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Review article

Modification of the association between high ambient temperature and health by urban microclimate indicators: A systematic review and meta-analysis

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ABSTRACT

Background: Landscape characteristics, including vegetation and impervious surfaces, influence urban microclimates and may lead to within-city differences in the adverse health effects of high ambient temperatures.
Objective: Our objective was to quantitatively summarize the epidemiologic literature that assessed microclimate indicators as effect measure modifiers (EMM) of the association between ambient temperature and mortality or morbidity.
Methods: We systematically identified papers and abstracted relative risk estimates for hot and cool microclimate indicator strata. We calculated the ratio of the relative risks (RRR) and 95% confidence intervals (95% CI) to assess differences in health effects across strata, and pooled the RRR estimates using random effects meta-analyses.
Results: Eleven papers were retained. In the pooled analyses, people living in hotter areas within cities (based on land surface temperature or modeled estimates of air temperature) had 6% higher risk of mortality/morbidity compared to those in cooler areas (95% CI: 1.03–1.09). Those living in less vegetated areas had 5% higher risk compared to those living in more vegetated areas (95% CI: 1.00–1.11).
Discussion: There is epidemiologic evidence that those living in hotter, and less vegetated areas of cities have higher risk of morbidity or mortality from higher ambient temperature. Further research with improved assessment of landscape characteristics and investigation of the joint effects of physiologic adaptation and landscape will advance the current understanding.
Conclusion: This review provides quantitative evidence that intra-urban differences in landscape characteristics and micro-urban heat islands contribute to within-city variability in the health effects of high ambient temperatures.

1. Introduction

We are living in a time of rapid urbanization. Approximately half of the world's population lives in urban areas, and this percentage is projected to increase in the coming decades (United Nations, 2014). Transformation of the natural landscape to human-made materials, such as concrete and asphalt, is inherent to urbanization processes (Grimm et al., 2008). These landscape modifications can increase localized temperatures, even in the absence of climate change effects from greenhouse gas emissions (Georgescu et al., 2014; Grimm et al., 2008).

Indeed, urban areas experience higher temperatures than surrounding rural areas (Arnfield, 2003; Oke, 1982). This phenomenon, known as the urban heat island (UHI) effect, occurs primarily at night. The effect is attributable to several characteristics of the urban landscape and built environment. First, urban areas have high amounts of impervious surfaces, such as concrete and asphalt, which absorb heat during the day and release it slowly at night. Additionally, the low amounts of vegetation and water in urban settings, which have evaporative, cooling effects, contribute to warmer temperatures. High-rise buildings also trap heat and absorb solar energy.

In addition to urban versus rural differences, land use and landscape characteristics within a given city, including high building densities and low amounts of trees and other vegetation, may contribute to micro-

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urban heat islands, or hotter areas (Huang et al., 2011; Wong et al., 2016). In turn, these within-city heat islands may contribute to intra-city variability in the health effects of high ambient (air) temperatures (Betts and Sawyer, 2015; Harlan et al., 2006, 2013; Jenerette et al., 2016).

In the short term, the relationship of landscape features to localized temperatures and health has important implications for the threshold temperatures that inform heat warning systems; differences in temperatures within a city might imply the need to adjust heat warning systems accordingly, to tailor them locally. In addition, the relationship of landscape characteristics with the adverse health consequences of high ambient temperatures has important implications for long term environmental interventions aimed at reducing the presence of urban heat islands and their associated health burden. Community-level landscape policies may be attractive because of the potential co-benefits of urban greening, such as improved mental health and greater uptake of physical activity (Lee and Maheswaran, 2011).

In this paper, we report results from a quantitative review of the epidemiologic literature that assessed effect measure modification (EMM) of the association between ambient temperature and morbidity/mortality by microclimate indicators. Herein, we use the term "microclimate indicators" to describe measured characteristics that either affect or represent the experience of differential ambient temperature within a city. Specifically, we aim to: 1) summarize results from epidemiologic analyses that evaluated microclimate indicators as EMMs of the association between ambient temperature and human morbidity and mortality; 2) describe the landscape characteristics and other microclimate indicators that have been assessed as EMMs; and 3) derive quantitative estimates of differences in the association between high ambient temperatures and morbidity/mortality across hot/cool categories of microclimate indicators. This review is focused on microclimates within, rather than between, cities. Results from this paper describe the extent to which characteristics of the within-city urban landscape modify the association between high ambient temperatures and human health, and may inform the design of future epidemiologic work.

2. Methods

2.1. Literature search

We submitted groups of terms that represented the following four concepts to Pubmed, Ovid, and Web of Science: 1) temperature; 2) mortality/morbidity, with specific terms for cardiovascular, respiratory, coronary, allergy, asthma, and heat distress, based on *a priori* knowledge that these conditions have been associated with high ambient temperatures; 3) microclimates, urban heat island, landscape or built environment characteristics, with specific terms for trees, green space, impervious surfaces, and cool roofs; and 4) heterogeneity, interaction, or vulnerability, with the aim of identifying papers that evaluated EMM. The complete set of terms that we used is given in Supplementary materials 1. We restricted the literature search to peer-reviewed articles focused on human populations that were published in English. In PubMed, we specified that the search terms could appear in all fields or as MeSH terms. In Web of Science, we specified that these terms should appear as a topic field. In Ovid, we specified that terms could appear in all fields. The literature search was conducted on May 5, 2016. We did not restrict the articles to any publication dates. We identified additional papers by reviewing reference lists.

