Surface temperature variation in Sri Lanka

GEOSTATISTICAL EXPLORATION OF SURFACE TEMPERATURE VARIATION IN SRI LANKA FROM 2010-2019

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NOVA IMS | GEOSTATISTICS FINAL PROJECT

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Abstract

Urbanization is a known cause for local temperature increases and as Sri Lanka experiences more development, increase in temperature becomes a threat to already elevated temperatures. To evaluate average yearly temperature changes, data from 21 Sri Lankan weather stations from 2010 to 2019 were collected to identify any temperature trends due to increased urbanization. Inverse Distance Weighting (IDW) was used to predict surface temperature for areas without sampled data, then averaged together into two periods. The difference of these two periods were used to show temperature change in Sri Lanka over the last ten years. The results show an overall increase in surface temperature between 2010 and 2019, however more evidence is required to assume if this increase is a product of the urbanization effect. As an additional step, the study used Markov chain analysis to predict temperatures in 2020 and showed an increase in all-weather stations except Kankasanthurai and Mahailupallama, is confirming that country is at risk in terms of temperature rise.

Introduction

Comfortable temperature is a key factor for a human beings healthy living. Unfortunately, some people often suffer from living in areas of elevated temperature without any escape. Urbanization can have a profound effect on a country's microclimate due to deforestation, industrial activities, air pollution from fossil fuel use, multi-story buildings and more. Sri Lanka, a developing country situated in South Asia, faces weighty issues such as scarcity of land for its ever-growing population, as well as its recent developments. The Sri Lankan government introduced a national initiative for development in transportation and tourism that began in 2011. Some government plans include building 1000 kilometers of highways around the island, as well as six metro regions before the end of 2030. The World Bank has given focus to Sri Lanka to help invest in urbanizing their country to transform their economy, in their efforts to end extreme global poverty and boost shared prosperity (World Bank Group, 2015).

Although the goal for these development plans are economic growth and to move people out of poverty (Clottes, 2014), these unprecedented developments could directly affect the natural ecosystem of the country, leading to change in temperature and precipitation patterns. There is much evidence that the urbanization effect can have partial responsibility for causing urban heat islands (UHI) like cases in southeast China where rapid urbanization has occurred (Zhou, 2004). Since Sri Lanka has seen rapid economic and urban growth since 2011, this study aims to evaluate surface temperature changes in Sri Lanka from 2010 to 2019. Although the ten-year period is not enough to determine an urbanization effect, the analysis will provide insight on potential surface temperature trends.

Methods and analysis

The effects of urban heat island caused by rapid development can be assessed by taking sampled surface temperature measurements from weather stations over an extensive time period. The purpose of the study is to evaluate only a beginning trend for temperature changes on the island of Sri Lanka. More data over a longer period of time will be required to make assumptions in regard to urbanization.

Data and study area

This study is based on open source data collected from 21 weather stations across the country of Sri Lanka, showing daily temperature data obtained from the National Center for Environmental

Information at NOAA. The daily temperature summaries for each weather station were converted from text to CSV format and opened in Excel to extract the data required for the study, in this case, daily average temperature for each weather station from 2010 to 2019. Then, the values were averaged for each month, and after, the months were averaged together to determine the yearly temperature averages that would be used to create the first maps. The coordinates for each of the weather stations was needed to perform spatial analyses. This information was obtained from the World Meteorological Organization (WMO) and added to the excel sheet in ordinance with the weather stations. Finally, the excel sheet was converted into an attribute table, which created a shapefile that was used for spatial analysis in ArcMap.

Exploratory data analysis

To begin, an exploratory data analysis was conducted on the temperature data. To handle missing data for the weather stations at Vawunia from 2016 to 2019 and Kankasanthurai for 2019, the years with data were averaged together and used for the missing value. Due to lack of weather stations for the analysis, removing the weather stations with missing values would not make sense.

Descriptive statistics

The descriptive statistics for the 10 years of temperature data were created, and the tables were divided by the two periods (2010 to 2014, 2015 to 2019). From this analysis, the following assumptions can be made:

1. The temperature values were measured at [n = 21] weather stations in Sri Lanka.
2. The temperature data distributions for each year are skewed with a left tail [negatively asymmetric], because the median is higher than the mean.
3. The overall average mean temperatures of weather stations for each individual year are similar, showing insignificant variation over the ten years. However, period 1 is slightly lower.
4. The standard deviation is small, indicating that the temperature has little variation over the extent of the study area.
5. Minimum temperature values were observed at Nuwaraeliya for all ten years, which is located center of Sri Lanka in a mountainous area. The maximum values were seen at Pottuvil in all years, except Jaffna in 2010.

