Trees and Life, Heat and Death: Integrating Temperature and Green Spaces with Social Determinants of Health in Hamilton, Ontario, Canada.

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Abstract

Objectives

Climate change has wide-reaching implications for planetary and human health; one of its rising impacts is deaths related to extreme heat. This study attempts to integrate remotely sensed measures of temperature and greenness into the methodology of Code Red, a study examining the relationship between health and a variety of social determinants in Hamilton, Ontario, Canada, initially using data from 2006-2008, with the aim of examining whether heat and temperature could explain differences in the average age of death across different neighbourhoods alongside socioeconomic variables.

Methods

Land surface temperature (LST) and normalized difference vegetation index (NDVI) were calculated for each census tract of Hamilton using Landsat satellite data for Jun-Aug of 2006-2008. They were then entered into a factor analysis along with 14 other variables utilized in the initial Code Red study. A multiple least-square regression was then run between the resulting factors and average age of death.

Results

Temperature and greenness loaded significantly along with income and education related variables onto a factor referred to as the "working class" factor. This factor had a highly significant ($p<0.001$) correlation with average age of death in multiple regression.

Conclusion

Temperature and greenness have a significant correlation with socioeconomic deprivation and age of death, and may have value both as a predictor variable for death and a potential cause of increased deaths. Further studies may make use of detailed cause of death data or change-over-time analysis.

Keywords: climate, health, greenspace

Introduction

Within healthcare and health research, it has become increasingly clear that disease and health outcomes are heavily influenced by the environment in which people live, as well as their socioeconomic determinants.

In 2010, a groundbreaking study, Code Red, was published in the local newspaper, The Hamilton Spectator. [1] The study was a partnership between academia and the newspaper, and illustrated the vast differences in the average age of death as well as hospitalizations and ER usage across different census tracts in Hamilton, Ontario, Canada. [1] It shed light onto how census tracts located near the historical industrial area in the lower city were "worlds apart" from those in the suburban boroughs of Hamilton. Census tracts of high socioeconomic status exhibited a high average age of death, and those of low SES, in the lower city, exhibited a low average age of death. Within the medical paradigm that social determinants have a major impact on health and disease, this may seem obvious; however, it implies that improving peoples' SES and reducing inequity may be the most effective way to improve health outcomes for urban populations - targeting "upstream" causes rather than treating "downstream" effects. [2]

As climate change leads to various effects such as temperature increase, increased natural disasters, and changing spread of disease, there is a significant interest in its interactions with health and quality of life. There are numerous studies in different continents exploring the association of temperature, especially extreme heat or cold, with mortality. In general, an intuitive U-shaped pattern is present - mortality increases with periods of extreme cold or heat. [3-4] Excess mortality from cold appears to be mediated mostly by infectious diseases such as influenza, whereas heat disproportionately affects older populations, those who are ethnically marginalized, and those with low education. [3-4]

Gasparrini et al., using data from 451 locations in 23 countries across all continents projected up to a 3% increase in excess heat-related mortality in North America in the next 80 years. [5] This effect is projected to be far larger in other areas of the world such as Southeast Asia, with projections up to 15% for the same time period, and did not account for the effect of climate change on phenomena such as natural disasters, sea level rise, or other major disruptors. Heat-related deaths in North America and Europe most commonly occur on days of extreme heat in the summer months, or over multiple days in heat waves. Heat related deaths are also often difficult to attribute to heat as a cause, as it often exacerbates pre-existing conditions, such as congestive heart failure, chronic lung diseases, and chronic kidney disease; though the effect is epidemiologically far more apparent during heat waves. [3-4] Climate projections predict a significant rise in average temperature and days of extreme heat over the next few decades even under low-emission circumstances; it is clear that with increasing overall summer days with extreme heat, as well as frequency and severity of heat waves, heat-related deaths will see a gradual rise. [6, 23, 24]

Hamilton's 2024 Community Health Status Report draws some attention to the impacts of rising heat, projecting a 4℃ increase in all-season temperature by 2050-2080 and a sharp upward trend in the number of heat warning days (either daytime highs >31℃, with nighttime lows >20℃; or Humidex above 40℃) per year. [9] It also identifies that socioeconomic factors such as housing instability or low income are associated with higher heat-related emergency visits, and maps some areas most vulnerable to heat, mostly in the inner city. [9]