Two authors (LHS and TB) divided an identical list of fifty randomly selected titles and abstracts. These two authors each reviewed the fifty abstracts and excluded papers according to a pre-specified set of criteria, described below. The two authors then compared results and discussed any discrepancies in the papers excluded. After agreeing upon a final set of criteria, the two authors (LHS and TB) each reviewed half of the remaining abstracts and titles.

Papers were excluded if they:

1) Were a commentary, editorial, review paper, case report, or meta-analysis;
2) Did not evaluate associations with ambient temperature;
3) Did not investigate associations with either human morbidity or mortality;
4) Were not observational studies (predictive and risk assessment papers were excluded); or
5) Were occupational studies.

After this first exclusion step, the same two authors (LHS and TB) reviewed the full text of the remaining articles. In addition to the previously stated set of exclusion criteria, we excluded papers that:

1) Did not include a comparison or reference group;
2) Did not include the primary exposure (ambient temperature) and primary response (morbidity/mortality) as time varying characteristics;
3) Did not assess EMM of the overall association between temperature and morbidity/mortality by microclimate indicators;
4) Evaluated associations with infectious diseases (including diarrhea and parasitic diseases), and no other relevant mortality/morbidity effects of temperature;
5) Evaluated differences in effect across urban versus rural classifications, which are representative of regional rather than within-city differences;
6) Evaluated EMM of the association of ambient temperature with morbidity/mortality by microclimate indicators at a between- rather than within-city level;
7) Could not be included in the quantitative analysis because a ratio of the relative risks (RRR, described below) could not be calculated.

2.2. Paper review and data extraction

Two authors (LHS and AJD) abstracted information from the final set of selected articles using a structured spreadsheet and compared results. We extracted the following information from the final set of papers: author, publication date, study location, study design (case-crossover or time series), and study period (months and years). We also noted the ambient temperature definition(s) used (eg. apparent temperature, maximum daily temperature, etc.), and the health outcome evaluated (all-cause mortality, hospitalizations for myocardial infarction, etc.). We noted the covariates included in the statistical models. We also abstracted the following information about the microclimate indicators evaluated as EMMs: the definition of the microclimate indicators evaluated; the methods used to assess the microclimate indicator including data source and, if relevant, the modeling strategies used; the spatial scale at which the microclimate indicators were measured; and the scale at which the indicators were assigned to the cases. We also extracted all of the stratified quantitative results that corresponded to the assessment of EMM by a microclimate indicator. Many papers investigated a variety of exposure lags and/or exposure contrasts. For each quantitative stratified estimate, we noted the exposure lag and contrast to which the relative risk estimate corresponded (eg. risk comparing 26 °C days to 20 °C days, or increase in risk for every incremental degree increase in temperature). We also noted if and how the authors addressed the issue of confounding of the microclimate indicators by neighborhood level socio-demographic characteristics.

2.3. Terminology

A variety of terms have been used to describe the characteristics that create warmer and cooler areas within cities. For clarity and consistency, we use the following set of vocabulary within this manuscript:

- **Microclimate indicators** are characteristics that affect or represent localized temperatures within cities. The following terms are subtypes of microclimate indicators.
  - **Localized temperature indicators** are measures of localized temperature. These include land surface temperature and estimates of air temperature that have been derived from quantitative models.
    - **Land surface temperature** (Observatory, 2000), describes what the reading on a thermometer would be if it were to touch the surface of the earth.
  - **Vegetation** describes any type of vegetated land cover, including tree canopy, shrubs, and grass.
    - **Greenness** is an index of vegetation derived from the normalized difference vegetation index (NDVI). The NDVI is a dimensionless index that describes the difference between visible and near-infrared reflectance of vegetation cover and can be used to estimate the density of green on an area of land (Weier and Herring, 2000).

2.4. Quantitative analysis

2.4.1. Extraction of effect estimates

We abstracted effect estimates that were stratified by categories of microclimate indicators (eg. high versus low surface temperature, low versus high vegetation). When the stratified effect estimates were not reported, we attempted to contact and request the values from the corresponding author. For the meta-analyses, we selected a single pair of stratified effect estimates from each paper. When there were multiple effect estimates from which to choose, we selected estimates for which:

1) The outcome was all-cause mortality,
2) The exposure definition was daily mean temperature,
3) The exposure lag was zero days or the shortest lag that included or was closest to day zero (with the assumption that the study authors deemed this the most relevant exposure period),
4) The contrast corresponded to increases in risk for each one degree increase in temperature above a threshold value.

When it was possible, we converted effect estimates from categorical contrasts to estimates that corresponded to one degree increases in temperature.

This set of criteria was selected based on the goal of making the effect estimates most comparable to one another. In cases where we had to select from multiple options but the above stated criteria could not be followed, we selected the stratified estimates that corresponded to the parameters associated with the non-stratified estimate that was largest in magnitude (i.e. furthest from the null). If the non-stratified estimate was not reported, then we selected the estimate that corresponded to the largest stratified effect estimate (either stratum).

In one paper, the authors evaluated both day and night land surface temperature as EMMs (Burkart et al., 2016). In this case, we selected the effect estimate that corresponded to nighttime land surface temperature, since this is thought to be most representative of the urban heat island effect (Doick et al., 2014). When both vegetation and a more specific type of vegetation (eg. tree canopy) were examined in the same paper, we used the stratified estimates that corresponded to satellite based imagery, since this is the variable that was used most frequently.

If available, we selected the estimates that corresponded to the dichotomized EMM (i.e. hot vs. cool, or low vegetation vs high vegetation). We assigned each stratified estimate to a hot or cool category. For example, low vegetation categories were classified as “hot” and high vegetation categories classified as “cool.” When the EMM was evaluated and results reported according to more than two categories, we used fixed effects meta-analytic analyses to combine the coolest localized temperature indicator categories or highest vegetation categories.