Table 1. This table shows the descriptive statistics for Period 1 (2010 to 2014)

Description	2010	2011	2012	2013	2014
Mean	80,313222	79,846838	80,255637	79,880768	80,140248
Standard Error	1,1935493	1,2041285	1,2111327	1,2206864	1,2018449
Median	82,072778	81,658217	82,101639	81,706849	81,867123
Standard Deviation	5,4695299	5,5180099	5,5501075	5,5938879	5,5075454
Sample Variance	29,915758	30,448434	30,803693	31,291581	30,333057
Kurtosis	7,2459126	7,3209048	7,6037566	7,3100189	7,3633535
Range	23,319524	22,923061	23,494521	23,705306	23,349679
Minimum	61,210278	60,572702	60,702732	60,340274	60,869315
Maximum	84,529801	83,495763	84,197253	84,04558	84,218994

Count	21	21	21	21	21

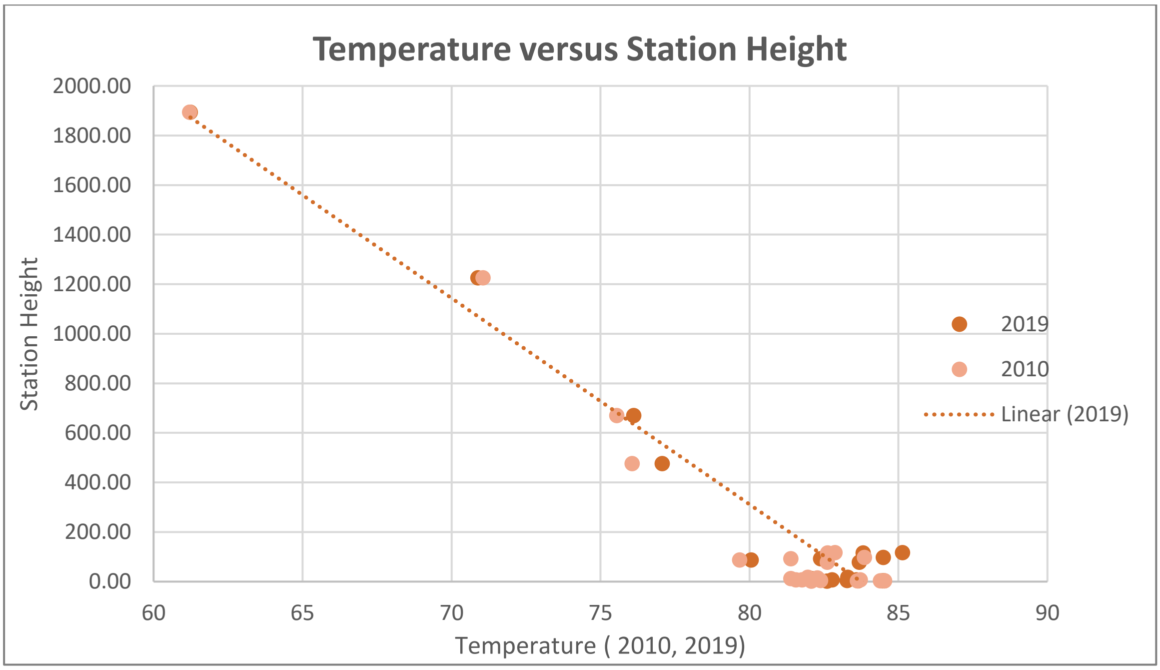
Table 2. This table shows the descriptive statistics for Period 2 (2015 to 2019)

Description	*2015*	*2016*	*2017*	*2018*	*2019*
Mean	80,47207	81,071187	80,527653	80,2987929	80,9159788
Standard Error	1,2045104	1,262752	1,2333638	1,24044437	1,23148895
Median	82,034593	82,755402	82,671667	82,3528481	82,77432
Standard Deviation	5,5197602	5,7866567	5,651983	5,68443022	5,64339134
Sample Variance	30,467752	33,485396	31,944912	32,312747	31,8478658
Kurtosis	7,6922373	6,4169299	7,3487573	7,00130247	7,28026825
Range	24,279935	25,511326	24,242526	24,5563126	23,894665
Minimum	60,959593	61,188674	60,736565	60,5990446	61,23596
Maximum	85,239528	86,7	84,979091	85,1553571	85,130625
Count	21	21	21	21	21

Scatterplot

The next step was to find a relationship between temperature and station height in elevation. To achieve this, a scatterplot of station elevation height and temperature for 2010 and 2019 was created. The scatterplot allows concluding that there is negative linear relationship between the variables. This means with higher elevation, there are lower temperatures and with lower elevation, there are higher temperatures. The inverse relationship is consistent between 2010 and 2019.

Figure 1. A scatterplot showing the relationship between station height (elevation) and temperature for 2010 and 2019



Data posting

The data posting map with graduated symbols supplies the first insight into the spatial distribution and the magnitude of the temperature values across the study area. As the next exploratory spatial data analysis method, 10 data posting maps were produced for the study area, since all 10 maps shows same distribution patterns of temperature values, map of the most recent year (i.e. 2019) were only used to describe the data posting. In the map (2019), larger symbols with darker tones indicate higher temperature and the smaller symbols with lighter tones indicate lower. It can also be noted that areas showing low temperature values, particularly at the center of the study area (blue circle), are in mountainous areas. Areas with higher temperature values gather around the borders of the country which are low elevation, coastal areas. Moreover, according to the data posting we can assure that there is no apparent trend over the study domain. However, the data set has one possible outlier (black circle). This is because the value for this location is lower than the value of the surrounding locations. In addition, other lows are in mountainous areas, and the concept is consistent with the temperature and altitude definitions, There-fore, these points may not be outliers. In order to detect the outliers in detail, 10 Voronoi maps were produced separately.