Green space and vegetation cover within cities is intertwined with health outcomes and with temperature due to its ability to reduce the urban heat island effect, which is when urban centres tend to have higher ambient temperatures than surrounding rural areas. [10] Higher vegetation cover also reduces atmospheric CO_2 by absorption, acting as a "carbon sink". Past research has also shown positive effects of local green space on mental health, physical activity, reduced cardiovascular disease, and possibly overall quality of life. [11-17]

Remotely sensed data from satellites, which is freely available through the US Geological Survey's Landsat and European Space Agency's Sentinel projects, provides imagery with a high spatial and temporal resolution on an automated basis. This has been used widely to analyze environmental phenomena on many scales, from continental land cover to ocean currents but also on small scales such as urban patterns of land use, vegetation, or heat. This has led to the emergence of the use of remote sensing in "regional science"; referred to as "the study of social problems that have a spatial dimension". [18] Social problems are heavily intertwined with health problems, and thus health also has its own spatial dimensions.

As climate becomes a more serious health issue - especially concerning the increasing number of extreme heat days in the summer months - we looked back at the Code Red data to see whether disparities in temperature and/or greenness were associated with disparities in socioeconomic status and health outcomes with Hamilton. At a local scale - could the spatial distribution of heat and greenness be part of the equation along with health outcomes and socioeconomic variables that were studied in the original Code Red study?

Data and Methods

Data for the original Code Red study were obtained from various sources (see Table 1). These data were mapped using a quintile classification scheme, dividing values into five equal groups, each representing 20% of the data, from the lowest to the highest. [27] Subsequent research examined various facets of Code Red from a statistical perspective, examining the relationship between the different variables and the average age of death. [1] The different determinants applied in the initial Code Red study that were published in the Hamilton Spectator were first entered into a factor analysis, with the data reducing to 3 main factors and were subsequently regressed onto the average age of death. This study's methodology aims to replicate the methodology used in the 2015 Code Red study, with the addition of greenness and temperature to represent the environmental influence.

Table 1: Data utilized in the original Code Red study

Variable	Description if applicable
Dwelling value[1]	Average dwelling value per census tract
% female lone parent[1]	
Median family income[1]	
% of people under low income cutoff[1]	Cutoff adjusted by household size and urban area size
% no post-secondary education[1]	
% with post-secondary education[1]	
% secondary school dropout[2]	
% aged 65+[1]	
% people who rent[1]	
Hospital admission rate[3]	per 1000 people, per year
Urgent admission rate[3]	per 1000 people, per year
Cardiovascular disease admission rate[3]	per 1000 people, per year
% of emergency room visits with patients reporting no family physician [3]	
Psychiatric admission rate[3]	per 1000 people, per year
% single, divorced, or widowed[1]	
% of people living alone[1]	
GINI coefficient[1]	Mathematically calculated index of income inequality

[1] 2006 Canadian Census of the Population; [2] Hamilton-Wentworth District and Hamilton-Wentworth Catholic District School Boards; [3] Canadian Institute for Health Information.

Greenness, measured using the Normalized Difference Vegetation Index (NDVI), and land surface temperature, derived from thermal infrared data, were computed for each census tract in the City of Hamilton using Google Earth Engine. The analysis utilized two Analysis Ready Data (ARD) image collections: Landsat 5 and Landsat 7 (both Tier One, Level 2). Images from June to August (the three hottest months) with less than 20% cloud cover were selected and converted to floating-point values. Composite images were then generated using a median reducer for relevant bands, producing a single image per variable by computing the median pixel value across the image stack.