2.4.2. Ratio of the relative risks and meta analysis

For each pair of stratified effect estimates, we calculated the ratio of the relative risks (RRR) and the associated 95% confidence interval (Altman and Bland, 2003). The RRR was calculated as the relative risk for the hot category divided by the relative risk for the cool category. The formulas and the Stata code used to calculate the RRR estimates and the 95% confidence intervals are shown in Supplemental materials 2. We used random effects meta-analysis to derive pooled RRR estimates and 95% CIs (DerSimonian and Laird, 1986). Inconsistency across studies was assessed using the I^2 statistic (Higgins et al., 2003). Larger I^2 statistics represent greater inconsistency in the RRR estimates. We used random rather than fixed effects meta-analyses because, in preliminary analyses using fixed effects models, there was evidence of heterogeneity across studies ($I^2 > 65\%$). Random effects models allow between study heterogeneity to contribute to the variance (Borenstein et al., 2010; Higgins et al., 2003). Specifically, random effects meta-analysis weights the estimates using the following two steps: 1) each individual estimate is weighted by the inverse of its variance, 2) the resulting inverse variance weighting is unweighted using a random effects variance component that corresponds to the amount of heterogeneity (the extent of variability between the RRR estimates) in the analysis (DerSimonian and Laird, 1986). Results from the meta-analyses are reported in forest plots. We conducted Egger's test for small-study effects and examined funnel plots to identify evidence of publication bias.

We performed several sensitivity analyses. We investigated the impact of each paper by repeating the analyses and dropping each RRR estimate, one by one. We restricted the analysis to include only effect estimates representing associations with mortality, rather than morbidity. For estimates that we combined because they were reported using more than two categories, we repeated the analysis after combining the categories in two alternative ways: 1) we contrasted the coolest category with the hottest categories combined, and 2) we dichotomized the categories at the middle. We also restricted the papers to those that evaluated associations among individuals ages 65 + only. We also restricted RRR estimates to those that corresponded to degree increases in temperature over a threshold value. There were too few RRR estimates to conduct any other sensitivity analyses related to the temperature contrast. We also conducted a sensitivity analysis that restricted contributing papers to those that assessed localized temperature indicators using statistical models of air temperature, and a sensitivity analyses restricted to papers that assessed vegetation using the NDVI.

2.4.3. Assessment of differences in effect across microclimate indicators

A primary motivation for performing this review was to evaluate the extent to which there is evidence of within-city differences in the effects of ambient temperature on morbidity and mortality attributable to microclimate indicators. We used Cochran's Q test statistic to assess differences across hot and cool strata. The expression used to calculate Cochran's Q test statistic is nearly identical to that for Wald's chi-square statistic and is appropriate for assessing differences across estimates (Kaufman and MacLehose, 2013). We performed the evaluation for each pair of effect estimates from each paper. We also used Cochran's Q test statistic to assess differences across the stratified pooled estimates.

All analyses were conducted using Stata version 13.1.

3. Results

3.1. Papers identified and included

After duplicates were removed, we identified 1077 papers through the automated searches, and an additional 39 by review of reference lists (Fig. 1). After removing duplicates, 1116 records remained. After reviewing the title and abstracts of the 1116 abstracts, 984 were excluded. We reviewed the full text of the remaining 132 papers. We

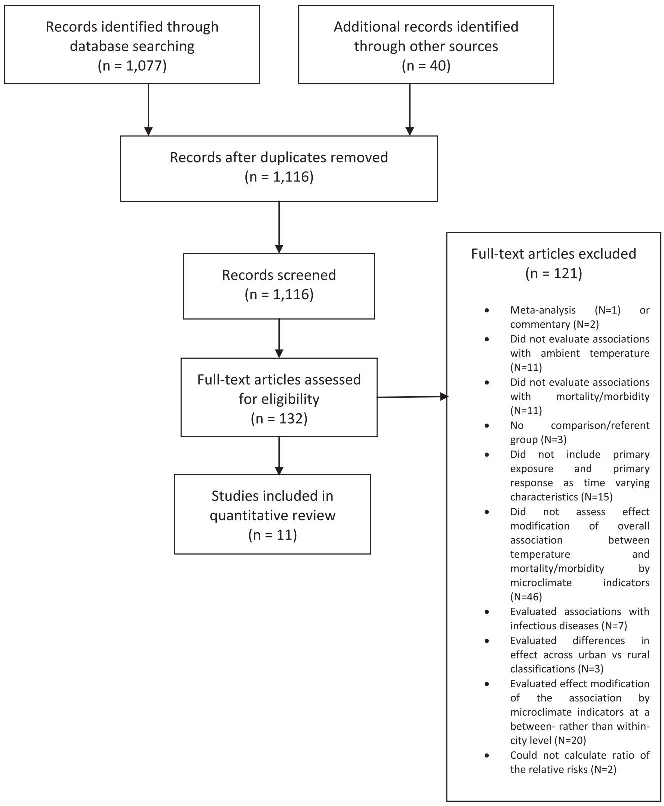

Fig. 1. Flow chart showing papers included and excluded from the systematic review.

excluded 121 additional papers because they: were a meta-analysis (N = 1) or commentary (N = 2), did not evaluate associations with ambient temperature (N = 11), did not evaluate associations with mortality/morbidity (N = 11), did not include a comparison group (N = 3), did not characterize the primary exposure and response variables as time varying characteristics (N = 15), did not assess EMM of the overall association between temperature and mortality/morbidity by microclimate indicators (N = 46), evaluated associations with infectious diseases only (N = 7), evaluated differences in effect across urban/rural classifications only (N = 3), evaluated EMM of the association by microclimate indicators at a between- rather than within-city level (N = 20), or could not be included in the quantitative review because a RRR could not be calculated (N = 2). A total of 11 papers are included in this quantitative review.