Figure 2. This map shows the data posting over the study area with graduated symbols representing temperature average for 2019

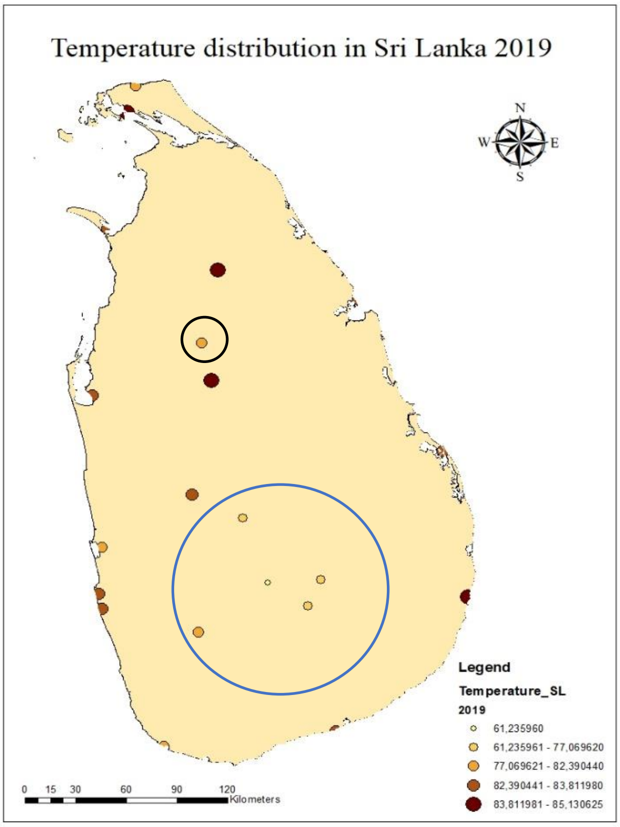
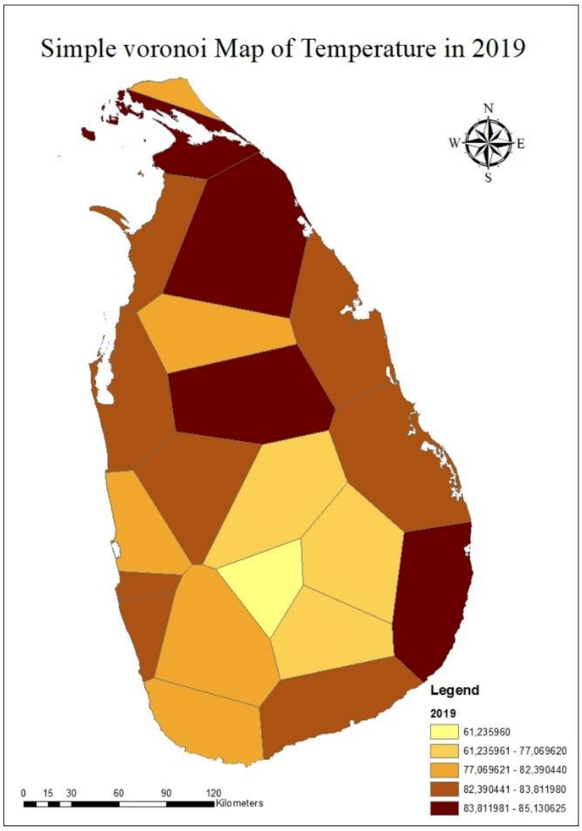


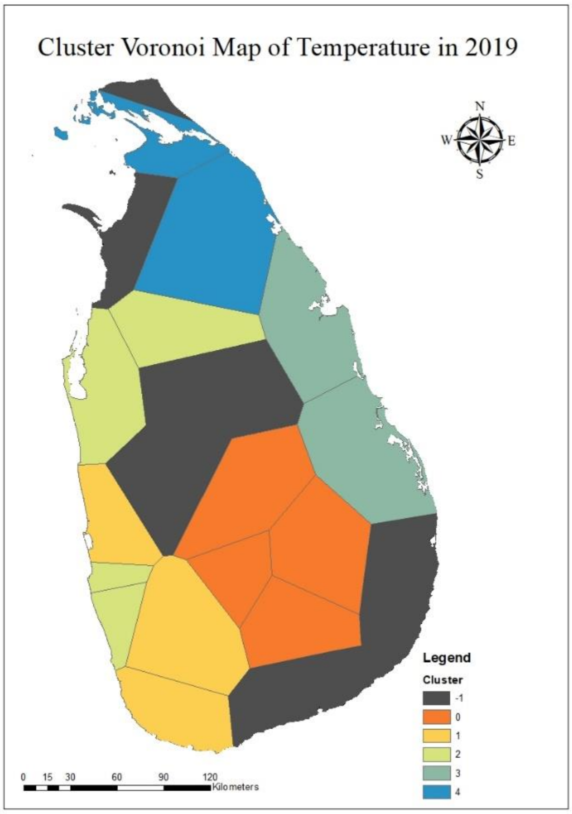
Figure 3: Simple Voronoi Map for temperature in 2019



Theisen polygon (Voronoi Maps)

Theisen polygons, also known as Voronoi maps, are used to divide an area into planes based on the distance between two data points. The main principle of the Voronoi map is related to the concept that every point in the region is closer to the center of the region than other all possible data centers. A simple clustered Voronoi map of the study area has been created to examine data heterogeneity and uniformity, for highlight local differences and extremes, identify possible outliers and global trends. Similar to the results obtained from the indicator maps, simple Voronoi map of temperature also allows to conclude that there is no apparent trend in the study area and further it is depicting that the minimum temperature values are positioned inland, in the center of the study region while maximum values are extended to the coastal boundary of the study area where there are very low altitude values can be observed. The Cluster Voronoi map (Figure 4) depicts 6 polygons that might correspond to spatial outliers. However, all points representing 6 polygons may not be outliers.