The heat variable was derived from the Landsat 7 thermal infrared band (Band 6), using the precomputed surface temperature product in the Analysis Ready Data (ARD) collection. The temperature values, originally in Kelvin, were converted to degrees Celsius by subtracting 273.15 from each pixel. NDVI was calculated using the Google Earth Engine NDVI function: $NDVI = \frac{NIR - RED}{NIR + RED} = \frac{Band5 - Band4}{Band5 + Band4}$ with surface reflectance bands from the Landsat 5 TM composite (Landsat 7 surface reflectance was not used due to the failure of the Scan Line Corrector). The heat and greenness variables were then aggregated by mean within each census tract using an imported shapefile of 2006 census tracts in the City of Hamilton. Bivariate quantile mapping was then performed in ArcGIS Pro comparing the average age of death with NDVI and land surface temperature respectively.

To analyze the relationships between heat and greenness with average age of death and other variables explored in the original Code Red studies, the original 17 variables (table 1) along with heat and greenness were put through a factor analysis in R using varimax rotation. The Scree test verified that retaining the top 3 factors explained sufficient variance. Along with producing factor loadings, factor scores were calculated for each census tract in R. Least-squares multiple regression was then performed in R using the resultant factor scores to examine correlations between the factors and the average age of death.

Results and Analysis

The range of LST was 27.7-42.3℃, and the range of NDVI was 0.157-0.781, with no significant outlier census tracts for these two variables. The two bivariate maps (Figs. 2-3) show average age of death plotted against land surface temperature and greenness split into quintiles over the census tracts of Hamilton, averaged over only the hottest three months in 2006-2008. LST and NDVI share largely similar but not exactly matching distributions against average age of death, with the highest temperature and lowest NDVI being clustered with a low age of death in the lower city near Hamilton Harbour. Areas of high average age of death with high greenness and low temperature are mostly suburban built up areas such as in Dundas and Ancaster, although, there are also some suburban-rural sparse areas that have a low average age of death with high greenness and low temperature.