3.2. Study characteristics

Table 1 describes the 11 papers included in the review. All of the papers were published relatively recently; 2009 was the earliest publication year. Seven papers described case-crossover analyses (Gronlund et al., 2015, 2016; Ho et al., 2016; Madrigano et al., 2013; Milojevic et al., 2016; Smargiassi et al., 2009; Xu et al., 2013) and four described time series analyses (Burkart et al., 2016; Goggins et al., 2012, 2013; Son et al., 2016).

The papers used data from North America, Europe, and Asia. The European studies were conducted in London (Milojevic et al., 2016), Lisbon (Burkart et al., 2016), and Barcelona (Xu et al., 2013). The North American studies were conducted in Montreal (Smargiassi et al., 2009) and Vancouver, Canada (Ho et al., 2016), and numerous cities across the United States (Gronlund et al., 2015, 2016; Madrigano et al., 2013). The Asian papers were based in Hong Kong (Goggins et al., 2012), Kaohsiung City, Taiwan (Goggins et al., 2013), and Seoul, Korea (Son et al., 2016). Three papers restricted the study population to individuals ages 65 and older (Burkart et al., 2016; Gronlund et al., 2015, 2016). In one paper, the study population was restricted to those ages 25 and older (Madrigano et al., 2013). The remaining papers did not make any age restrictions.

3.3. Health outcomes

Most papers evaluated associations with all-cause mortality or all natural-cause mortality. Gronlund et al. (2015) evaluated associations with cardiovascular and respiratory mortality. Morbidity health outcomes included acute myocardial infarction (Madrigano et al., 2013) and emergency hospitalizations for heat, renal, or respiratory causes (Gronlund et al., 2016).

3.4. Ambient temperature definition and parameterization

Ambient temperature was quantified in a variety of ways. Daily mean ambient temperature was the most commonly used measure (Goggins et al., 2012, 2013; Smargiassi et al., 2009; Son et al., 2016). Other measures were daily mean apparent temperature (Gronlund et al., 2015; Madrigano et al., 2013) or the daily mean humidex (Ho et al., 2016), daily maximum temperature (Gronlund et al., 2015, 2016; Xu et al., 2013), daily minimum temperature (Gronlund et al., 2015), and the universal thermal climate index (Burkart et al., 2016). Temperature was parameterized in a variety of ways, including as a binary indicator variable representing extreme heat, or using a hockey stick term, coded as a linear term when the temperature was above a threshold value and zero otherwise. Some studies modeled temperature using a strict linear term, and some included flexible terms to allow nonlinearity in the relationship between ambient temperature and the outcome.

Because of the variety of temperature parameterizations, the effect estimates corresponded to different contrasts. For example, some papers reported changes in risk associated with a one degree increases in temperature, some reported changes in risk associated with incremental increases in temperature above a threshold value, and others contrasted risk at temperatures below and above a certain percentile of the distribution within a specified area and time period.

3.5. Covariates

Most time series analyses adjusted for long-term trends, seasonality, and day of the week. Papers describing results from case-crossover studies adjusted for fewer covariates since, by design, this approach adjusts for potential confounding by long-term trends, seasonality, and time-invariant variables, including individual level characteristics (Maclure, 1991). To investigate whether modification of the association between temperature and mortality was affected by individual characteristics, Son et al. (2016) further stratified models by sex and age.

Because of the potential that neighborhood level socioeconomic status was highly correlated with the microclimate indicators, some papers further stratified analyses by indicators of neighborhood level socioeconomic status (Goggins et al., 2012; Smargiassi et al., 2009), or adjusted for indicators of socio-demographic deprivation (Milojevic et al., 2016). Specifically, Goggins et al. (2012) stratified analyses by the median household income of neighborhoods. They found that, among both low and high SES area residents, risk of mortality was higher in hot versus cool areas. Smargiassi et al. (2009) stratified results by home lodging values. Those who lived in hot areas (estimated based on land surface temperature) with higher home lodging values had higher risk of dying in association with high daily ambient temperatures compared to those who lived in cooler areas with high lodging prices. Milojevic et al. (2016) found that adjusting for neighborhood level socioeconomic deprivation had little effect on the association between temperature and mortality across localized temperature categories. In two papers, the authors adjusted for possible confounding effects of several modifying variables by including multiple interaction

Table 1
Description of papers included in the systematic review and meta-analysis.