Figure 4: Clustered Voronoi Map of Temperature in 2019



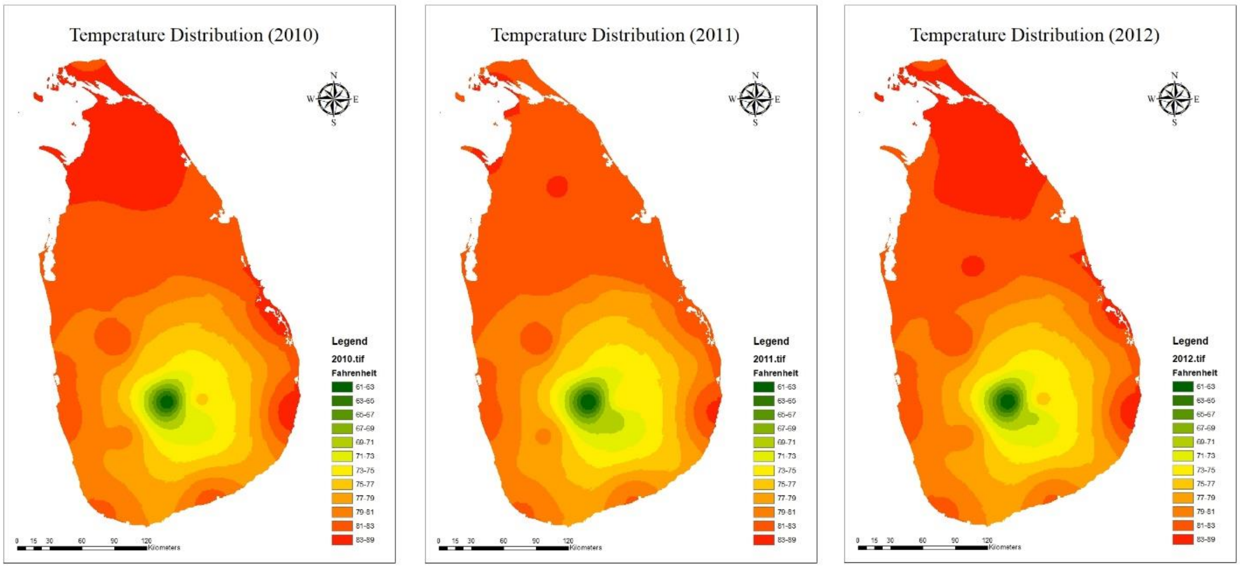
Spatial analysis

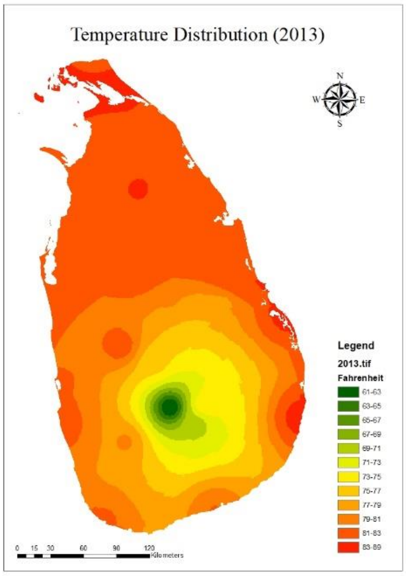
To begin the spatial analysis, ten maps were produced for each year of data (2010 to 2019). Because of the limited number of weather stations, only Inverse Distance Weighting (IDW) could be used to interpolate surface temperatures. The temporal data was divided into two periods from 2010 to 2014 and 2015 to 2019 and then each group of map periods were averaged together. After, the difference between the two periods was calculated to determine temperature change between the two 5-year periods, whether it has increased or decreased in certain areas.

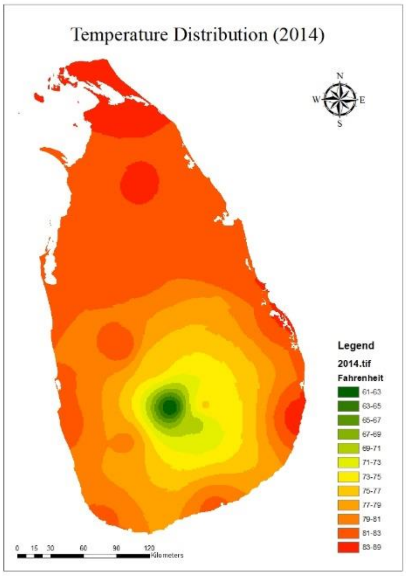
Inverse Distance Weighting

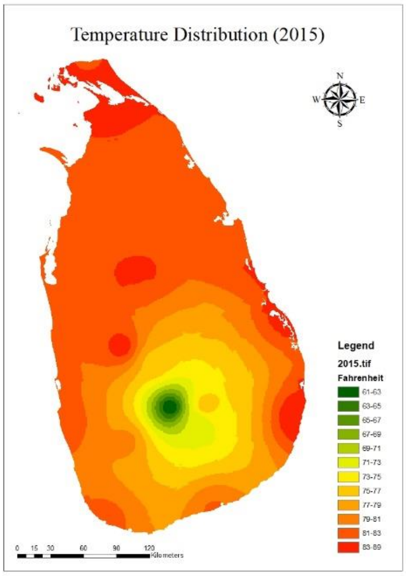
Inverse Distance Weighting is a deterministic method used to interpolate surfaces using a scattered set of points. This method uses distance from known points to determine weights for predicting. When creating surfaces for each of the years, equal intervals were used to compare