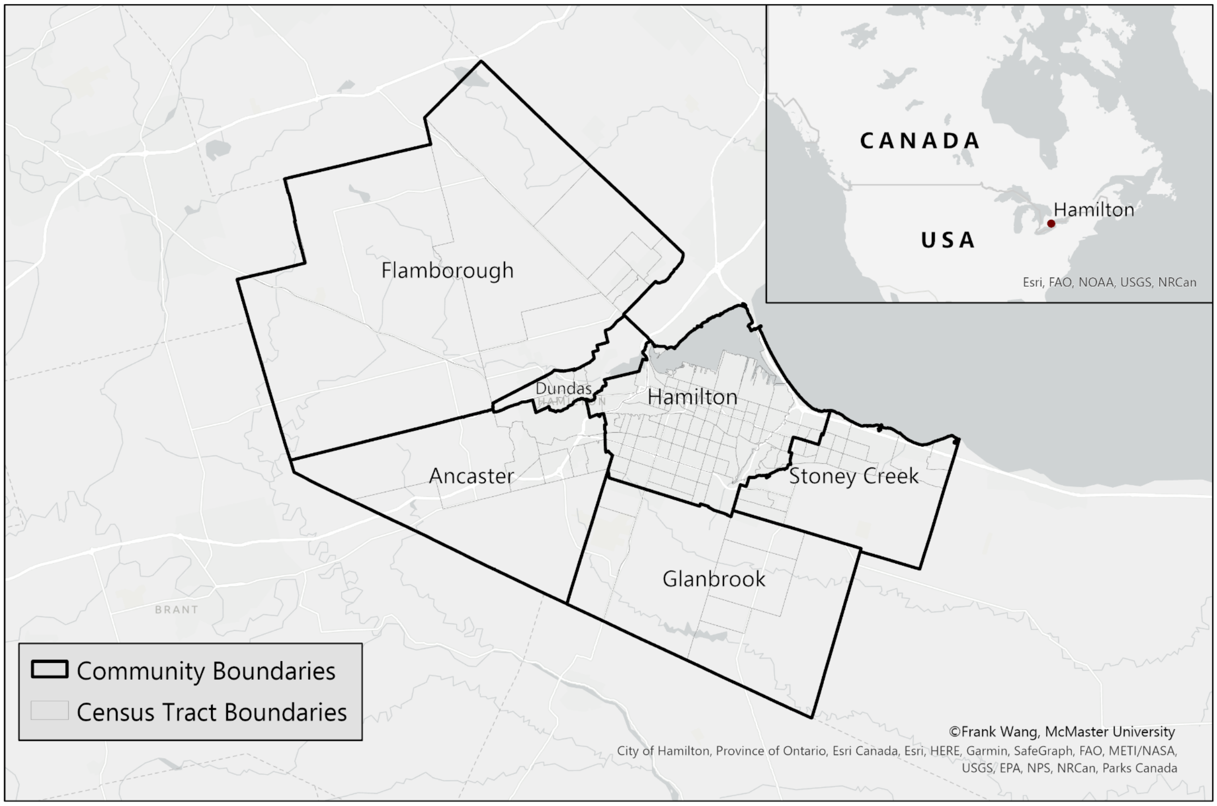

Figure 1: Study area of Hamilton. Community boundaries and 2021 census tracts are shown.

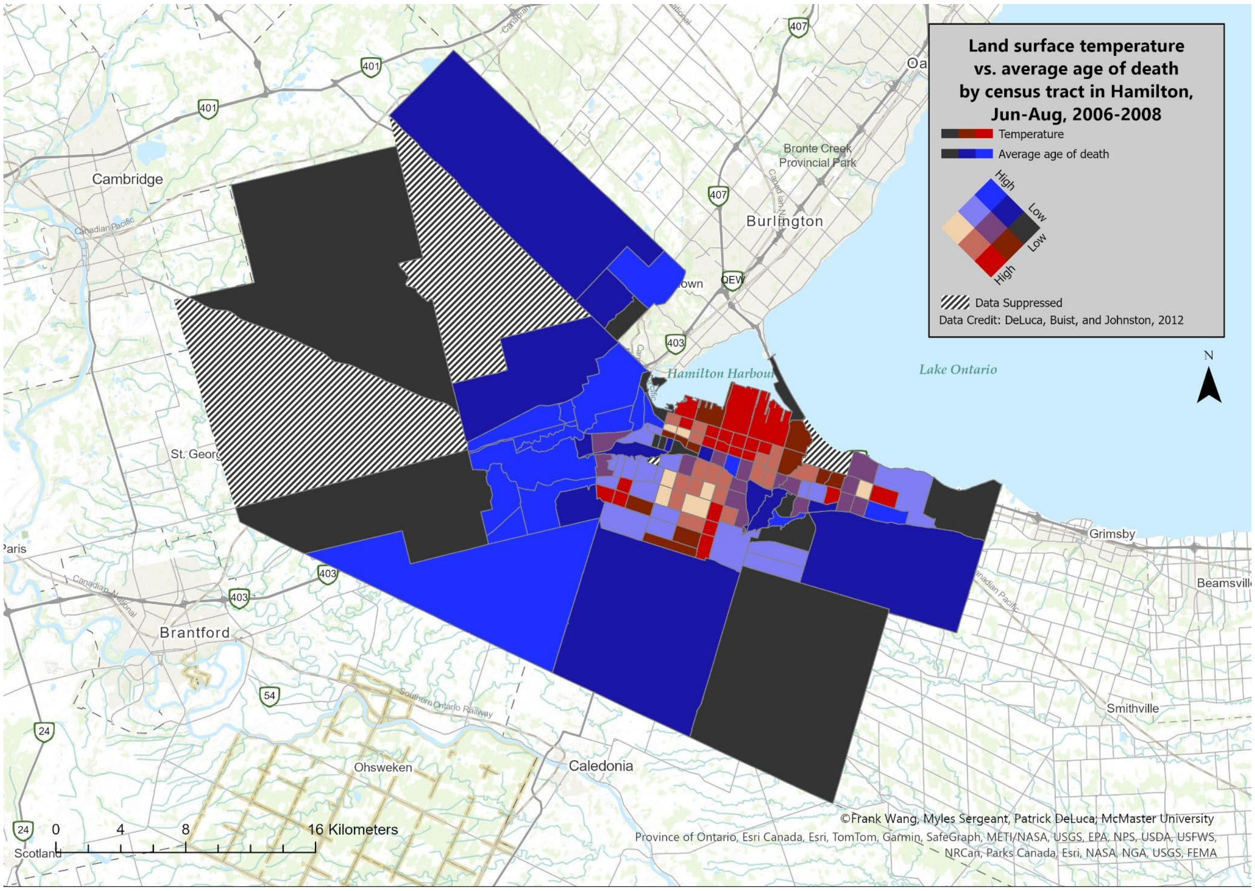

Figure 2: Bivariate choropleth map of land surface temperature and average age of death quintiles in Hamilton, Jun-Aug, 2006-2008