Author, date	Study design	Location	Study period	Study population	Outcome	Temperature definition	Temperature parameterization	Temperature contrast	Covariates
Smargiassi 2009	Case-crossover	Montreal, Canada	June-Aug 1990–2003	All Montreal residents	Natural cause mortality	Daily mean T	Natural cubic spline functions, constrained to be continuous at the 5th 33th, 66th and 95th percentiles	26 °C vs 20 °C	Ozone, Residential property values of postal code
Goggins 2012	Time series	Hong Kong, China	June-Sept, 2001–2009	All Hong Kong residents	Natural cause mortality	Daily mean T	Piecewise linear term: T-29 °C if T > 29 °C and 0 otherwise	1 °C increase > 29 °C	Day of year, day of study, day of week, mean relative humidity, daily total solar radiation, wind speed, PM_{10}, Median household income
Goggins 2013	Time series	Kaohsiung City, Taiwan	May-Oct 1999–2008	All residents	Natural cause mortality	Daily mean T	Linear terms and two piecewise linear terms (T-29 °C where T > = 29 C, 0 otherwise and 29 °C –T where T < 29 °C)	1 °C increase 1 °C increase > 29 °C,	,Day of study, day of year, day of the week, pollutants (SO_2, PM_{10}, NO_2,CO,ozone)
Madrigano 2013	Case-crossover	Worcester, MA	April-October 1995, 1997, 1999, 2001, 2003	Patients ages 25+ hospitalized with independently confirmed acute MI	All cause mortality following acute MI, acute MI	Daily mean apparent T	Linear term, binary indicator variables	Per 12.3 °C increase (IQR), > 95th % vs < = 95th %	Ozone, $PM_{2.5}$, absolute humidity, day of the week
Xu 2013	Case-crossover	Barcelona Spain	May-Oct, 1999–2006	All residents	All cause mortality	Daily maximum T	Binary indicator variables	> 95th % vs < = 95th %	None
Burkart et al., 2016	Time series	Lisbon, Portugal	June-August 1998–2008	Ages 65+	All cause mortality	Universal thermal climate index (UTCI)	T − 99th/95th % if T > 99th/95th % and 0 otherwise	1 °C above the 99th %, 1 °C above the 95th %	Long-term and seasonal trends, PM_{10}, ozone, percent of parish population > 65, building density, proportion of college graduates, percent of population receiving social benefits, proximity to coastal water
Gronlund 2015	Case-crossover	8 cities in Michigan, US	May-Sept 1990–2007	Ages 65+	Cardiovascular and respiratory disease mortality	Daily mean apparent T, maximum daily T, minimum daily T	Binary indicator variables	> 99th % < = 99th %, > 97th % vs < = 97th %	Ozone, interaction terms with the following potential effect measure Modifiers: at the individual level, non-married, no high school degree, male, black, At the zip code level, % age 65+ and living alone, % below poverty level, % of homes built before 1940, % homes built 1940–1959, % homes built 1960–1979
Gronlund 2016	Case-crossover	109 US cities, with effect estimates combined by meta analysis	May-Sept 1992–2006	Ages 65+	Emergency hospitalizations for heat, renal, or respiratory causes	Daily maximum T	Three indicator terms (0–90th %, 90th–97%, > 97%)	> 97th% vs < 90th %	Interaction terms with the following potential effect measure modifiers: male, black, ages 78+, % non-green, % no High school, % black, % built < 1940
Ho 2016	Case-crossover	Vancouver, Canada	1998–2014. Restricted based on daily mean air T values	All residents	All cause mortality	Daily mean humidex (measure of apparent T)	Linear term	1 °C increase	None
Milojevic 2016	Case-crossover	London, England	June-Aug 1993–2006	All residents	All cause mortality	Daily mean T	Binary indicator variable	> 22.3 °C vs < = 22.3 °C	Day of week, influenza count, Additional adjustment for socioeconomic deprivation score, age
Son 2016	Time series	Seoul, Korea	May-September 2000–2009	All residents	All cause mortality except external causes	Daily T	Segmented linear variable	1 °C above the 90th %	Time and seasonal trends, day of week, relative humidity, daily PM_{10} and ozone, % of district receiving social benefits, % of district with

(*continued on next page*)

Table 1 (*continued*)

Author, date	Study design	Location	Study period	Study population	Outcome	Temperature definition	Temperature parameterization	Temperature contrast	Covariates
									residents ages > 65 years, area of district, offset for population size of district. Further stratification of models by sex and age.

Abbreviation: T, Temperature; IQR, interquartile range,; COPD; MI, myocardial infarction; PM, particulate matter; SO_2, sulfur dioxide; CO, carbon monoxide; NO_2, nitrogen dioxide.

terms in the same model (Gronlund et al., 2015, 2016).

3.6. Definition and characterization of microclimate indicators

Table 2 presents information about the microclimate indicators that were evaluated as modifiers of the association between ambient temperature and morbidity/mortality. Six papers characterized localized temperature indicators within one or multiple cities (Burkart et al., 2016; Goggins et al., 2012, 2013; Ho et al., 2016; Milojevic et al., 2016; Smargiassi et al., 2009). Two of these papers (Burkart et al., 2016; Smargiassi et al., 2009) used satellite imagery to assign land surface temperatures to decedents' addresses at the postal code or parish level, respectively. Specifically, Smargiassi et al. (2009) used two satellite images, one from August 2011 and a second from July 1990, taken by the Landsat Enhanced Thematic mapper Plus (ETM+) instrument, which has a temporal resolution of 16 days and a spatial resolution of 30 m. Burkart et al. (2016) used 104 daytime and 104 nighttime land surface temperature images from all summer months (June, July, August) for years 2000–2008 from the MODerate Resolution Imaging Spectroradiometer (MODIS). Each image had a spatial resolution of one km and a temporal resolution of 16 days.

Four papers used models to derive localized temperature indicators (Goggins et al., 2012, 2013; Ho et al., 2016; Milojevic et al., 2016). These models were similar in that they all combined air temperature data with land use and/or landscape characteristics to represent spatial differences in temperatures within a city. The resulting localized temperature indicators were assigned at varying spatial scales; most were assigned at the neighborhood level (eg. postal code, census tract or block group, etc.). Milojevic et al. (2016) assigned addresses to one km resolution grids and Ho et al. (2016) assigned addresses to temperature maps with a 60 m resolution.

