73]. This condition can be observed in Colombo particularly in impervious areas where green space coverage is low and at the same time surface materials with high thermal admittance such as concrete, asphalt, or black roof are dominant [40]. Those materials can accumulate heat more intensely leading to the formation of the UHI. Moreover, a decrease of the water bodies, as well as low soil moisture can also contribute to more sensible heat since less water was available for evapotranspiration [74].

Another factor that has to be considered in increasing the average temperature in Colombo is the low SVF [6]. The SVF has an inverse relation to shading effects at which the low SVF indicates a less shading effect available and vice versa. The low SVF contributes to the increased urban temperature of Colombo particularly in urban areas where the compact mid-rise and high-rise zones increased between 2010 and 2017 [68].

The average temperature was reduced in the greening scenarios as demonstrated by simulating the regeneration of the vegetation cover of 1997 in 2015, which was done by providing up to 30% of green space coverage in urban areas. The model indicated that increasing the quantity of green space decreased the average temperature as well as both the day time and the night time UHI particularly within the area where built-up and impervious areas were re-converted to green space. These changes reduced the average temperature possibly through one or a combination of ecosystem services provided by green areas such as intercepting solar radiation, evapotranspiration, and modifying air movement [75]. The sensitivity of UHIs to UGS from the greening simulations also showed that an appropriate quantity and distribution of green space can provide cooling effects to lower the air temperature [14] through evapotranspiration [76], which can be explained by the fact that approximately 1000 MJ is consumed by a single tree for heat energy in the transpiration process [28]. The decreased temperature in urban areas can influence temperature differences between urban and suburban areas that lead to prevent UHI formation.

Moreover, the urbanization extension increased the average temperature as well as the extent of the affected areas. Extension of the built-up areas was represented by reducing the amount of available green space to 0% in suburban areas. From the simulations, it was shown that the expansion of urbanization towards the suburban areas had caused more regions to be affected by increased

temperature (higher than 27 °C), although increasing the average temperature was small (0.03 °C). Increasing the average temperature as the impacts of future urban expansion have been investigated in some Asian cities, for example in Ho Chi Minh City [49], where the impact of urbanization on increasing temperature can be approximately 20–30% of global warming. Future urbanization might not significantly increase the urban temperature as well as the intensity of UHIs but it might extend the UHI [77]. The increased average temperature was mainly a result of the decreasing green space and reduced or loss of the water body as discussed above. However, there is a situation in the real world where the increased temperature can also be influenced by the energy exchange between adjacent areas. The exchange can happen through advection of sensible heat from urban to suburban areas [78]. For instance, increased air temperature about 1 K between 1970 and 2000 in the Old City, a built-up historical area in Jakarta, was influenced by high temperature from adjacent areas where new urban development took place [5].

Different size and spatial distribution of the green space show influence on the average temperature. The simulation results show that the variation in spatial temperature distribution is consistent with findings from previous UHI studies in Colombo which show temperature differences between urban and suburban areas [6,40,41,63]. Moreover, the simulated temperature in UrbClim is the average temperature that is calculated based on grid values. In reality, the value should be considered only as an indication of high temperatures from specific places such as a car park, which influences ambient temperature in the immediate surrounding. Such sub-grid scale effects are not captured by the current model with 250 m grids. However, the indication from UrbClim simulation is useful to understand UHIs particularly when a UHI study is started by having limited information about urban detail such as urban canopy geometry [54].

Furthermore, the average UHI intensity in this study, which are 0.26 °C in the daytime and 1.41 °C in the night time, seem to be lower than that in another Asian city such as Delhi where the average urban–rural temperature differences can be more than 4 °C [65]. The lower UHI intensity in Colombo is related to the regional climate characteristics. Located in the tropical monsoon climate, Colombo receives the amount of rainfall over the year with total annual precipitation about 2500 mm. The influence of precipitation to the UHI intensification is also observed in Rennes, France, where the average UHI intensity at the daytime and the night time are 0.5 °C and 2 °C, respectively [79].