Figure 3: Bivariate choropleth map of greenness (measured by NDVI) and average age of death quintiles in Hamilton, Jun-Aug, 2006-2008

The three factors and the variable loadings, shown in Table 2, are largely similar as those in the original Code Red study, with the addition of NDVI and LST loading predominantly onto Factor 2, described in Code Red as the "working class" factor. [1] This factor includes indicators for individual and household income, as well as variables related to education, particularly secondary and post-secondary. Of the other factors, Factor 1, described as the "poverty" factor, includes variables related to social isolation, such as living alone or lone-parent households, as well as instability of housing, such as % who rent. [1] There is also a moderate influence from income and education, and healthcare-related variables such as admission rate and % without a family doctor. Lastly, Factor 3, described as the "aging" factor, relates to aging populations and the use of the healthcare system expressed in admission rates. [1] There is also a slightly lower proportion of total variance explained by these three factors, which can be explained by the higher total number of variables entered into factor analysis. (Table 2)

Table 2: Factor Analysis results using LST and NDVI in addition to Code Red variables (factor loadings below 0.2 omitted).

Variable	Factor 1 (poverty)	Factor 2 (working class)	Factor 3 (aging)	Communality
Dwelling Value	-0.333*	-0.822***		0.80
Female Lone Parent Family	0.532**	0.652**		0.73
Median Individual Income 15+	-0.584**	-0.729**		0.85
Median Family Income	-0.559**	-0.756***		0.86
Percent Under Low Income Cut Off	0.817***	0.486*		0.90
Percent No Post-Secondary Education		0.830***		0.76
Percent Post-Secondary Education	0.255*	-0.854***		0.79
Percent Secondary School Dropout	0.542**	0.525**		0.59
Percent Age Greater than 65			0.685**	0.51
Percent Rent	0.832***	0.261*		0.78
Hospital Admission Rate per 1000	0.319*	0.273*	0.852***	0.90
Urgent Admission Rate per 1000	0.382*		0.894***	0.99
Cardiovascular Disease Admissions per 1000		0.312*	0.789***	0.74

Percent of People without a Family Doctor	0.840***			0.71
Rate of Psychiatric Admissions per 1000	0.764***	0.312*		0.72
Percent Single, Divorced, Widowed	0.817***	0.413*		0.9
Percent of People Living Alone	0.737**		0.318*	0.66
Gini Coefficient	0.723**			0.57
Land Surface Temperature		0.800***		0.66
NDVI	-0.277*	-0.747**		0.67
Proportion of Variance Explained	0.31	0.30	0.15	
Cumulative Variance Explained	0.31	0.61	0.76	

Factor loadings less than 0.25 omitted.
* low loading (±0.25-0.5)
** moderate loading (±0.5-0.75)
*** high loading (±0.75-1)

In the multiple least-squares regression model, Factor 2 (working class) exhibits a significant negative relationship with age of death, while Factor 3 (aging) shows a positive association (Table 3). Lower income, education, higher temperatures, and reduced greenness all contribute to a lower average age of death. Factor 3 is linked to aging and hospital visits, explaining its positive association with higher average age of death, since a high average age of death reflects an elderly population that can live longer with usage of the health system. (Table 3). Factor 1 (poverty) is not statistically significant, differing from the Code Red 2015 paper, likely due to the introduction of temperature and greenness variables into the factor loadings. [1]

Table 3: Multivariate Regression Results with average age of death against the 3 derived factors.