Six papers (Burkart et al., 2016; Gronlund et al., 2015, 2016; Madrigano et al., 2013; Son et al., 2016; Xu et al., 2013) evaluated an indicator of vegetation as an EMM. Two papers (Gronlund et al., 2015, 2016) used the United States National Land Cover dataset, which has a 30 m × 30 m resolution, to assess vegetation (Homer et al., 2012). Three papers (Burkart et al., 2016; Madrigano et al., 2013; Son et al., 2016) used the Normalized Difference Vegetation Index (NDVI). In all of these papers, the NDVI was calculated from bands one and two of the MODerate resolution Imaging Spectroradiameter (MODIS) on NASA's Terra satellite and had a 250 m resolution (Carroll et al., 2001–2006). Burkart et al. (2016) included 54 NDVI images from all summer months for years 2008-2008. Madrigano et al. (2013) included a single NDVI image from the summer of year 2000. Each pixel in the image had a 250 m resolution, and the authors then averaged the pixels over 3 × 3 neighboring cells to derive 750 m square resolution measures. Son et al. (2016) used 110 images from May to September of years 2000–2009. Xu et al. (2013) used 250 m resolution images from the MODIS vegetation continuous fields for the period 6 March 2002 to 6 March 2003 (the mid-point of the study) to estimate percent tree cover (NASA 2016).

A handful of papers evaluated individual landscape characteristics in addition to, or instead of, vegetation or localized temperature indicators. These characteristics included proximity to water, elevation, housing density, proportion of a residential area comprised of single dwelling units, and buildings with two or more stories. Proximity to water or percentage of the postal code covered by water was estimated using National Land Cover data or a digital elevation model data (Burkart et al., 2016). US Census data were used to estimate, at the census block or tract level, median housing density (Madrigano et al., 2013) proportion of households that were single dwelling units rather than apartment blocks (Xu et al., 2013) or multiple dwelling units (Madrigano et al., 2013).

Table 2
Microclimate indicators examined in each paper.

Author (date)	Microclimate indicator	Spatial resolution for assignment of microclimate indicator	Assessment details
Smargiassi 2009	Land surface temperature	Postal code	Thermal surface temperature maps from 1990 and 2001 from Landsat-7/Thematic Mapper ETM satellites
Goggins 2012	Urban heat island index	Tertiary planning unit	Urban heat island index created using a physiologic equivalent temperature model, which incorporated data on vegetation (satellite imagery), wind velocity based on frontal densities of urban forms. Calculated at 100 m × 100 m resolution and then mean value for each planning unit was derived.
Goggins 2013	Urban climate map	District of residence	Urban climate maps, developed for 500 × 500 m grid cells, which incorporated factors that influence the thermal environment (topography, population density, land use, urban heat island intensity), and the dynamic potential by providing ventilation and cooling (natural landscape, water bodies, prevailing wind, and land and sea breeze).
Madrigano 2013	Recreation/conservation area, Having a large (> 100,000 m^2) lake or reservoir within 400 m of residence, elevation, greenness (mean NDVI), housing density, number of units in building; with all characteristics evaluated individually	Census tract or block group	Census variables: median value for area (tract or block group) for housing density, %housing units with > 4 units; Open space (parkland), water bodies, elevation at residence (all from MassGIS website); Greenness: Mean NDVI in summer 2000 (250 m resolution) 16-day composite vegetation index data, averaged over 3 × 3 neighboring cells (750 m square) to assign to residence
Xu 2013	Percentage of residents perceiving little surrounding greenness; percentage of single dwellings (as opposed to apartment blocks) at census tract Level; percent tree cover around residence	Percent tree cover in a buffer of 500 m around residence weighted by the area of each vegetation continuous field raster falling within the buffer	Percentage of single dwellings in the census tract, based on census data. Percent tree cover assessed using data from the MODIS vegetation continuous field (VCF) data (250 × 250 m resolution).
Burkart et al., 2016	Spatial mean land surface temperature at parish level, greenness (NDVI) at parish level, mean distance to the Atlantic Ocean and Tagus Estuary Coast for the entire parish	Parish	Satellite imagery data (MODIS) for LST and NDVI, spatial resolutions of 1 km and 250 m, respectively; Digital elevation model from the NASA shuttle radar topographic mission (resolution of 90 m) used to calculate distance to water
Gronlund 2015	Percent vegetation	Zip code	National land cover data, 30 m resolution (years 1992, 2001, and 2006)
Gronlund 2016	Percent vegetation	Zip code	National land cover data, 30 m resolution (years 1992, 2001)
Ho 2016	Heat exposure maps for land surface temperature, daily air temperature, and maximum daily humidex.	Maps had a 60 m resolution, assigned at the residential address level	Maximum air temperature and humidex maps were developed using nonlinear random forest models that incorporated information on land surface temperature (Landsat images on days with a maximum air temperature ≥ 25 °C), normalized difference water index, skyview factor, elevation and solar radiation.
Milojevic 2016	Urban heat island	1 km grids	Numerical simulations with a weather forecast model, which incorporated parameters for urban land use and geometry of street canyons, were used to model ambient temperatures at 1.5 m height.
Son 2016	Greenness (NDVI) at the administrative area, converted to a percentage scale	Administrative units (25 total)	Greenness: Mean NDVI, 16 day composite periods for May to September 2000–2009 (250 m resolution)