However, it was noticed that UrbClim model tends to overestimate air temperature values particularly when the results for January 1997 and 2015 were compared against the observed air temperature. The bias between the simulated and the observed temperature was related to the nature of data since the correlation test was made by comparing the point source observation data with the spatially averaged grid values from the model. The bias is also influenced by the difference in land-use classes. The land use of the grid point in UrbClim is classified as the urban class while the point measurement is located within a small grassy patch of about 50m×50m size, which is not large enough to influence the land cover of the model grid. Located in the urban land-use classes in the simulation, the temperature at the grid point during the daytime is higher than at the point measurement and it is decreased slowly until the evening. Both these observations, namely, the higher peak and slower drop in temperature in the urban areas compared to green (e.g., grass) areas is expected. Urban areas absorb higher amount of thermal energy during the daytime and is slowly released in the evening [51]. This overestimate results from UrbClim were also observed in the UHI study for the city of Ghent (Belgium) and Bilbao (Spain) with the correlation coefficient between simulated and observed data were recorded as 0.95 and 0.90, respectively [54]. This therefore can be considered as a consistent issue with the UrbClim model.

Compared to some similar cases one of the obvious limitations of the present study is the fact that the availability of only one weather station within the study area. This is largely an unavoidable issue not only in this case study but many potential future studies in data-poor environments, unless data is augmented by techniques such as low-cost citizen observatories [80].

## 5. Conclusions

In the present study, we have investigated the influence of green space on the spatial and temporal distribution of urban temperature as well as UHIs. The investigation is made by changing the size and distribution of green space using two sets of simulation named “urbanization impact simulations” and “greening simulations”. These simulations are conducted using UrbClim, a boundary urban climate model, with a spatial resolution of 250 meters and two different land-use maps from 1997 and 2015, which are generated from Landsat images by using the LCZ framework.

It is observed that urbanization alters urban landscape from green to grey environments, and that affects the spatial temperature distribution. Two urbanization impact simulations show that the decreasing green space both in urban and suburban areas can increase the average temperature as well as extend areas affected by high temperature. On the other hand, the greening simulations show that the increasing size of green space can decrease average air temperature and it can minimize the spread of high temperature. Moreover, increasing urban temperature and UHI can be influenced by other aspects such as the SVF and urban morphology, which are not considered in this study.

It should be noted that while this study has used a relatively finer resolution of 250 m (in comparison to typical mesoscale atmospheric simulation studies), still the temperature values produced by the model are grid-average values that ignore a lot of sub-grid-scale heterogeneity. Therefore, the seemingly moderate increases in temperature reported at grid-average scale should only be considered as a symptom of (much higher) sub-grid-scale temperature variations. Actual temperature hotspots may demonstrate temperature increases often much larger than the grid-average value. Further studies, ideally in conjunction with field observations, should be done to establish such sub-grid-scale temperature relationships.

The numerical urban climate simulations with UrbClim using the variations of green space size and distribution show that the spatial and temporal distribution of urban temperature is sensitive to the size and distribution of green space. It can be seen from the variations in temperature differences between urban and suburban areas where green space is modified. Moreover, a numerical experiment that combines various scenarios including land-use change, mitigation and adaptation (greening scenarios), and urban expansion, is still necessary while UHI studies combine those scenarios are limited. Hence, it is relevant to establish the relationship between green space, urban planning, and UHIs, and ascertain the sensitivity of the UHI effect to the presence of green space.

**Author Contributions:** Methodology, I.D., D.L., A.P.; Investigation, D.M., I.D., A.P.; Software, D.L.; Validation, D.M. and I.D.; Formal Analysis, I.D.; Writing—Original Draft, D.M.; Writing—Review and Editing, D.M., D.L., C.Z., A.P.; Visualization, D.M. and I.D.

**Funding:** This work is funded by multiple sources including the NUFFIC master scholarship for Ishara Ducton and the BUDI-LPDP (Indonesia Endowment Fund for Education) PhD scholarship for Dikman Maheng.

**Acknowledgments:** The work described in this paper is a part of MSc thesis work conducted by Ishara Ducton for the partial fulfilment of requirements for the Master of Science degree at the IHE Delft Institute for Water Education, Delft, The Netherlands. The authors also acknowledge the use of data from ECMWF and USGS as well as VITO that provides the main component of UrbClim and the downscaled meteorological data from the ECMWF. The UrbClim’s simulations were done by using the high performance computing provided by SURFsara, the Netherlands. The authors thank Mohanasundar Radakrishnan for the English correction.

**Conflicts of Interest:** The authors declare no conflict of interest.

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