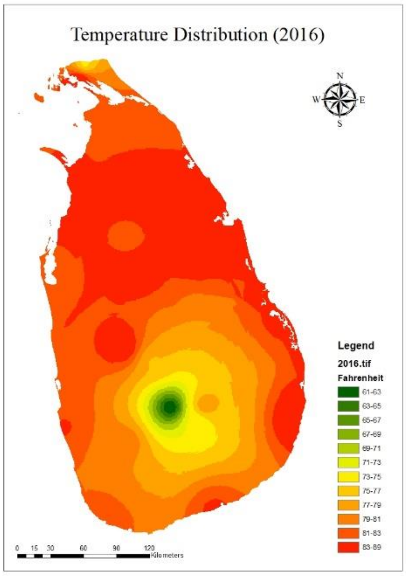
Figure 5. Ten maps using Inverse Distance Weighting (IDW) to show predicted surface temperatures for Sri Lanka from 2010 to 2019

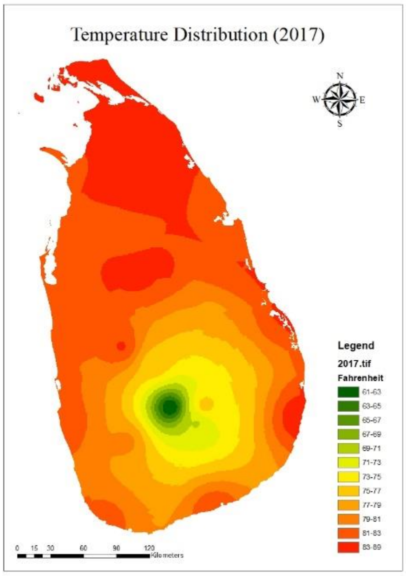


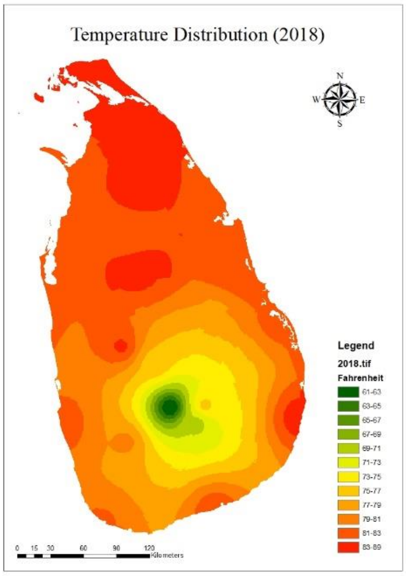


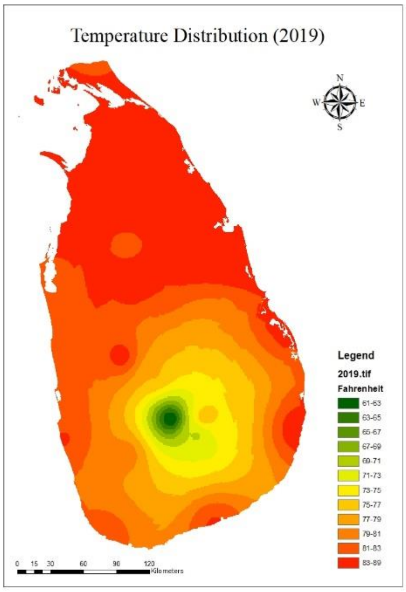












the results more effectively. Temperature change in the study area shows little variance over the ten years. However, year 2016 seems to have a cooling trend in the northern tip and a warming trend just below it compared to earlier years. For the center of the study area in the southern part, the temperatures show very cool values in comparison to the borders and northern portion of the country. This cooling is due to the region having a high elevation and mountainous terrain. The northern part of the country, as well as coastal areas is consistently warmest part of the country. Another interesting observation is that 2019 shows the hottest values of any other year. Each of these maps were then converted into raster format before beginning the analysis with the Raster Calculator tool. With the raster calculator, the final map products were produced to show the surface temperature changes over the last ten years.

Final results and discussion

The ten interpolated surface temperature maps were combined into two periods using the Raster Calculator tool (see Equations 1 and 2). The result produced two maps showing the average temperature distribution over each period (Figure 6). From these maps, an overall increase in temperature for the two periods can be seen. For the final map, the difference between the two maps was calculated using the Raster Calculator tool to show the overall temperature change from 2010 to 2019 (Equation 3).