3.7. Differences in effect across hot/cold strata

We extracted all relevant stratified estimates from each paper, and calculated the RRR and 95% CI. We used the Cochran's Q statistic to evaluate evidence of differences in the association between temperature and mortality/morbidity across hot/cold strata (Table 3). The effect estimates that contributed to these RRR estimates are given in Supplemental Table 1. RRR estimates that were 1.0 or greater indicate the risk of morbidity/mortality in association with high ambient temperatures was higher for the "hot stratum" than the "cool" stratum. The only paper for which RRR estimates were < 1.0 was that by Madrigano et al. (2013); fifteen of twenty of the RRR estimates from this paper were in the unexpected direction (< 1.0). In eight of the 11 papers, for at least one set of stratified results, there was evidence of differences in the association between temperature and mortality/morbidity across strata, based on a threshold of $p < 0.20$ for Cochran's Q statistic. Using this same criterion, there was evidence of differences across strata in five (Burkart et al., 2016; Goggins et al., 2012, 2013; Ho et al., 2016; Smargiassi et al., 2009) of the six papers (Burkart et al., 2016; Goggins et al., 2012, 2013; Ho et al., 2016; Milojevic et al., 2016; Smargiassi et al., 2009) that investigated localized temperature indicators and in three (Burkart et al., 2016; Gronlund et al., 2015; Madrigano et al., 2013) of the six papers (Burkart et al., 2016; Gronlund et al., 2015, 2016; Madrigano et al., 2013; Son et al., 2016; Xu et al., 2013) that investigated vegetation as a modifying variable.

Within-study differences across strata appeared to be affected by the temperature contrast used. For example, Madrigano et al. (2013) observed differences in the association between all-cause mortality following acute myocardial infarction and high daily mean apparent temperatures above the 95th percentile of the distribution across categories of NDVI (RRR: 0.50, 95% CI: 0.27–0.95). However, there was no evidence of differences across NDVI categories when associations of

Table 3
Ratio of the relative risks and heterogeneity statistics for stratified estimates reported in the papers included in the quantitative analysis.

Author	Heat definition	Units for heat contrast	Outcome	Lags	Categories for the stratification variable	RRR	Cochran's test	
							Chi square	p-value
Smargiassi 2009[a]	Daily mean temperature	26 °C vs 20 °C	Natural cause	0	LST: Hot (> 75th%) vs cool (≤ 75th%)	1.13, 1.07–1.20	18.3	< 0.01
Smargiassi 2009	Daily mean temperature	26 °C vs 20 °C	Natural cause restricted to those who died at home	0	LST: Hot (> 75th%) vs cool (≤ 75th%)	1.09, 0.94–1.25	1.3	0.25
Goggins 2012[a]	Daily mean temperature	1 °C increase > 29 °C	Natural cause mortality	0–4	Hot (UHII > median) vs cool (UHII ≤ median)	1.03, 0.99–1.08	2.0	0.15
Goggins 2012	Daily mean temperature	1 °C increase > 29 °C	Natural non-cancer mortality	0–4	Hot (UHII > median) vs cool (UHII ≤ median)	1.03, 0.97–1.09	0.9	0.35
Goggins 2013[a]	Daily mean temperature	1 °C increase > 29 °C	Daily natural cause mortality	0–4	Level 1 & 2 combined = high thermal load low dynamic potential, medium thermal load, medium dynamic potential vs Level 3 = Low thermal load and high dynamic potential	1.04, 0.98–1.11	1.8	0.18
Goggins 2013	Daily mean temperature	1 °C increase	Daily natural cause mortality	0–4	Level 1 & 2 combined = high thermal load low dynamic potential, medium thermal load, medium dynamic potential vs Level 3 = Low thermal load and high dynamic potential	1.04, 1.01–1.06	6.7	0.01
Madrigano 2013[c]	Daily mean apparent temperature	1 °C increase	All-cause mortality following MI	0	NDVI < 202.1 vs NDVI ≥ 202.1	1.00, 0.96–1.04	0.01	0.90
Madrigano 2013	Daily mean apparent temperature	1 °C increase	All-cause mortality following MI	0	Lives > 400 m of large water body vs Lives within 400 m of large water body	1.02. 0.95–1.09	0.28	0.59
Madrigano 2013	Daily mean apparent temperature	1 °C increase	All-cause mortality following MI	0	Elevation ≤ 202 m vs elevation > 202 m vs	0.94, 0.89–1.00	4.21	0.04
Madrigano 2013	Daily mean apparent temperature	1 °C increase	All-cause mortality following MI	0	≥ 5% more than 4 units in building vs < 5% more than 4 units in buildings	1.00, 0.96–1.05	0.01	0.94
Madrigano 2013	Daily mean apparent temperature	1 °C increase	All-cause mortality following MI	0	< 7% recreation/conservation area vs ≥ 7% recreation/conservation area	0.99, 0.97–1.01	0.94	0.33
Madrigano 2013	Daily mean apparent temperature	1 °C increase	Acute MI	0	Lives > 400 m of large water body vs Lives within 400 m of large water body	1.00, 0.96–1.04	0.00	0.97
Madrigano 2013	Daily mean apparent temperature	1 °C increase	Acute MI	0	Elevation ≤202 m vs elevation > 202 m vs	0.98, 0.96–1.04	0.01	0.91
Madrigano 2013	Daily mean apparent temperature	1 °C increase	Acute MI	0	NDVI ≥ 202.1 vs NDVI < 202.1	0.97, 0.94–1.01	2.63	0.11
Madrigano 2013	Daily mean apparent temperature	1 °C increase	Acute MI	0	≥ 5% more than 4 units in building vs < 5% more than 4 units in buildings	0.98, 0.95–1.01	2.04	0.15
Madrigano 2013	Daily mean apparent temperature	1 °C increase	Acute MI	0	≥ 7% recreation/conservation area vs < 7% recreation/conservation area	1.00, 0.97–1.03	0.04	0.84
Madrigano 2013	Daily mean apparent temperature	> 95th % vs ≤ 95th %	Acute MI	0	≥ 7% recreation/conservation area vs < 7% recreation/conservation area	0.94, 0.57–1.54	0.07	0.80
Madrigano 2013	Daily mean apparent temperature	> 95th % vs ≤ 95th %	Acute MI	0	Lives > 400 m of large water body vs Lives within 400 m of large water body	0.63, 0.32–1.21	1.97	0.16
Madrigano 2013	Daily mean apparent temperature	> 95th % vs ≤ 95th %	Acute MI	0	Elevation ≤ 202 m vs elevation > 202 m vs	1.11,0.58 −2.12	0.09	0.76
Madrigano 2013	Daily mean apparent temperature	> 95th % vs ≤ 95th %	Acute MI	0	NDVI < 202.1 vs NDVI ≥ 202.1	1.15, 0.70–1.89	0.31	0.58
Madrigano 2013	Daily mean apparent temperature	> 95th % vs ≤ 95th %	Acute MI	0	≥ 5% more than 4 units in building vs < 5% more than 4 units in buildings	0.99, 0.60–1.62	0	0.97
Madrigano 2013	Daily mean apparent temperature	> 95th % vs ≤ 95th %	All-cause mortality following MI	0	≥ 7% recreation/conservation area vs < 7% recreation/conservation area	0.97, 0.52–1.84	0	0.95
Madrigano 2013	Daily mean apparent temperature	> 95th % vs ≤ 95th %	All-cause mortality following MI	0	Lives > 400 m of large water body vs Lives within 400 m of large water body	1.11, 0.45–2.72	0.05	0.82
Madrigano 2013	Daily mean apparent temperature	> 95th % vs ≤ 95th %	All-cause mortality following MI	0	Elevation ≤ 202 m vs elevation > 202 m vs	0.83, 0.38–1.84	0.2	0.65
Madrigano 2013	Daily mean apparent temperature	> 95th % vs ≤ 95th %	All-cause mortality following MI	0	NDVI < 202.1 vs NDVI ≥ 202.1	0.50, 0.27–0.95	4.56	0.03