	Value	Standard Error	t-value	p-value
Intercept	75.1104	0.3019	228.784	< 2e-16
Factor 1 Coefficient	-0.4016	0.3095	-1.298	0.197
Factor 2 Coefficient	-2.1500	0.3097	-6.943	1.85e-10
Factor 3 Coefficient	1.4343	0.3073	4.667	7.74e-6

Adjusted $R^2 = 0.3533$

Discussion

The findings of this ecological study using publicly available socioeconomic and remotely sensed data in tandem with data from local health agencies indicate that temperature and greenness variables load well onto Factor 2 of the factor analysis (named the "working class" factor) [1], alongside other key socioeconomic indicators such as income, education level, and the proportion of lone-parent households. This suggests that LST and NDVI are not just environmental metrics but also social indicators, capturing similar patterns of urban deprivation as traditional census variables. While it is difficult—if not impossible—to establish causation using census and remotely sensed data, the inclusion of temperature and greenness as "part of the equation" reinforces their role in illustrating disparities in health outcomes. Studies integrating remotely sensed greenness data with census variables had similar findings, reinforcing the link between green space and urban affluence. [20]

It is possible that differences in age of death, socioeconomic variables, and temperature/greenness may be confounded by the general inner-city vs. suburban structure of Hamilton as well as population density, but there are counter-examples that do not follow that trend such as downtown Dundas, which is relatively built up and densely populated but with high greenspace and socioeconomic status. It is also possible that the industrial land use near the residents of the worst-off areas has an unfair influence on outcomes compared to the rest of the city; industrial land use will naturally lead to less green space, higher temperature (through low albedo and heat generation), and possibly worse health outcomes e.g. through exposure to workplace hazards.

Most published studies exploring the relationship between temperature and health do not describe geographical differences within cities, instead studying differences between cities globally, nationally or regionally. This study shows one possible methodology of examining patterns within a city, showcasing inequality within very small geographic areas, in which one can see the stark contrast from the best-off to the worst-off in just a few kilometres - a matter of minutes if traveling by bus or car. These contrasts, and disparities in health outcomes, are not only reflected by differences in socioeconomic status, but can be directly seen and felt in terms of temperature and green space.

The City of Hamilton follows a pattern observed in other North American cities, where higher greenness and lower temperatures tend to be associated with wealthier neighborhoods and better health outcomes**.** Low-income communities often have reduced tree cover and more heat-absorbing infrastructure, leading to increased exposure to extreme heat and higher risks of cardiovascular disease and heat-related illness. [21] Similarly, psychiatric admissions may be more frequent in lower-income, high-density urban areas due to stress, lack of green spaces (which have proven mental health benefits), and broader socioeconomic challenges. [22] The burden of climate change is already making itself known in Hamilton – the ambient average summer temperature and the number of days above 30°C have significantly increased from 2008 to 2024 and are projected to increase further, even under modest emission projections. [9, 23, 24]

One of the important findings here is that when LST and NDVI have been introduced into the factor analysis and subsequent regression model, factor 1 (poverty) is no longer statistically significant, while the remaining two are. This is in contrast to DeLuca and Kanaroglou (2015) where all three factors are statistically significant. [1] While both LST and NDVI are important components of Factor 2 (and are important in health more generally), the introduction of these two new variables to this system ultimately resulted in a reallocation of the variance, which caused a shift in the factor structure, where the loadings were redistributed in such a way that made them less predictive of the average age of death across the city. Even though this was the case, the objectives of reducing the effects of the urban heat island, as well as preventing and preparing for the health effects of climate change should be on the radar for governance from the municipal to the federal level. Some studies, for example, have expressed that interventions such as large-scale tree planting or green buildings/roofing, which increase greenness and reduce the urban heat island effect, may reduce excess deaths from extreme heat. [25] A 2024 review on urban heat mitigation during extreme heat events found that various types of green space had a greatly significant cooling effect on surrounding urban areas, with botanical gardens for instance providing an average of -5°C cooling; other types such as street trees, city farms, parks, and playgrounds were also effective. [26]

While remotely sensed data is free, covers large areas in a systematic way, and is easy to work with large volumes of data, more reliable epidemiological studies could make use of meteorological data as well as more detailed health records that could specifically look at heat-related death or illness. Additionally, other relevant variables not captured by remote sensing or the Canadian census that can be measured through primary data collection at local scales, tailoring studies and recommendations to individual cities. A more robust study that may provide better evidence for heat as a driver of death could make use of recent death records (e.g. from 2021) and compare temporal trends in age of death, total deaths, and potential causes. Qualitative methods may also be a useful tool to gain insight into subjective or psychological effects of heat and greenness, and views from various parties regarding climate change and health.