$$Period\ 1 = (Map\ 2010 + Map\ 2011 + \cdots Map\ 2014)/5 \tag{1}$$

$$Period\ 2 = (Map\ 2015 + Map\ 2016 + \cdots Map\ 2019)/5 \tag{2}$$

$$Temperature\ Change = Period\ 2 - Period\ 1 \tag{3}$$

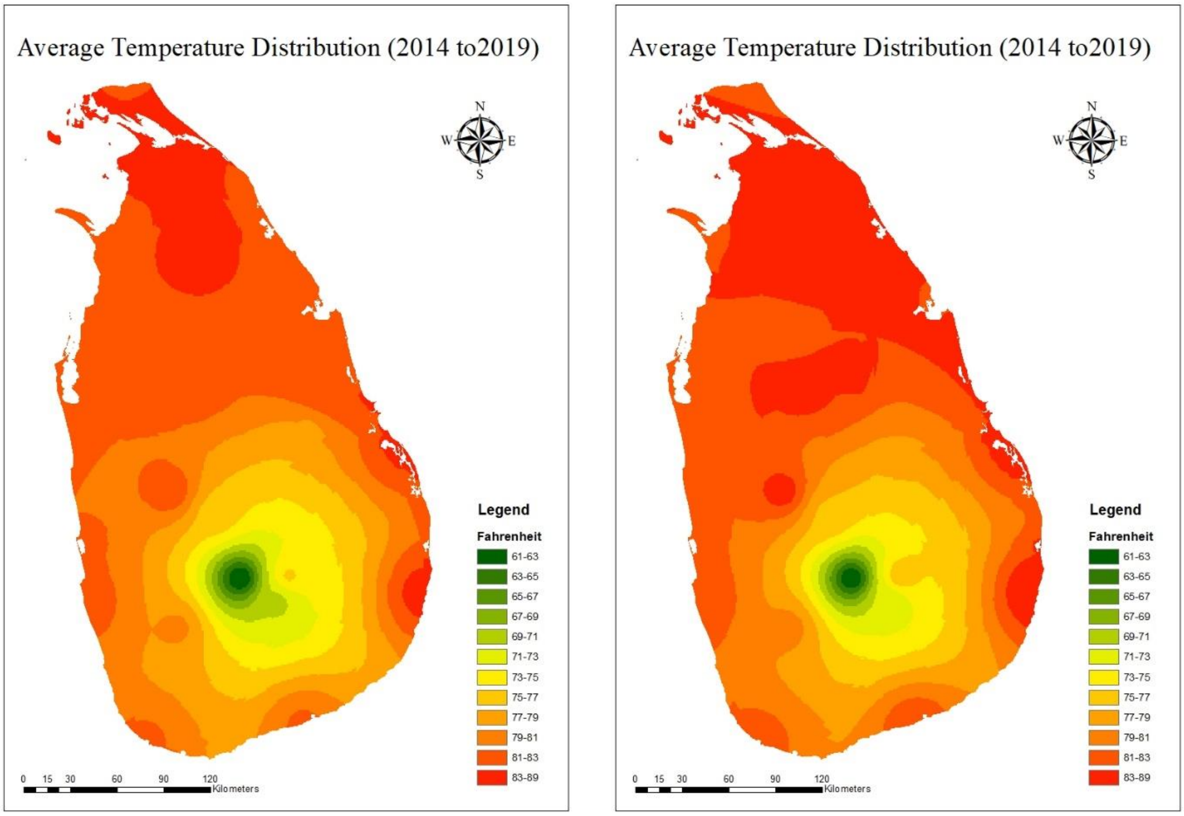
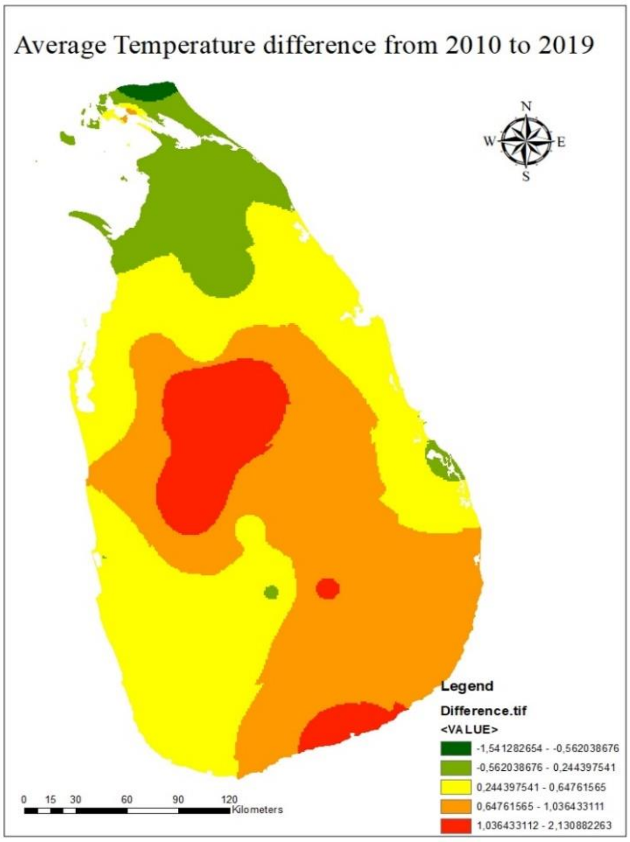


Figure 6. These maps show the average temperature distributions for periods 2010 to 2014 and 2015 to 2019

In the final map result, the average temperature difference from 2010 to 2019 was produced (Figure 7). Areas of red indicate an increase in temperature and areas of dark green indicate a decrease in temperature change. Cross-sections (Figure 8) from north to south of the study area show changes in temperature over distance, allows that there are some increase as well as a decrease in temperature in the past decade. The range of temperature change can be calculated as approximately 2.13 degrees Fahrenheit for the entire island. Ten years is not enough time to assume urbanization effect as the cause for higher temperatures. More data over many years along with supplementary information is required to make this assumption. However, the World Bank stated that it has been helping Sri Lanka improve its economy through urbanization in a fight against world poverty. It is also known that heavy development has occurred in southern area where temperatures have increased the most over the ten years.