Conclusion

This study followed the methodology of Code Red in the city of Hamilton but included land surface temperature and greenness as measured by NDVI (normalized difference vegetation index) compiled with the use of Google Earth Engine and Landsat imagery. The patterns of temperature and greenness largely reflect similar broad patterns as the average age of death taken from health records in Code Red, with the industrial/residential area near Hamilton Harbour in the lower city having the lowest age of death, highest temperature, and lowest greenness, with suburban areas such as Ancaster or Dundas having the opposite. Statistical factor analysis showed that temperature and greenness load significantly onto the second factor, referred to in Code Red as the “working class” factor, which highly correlated with average age of death through multiple linear regression. This shows that in Hamilton, temperature and greenness carries similar significance to various other, mostly socio-economic variables that can act as valuable indicators or possibly predictors of health, and carry implications for planning against climate change going forward. When tackling the upstream determinants of health, governments at all levels should be considering the effects of climate change and temperature with the same attention as well-established socioeconomic factors and thus should support initiatives to increase green space in the form of gardens, street trees, city farms, or parks to broadly promote health and prevent deaths in future heat waves.

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Appendix A: JavaScript script used in Google Earth Engine

Notes:

- "ct" is an imported shapefile of Hamilton 2006 census tracts.
- This is a demonstration specifically displaying the land surface temperature map.
- Some labels and variables in the script need to be changed to display the greenness map.

```
var collection = ee.ImageCollection('LANDSAT/LE07/C02/T1_L2')
  .filterDate('2006-04-01', '2008-03-31')
  .filter(ee.Filter.calendarRange(6, 8, 'month'));

var palette = ['FFFFFF', 'CE7E45', 'DF923D', 'F1B555', 'FCD163', '99B718',
               '74A901', '66A000', '529400', '3E8601', '207401', '056201',
               '004C00', '023B01', '012E01', '011D01', '011301'];

var palette2 = ['011301','011D01','012E01','023B01','004C00','056201',
                '207401','3E8601','529400','66A000','74A901','99B718',
                'FCD163','F1B555', 'DF923D','CE7E45','FFFFFF'];

var applyScaleFactors = function(image) {
  var opticalBands = image.select('SR_B.').multiply(0.0000275).add(-0.2);
  var thermalBand = image.select('ST_B6').multiply(0.00341802).add(149.0);
  return image.addBands(opticalBands, null, true)
              .addBands(thermalBand, null, true);};

var srColScaled = collection.map(applyScaleFactors);

var filtered = srColScaled.filter(ee.Filter.lt('CLOUD_COVER', 20));

var badComposite = srColScaled.median();
var goodComposite = filtered.median();

var temp = goodComposite.subtract(273.15);

var tempband = temp.select('ST_B6');

Map.addLayer(badComposite, {bands: ['SR_B3', 'SR_B2', 'SR_B1'], min: 0, max: 1, gamma:
1.1}, 'Bad composite');
```

```
Map.addLayer(goodComposite, {bands: ['SR_B3', 'SR_B2', 'SR_B1'], min: 0, max: 1, gamma:
1.1}, 'Good composite');
Map.addLayer(tempband, {min: 10, max: 50, palette: palette2}, 'therm');

var ndvi = goodComposite.normalizedDifference(['SR_B4', 'SR_B3']);