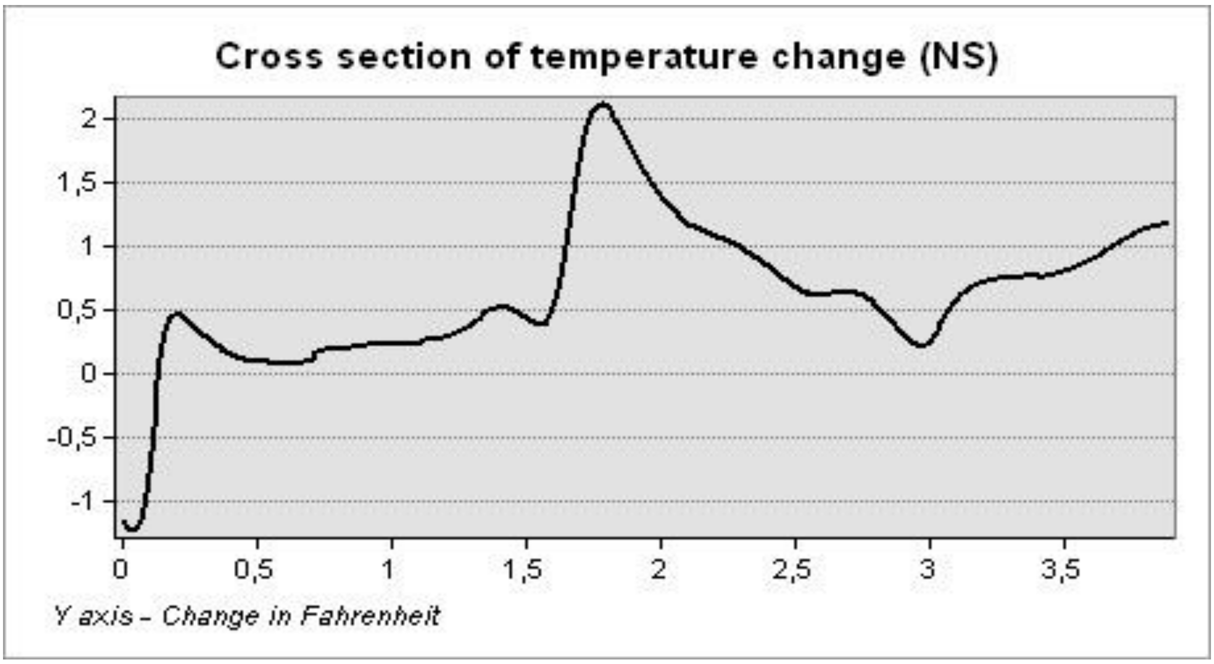
Figure 7: The final map showing the average temperature change from 2010 to 2019.



The study area shows that the very north tip experienced a drop in mean temperature, which is usually one of the hotter areas of Sri Lanka. Overall, most of the study area experienced some increase in temperature between the two periods. In addition, the government's initiatives to build infrastructures could also support the increase in urbanization. This study allows us to conclude, that overall, there has been a slight increase in temperature, and the recent growth in economy and infrastructures could be evidence for an urbanization effect using a climate-based analysis. However, as previously mentioned, more data is required to make this assumption.

For future research or validation of the results, this study could be coupled with a land use change assessment for the same years to compare urbanization changes with surface temperature changes. This study also occurs over a limited amount of time, so studying changes over decades could produce better results, as well as having more weather station data points for more accurate weight assignment during interpolation.

Figure 8: Cross section of temperature change from north to south



Markov Chain Model for predict temperature in 2020

At last, as an additional exercise, a model was attempted for (future pattern) temperature in year 2020 using the Markov Chain Model. A Markov chain is a stochastic model describing a sequence of possible events in which the probability of each event depends only on the state attained in the previous event. As accordance to the definition of Markov chain model, as the first step we converted the temperature values in to discrete time and discrete state space. For that temperature difference was calculated between consecutive years at all weather stations (Table 3) to check if temperature has increased or decreased in value, then produced a new table (Table 4) which shows two possible states, “increase (I)” or “decrease (D)”.

Table 3 :Temperature differences for consecutive years

Weather Station	2011-2010	2012-2011	2013-2012	2014-2013	2015-2014	2016-2015	2017-2016	2018-2017	2019-2018
Bandaranayake	-0,083	0,040	-0,249	0,080	0,231	0,807	-0,735	-1,015	1,502
Anuradhapura	-0,122	0,489	-0,437	0,038	0,244	0,625	-0,692	-0,304	1,157
Badulla	-0,589	0,767	-0,733	0,272	0,924	2,221	-2,624	-0,277	0,601
Batticola	-0,949	0,591	-0,070	-0,117	0,277	0,858	-1,188	-0,285	0,757
China bay	-0,550	0,793	-0,471	0,331	0,054	0,554	-0,650	-0,235	1,249
Colombo	-0,106	0,091	-0,042	0,062	0,259	0,727	-0,561	-0,276	0,856
Diyathalawa	-0,930	0,618	-0,646	0,468	0,749	2,120	-2,517	-0,485	0,446
Galle	-0,133	0,319	-0,219	0,118	0,548	0,265	-0,386	-0,641	0,822
Hambantota	-0,717	0,062	-0,216	0,778	-0,495	2,190	-0,746	-0,282	0,760
Jaffna	-1,174	0,671	-0,532	0,458	0,521	1,542	-1,749	-0,255	0,451
Kandy	-0,368	0,373	-0,402	0,492	0,116	0,587	-0,730	0,119	0,825
Kankasanthurai	-0,049	0,303	0,200	0,639	-0,815	-8,030	8,823	0,918	-2,284
Kurunegala	-0,117	0,450	-0,598	0,343	1,497	1,878	-2,875	0,207	0,407
Mannar	-0,541	-0,512	-0,214	0,065	0,305	0,405	-0,265	-0,510	1,290
Mahaillupallama	-0,264	0,683	-0,721	0,102	1,151	1,752	-0,595	0,176	-0,025
Puttalam	-0,415	0,444	-0,462	0,224	0,171	0,368	-0,060	-0,885	1,142
Nuwaraeliya	-0,638	0,130	-0,362	0,529	0,090	0,229	-0,452	-0,138	0,637
Pottuvil	-0,893	0,701	-0,152	0,173	1,021	1,460	-2,126	-0,208	0,154
Rathnapura	-0,315	0,447	-0,473	0,197	0,261	0,590	-0,788	-0,071	0,537
Ratmalana	-0,084	0,095	-0,036	0,035	0,306	0,708	-0,496	-0,360	0,723
vavunia	-0,757	1,029	-1,038	0,162	-0,447	0,726	0,000	0,000	0,954

Table 4: Converted discrete space showing weather temperature increase(I) or Decreases(D)

Weather Station	2011-2010	2012-2011	2013-2012	2014-2013	2015-2014	2016-2015	2017-2016	2018-2017	2019-2018
Bandaranayake	D	I	D	I	I	I	D	D	I
Anuradhapura	D	I	D	I	I	I	D	D	I
Badulla	D	I	D	I	I	I	D	D	I
Batticola	D	I	D	D	I	I	D	D	I
China bay	D	I	D	I	I	I	D	D	I

Colombo	D	I	D	I	I	I	D	D	I
Diyathalawa	D	I	D	I	I	I	I	D	I
Galle	D	I	D	I	I	I	D	D	I
Hambantota	D	I	I	I	D	I	I	D	I
Jaffna	D	I	D	I	I	I	D	D	I
Kandy	D	I	D	I	I	I	D	I	I
Kankasanthurai	D	I	I	I	D	D	I	I	D
Kurunegala	D	I	D	I	I	I	D	I	I
Mannar	D	D	D	I	I	I	D	D	I
Mahaillupallama	D	I	D	I	I	I	I	I	D
Puttalam	D	I	D	I	I	I	D	D	I
Nuwaraeliya	D	I	I	I	I	I	D	D	I
Pottuvil	D	I	D	I	I	I	I	D	I
Rathnapura	D	I	D	I	I	I	D	D	I
Ratmalana	D	I	D	I	I	I	I	D	I
vavunia	D	I	D	I	D	I	D	D	I

As the next step possible transitions of temperature over the time period were identified. There were 4 posible transitions as increase increase (II), decrease decrease (DD) , decrease increase (DI) and increase decrease (ID). Then the instances calculated to determine the probabilities of those transitions from past data (Table 5 and 6) and construct two matrices with number of instances and probabilities.

Table 5: Transition matrix with no of instances for past data (year 1 and 2 term used to represent the consecutive pairs as 2010 & 2011, 2011 & 2012 and so on.

		Year 2	
		I	**D**
Year 1	**I**	46	37
	D	22	63

Table 6: Transition matrix with probabilities (year 1 and 2 term used to represent the consecutive pairs as 2010 & 2011, 2011 & 2012 and so on.

		Year 2	
		I	**D**
Year 1	I	27,38	22,02
	D	13,10	37,50

The catch (in the context of the Markov chain) is that the probability of temperature rise or fall in 2020 depends on the temperature in 2019. So as the next step by combinig transition matrix and temperature change in 2019, we found the probabilities of getting a higher or lower temperature in 2020 at all weather stations.

Table 7: Predicted temperature in 2020 at all weather stations

Weather Station	2019-2018	Ability to get higher temperatures than 2019	Ability to get higher temperatures than 2019	Predicted temperature in 2020
Bandaranayake	I	27,38	22,02	Increase
Anuradhapura	I	27,38	22,02	Increase
Badulla	I	27,38	22,02	Increase
Batticola	I	27,38	22,02	Increase
China bay	I	27,38	22,02	Increase
Colombo	I	27,38	22,02	Increase
Diyathalawa	I	27,38	22,02	Increase
Galle	I	27,38	22,02	Increase
Hambantota	I	27,38	22,02	Increase
Jaffna	I	27,38	22,02	Increase
Kandy	I	27,38	22,02	Increase
Kankasanthurai	D	13,10	37,50	Decrease
Kurunegala	I	27,38	22,02	Increase
Mannar	I	27,38	22,02	Increase
Mahaillupallama	D	13,10	37,50	Decrease
Puttalam	I	27,38	22,02	Increase
Nuwaraeliya	I	27,38	22,02	Increase
Pottuvil	I	27,38	22,02	Increase
Rathnapura	I	27,38	22,02	Increase
Ratmalana	I	27,38	22,02	Increase
vavunia	I	27,38	22,02	Increase

Finally, by obtaining the highest probability value at each station, it was found that all weather stations were at risk of rising temperatures in 2020, except Kankasanthurai and Mahailupallama. In this method, the probabilities of hopping to a specific state depend only on the probabilities associated with the current state and not at all on the past states (memory loss property). Therefore, it is not the best way to achieve the result of a particular problem. But sometimes the best starting point is a simple model which performs better than a random guess.

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