Map.setCenter(-79.9206, 43.30, 12);

Map.addLayer(ndvi, {min: 0, max: 1, palette: palette}, 'NDVI');

var collection2 = ee.ImageCollection('LANDSAT/LT05/C02/T1_L2')
  .filterDate('2006-04-01', '2008-03-31')
  .filter(ee.Filter.calendarRange(6, 8, 'month'));

var srColScaled2 = collection2.map(applyScaleFactors);

var filtered2 = srColScaled2.filter(ee.Filter.lt('CLOUD_COVER', 20));

var badComposite2 = collection2.median();
var goodComposite2 = filtered2.median();

Map.addLayer(badComposite2, {bands: ['SR_B3', 'SR_B2', 'SR_B1'], min: 0, max: 1, gamma:
1.1}, 'Bad composite2');
Map.addLayer(goodComposite2, {bands: ['SR_B3', 'SR_B2', 'SR_B1'], min: 0, max: 1, gamma:
1.1}, 'Good composite2');

var ndvi2 = goodComposite2.normalizedDifference(['SR_B4', 'SR_B3']);

Map.addLayer(ndvi2, {min: 0, max: 1, palette: palette}, 'NDVI2');

var temp2 = goodComposite2.subtract(273.15);

Map.addLayer(temp2, {bands: ['ST_B6'], min: 10, max: 40, palette: palette2}, 'therm2');

Map.addLayer(ct, {}, 'cts');

var ndviclip = ndvi2.clip(ct);

var ctndvi = ndviclip.reduceRegions({
  collection: ct2006,
```

```
  reducer: ee.Reducer.mean(),
  scale: 30,
});

var empty = ee.Image().byte();

var fills = empty.paint({
  featureCollection: ctndvi,
  color: 'mean',
});

var fillsclip = fills.clip(ct);

Map.addLayer(fillsclip, {bands: ['constant'], palette: palette, min: 0, max: 1}, 'colored fills');

Map.addLayer(ctndvi, {bands: ['mean'], min: 0, max: 1, palette: palette}, 'ctndvi');

var percentilesndvi = ndviclip.reduceRegions({
  collection: ct2006,
  reducer: ee.Reducer.percentile([0,20,40,60,80,100]),
  scale: 30,
});

var tempclip = tempband.clip(ct);

var cttemp = tempclip.reduceRegions({
  collection: ct2006,
  reducer: ee.Reducer.mean(),
  scale: 30,
});

var empty2 = ee.Image().byte();

var fills2 = empty2.paint({
  featureCollection: cttemp,
  color: 'mean',
});

var fills2clip = fills2.clip(ct);
```

```
Map.addLayer(fills2clip, {bands: ['constant'], palette: palette2, min: 10, max: 45}, 'colored
fills2');

Map.addLayer(cttemp, {bands: ['MEAN'], min: 10, max: 45, palette: palette2}, 'cttemp');

var vis = {min: 10, max: 45, palette: palette2};

function makeColorBarParams(palette) {
  return {
    bbox: [0, 0, 1, 0.1],
    dimensions: '100x10',
    format: 'png',
    min: 0,
    max: 1,
    palette: palette2,
  };
}

var colorBar = ui.Thumbnail({
  image: ee.Image.pixelLonLat().select(0),
  params: makeColorBarParams(vis.palette),
  style: {stretch: 'horizontal', margin: '0px 8px', maxHeight: '24px'},
});

var legendLabels = ui.Panel({
  widgets: [
    ui.Label(vis.min, {margin: '4px 8px'}),
    ui.Label(
        ((vis.max-vis.min) / 2+vis.min),
        {margin: '4px 8px', textAlign: 'center', stretch: 'horizontal'}),
    ui.Label(vis.max, {margin: '4px 8px'})
  ],
  layout: ui.Panel.Layout.flow('horizontal')
});

var legendTitle = ui.Label({
  value: 'Land Surface Temperature',
  style: {fontWeight: 'bold'}
});
```

```
var legendPanel = ui.Panel([legendTitle, colorBar, legendLabels]);
Map.add(legendPanel);

Export.table.toDrive({
  collection: ctndvi,
  description: 'NDVICTs',
  folder: 'codered',
  fileFormat: 'csv'
});

Export.table.toDrive({
  collection: cttemp,
  description: 'tempCTs',
  folder: 'codered',
  fileFormat: 'csv'
});

Export.table.toDrive({
  collection: ct,
  description: 'CTs',
  folder: 'codered',
  fileFormat: 'csv'
});
```