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Table 3 (*continued*)

Author	Heat definition	Units for heat contrast	Outcome	Lags	Categories for the stratification variable	RRR	Cochran's test	
							Chi square	p-value
Madrigano 2013	Daily mean apparent temperature	> 95th % vs ≤ 95th %	All-cause mortality following MI	0	≥ 5% more than 4 units in building vs < 5% more than 4 units in buildings	0.57, 0.30–1.07	3.09	0.08
Xu 2013[a,b]	Daily maximum temperature	> 95th % vs ≤ 95th %	All cause mortality	0–2	% tree, 0 vs > 0%	1.01, 0.85–1.20	0.01	0.93
Xu 2013	Daily maximum temperature	> 95th % vs ≤ 95th %	All cause mortality	0–2	% tree, with 5 categories based on minimum, 10th, 30th, 70th, 90th percentiles	–	1.47	0.83
Xu 2013[b]	Daily maximum temperature	> 95th % vs ≤ 95th %	All cause mortality	0–2	0% single dwellings vs > 0% single dwellings	1.14, 0.96–1.36	1.98	0.16
Xu 2013	Daily maximum temperature	> 95th % vs ≤ 95th %	All cause mortality	0–2	% single dwellings with categories based on minimum, 10th, 30th, 70th and 90th percentiles	–	2.42	0.66
Gronlund 2015[a]	Mean apparent temperature	> 99th % ≤99th %	Cardiovascular mortality	0–3	% non-green (25th % vs 75th%)	1.19, 1.04–1.37	6.66	0.01
Gronlund 2015	Mean daily mean temperature	> 99th % ≤ 99th %	Cardiovascular mortality	0–3	% non-green (25th % vs 75th%)	1.30, 1.13–1.48	14.22	< 0.01
Gronlund 2015	Mean daily minimum temperature	> 99 h % ≤99 h %	Cardiovascular mortality	0–3	% non-green (25th % vs 75th%)	1.14, 0.99–1.31	3.27	0.07
Gronlund 2015	Mean daily maximum temperature	> 99th % ≤ 99th %	Cardiovascular mortality	0–3	% non-green (25th % vs 75th%)	1.29, 1.12–1.49	13.07	< 0.01
Burkart 2016[a,b]	Daily UTCI	1 °C above the 99th %	All cause mortality	0–2	LST night (highest quartile vs others)	1.07, 1.05–1.09	54.9	< 0.01
Burkart 2016	Daily UTCI	1 °C above the 99th %	All cause mortality	0–2	LST night (quartiles)	–	83.5	< 0.01
Burkart 2016[b]	Daily UTCI	1 °C above the 95th %	All cause mortality	0–2	LST night (highest quartile vs others combined)	1.02, 1.01–1.02	61.7	< 0.01
Burkart 2016	Daily UTCI	1 °C above the 95th %	All cause mortality	0–2	LST night (quartiles)	–	116.5	< 0.01
Burkart 2016[b]	Daily UTCI	1 °C above the 99th %	All cause mortality	0–2	LST day (highest quartile vs others)	1.08, 1.07–1.10	153.9	< 0.01
Burkart 2016	Daily UTCI	1 °C above the 99th %	All cause mortality	0–2	LST day (quartiles)	–	197.4	< 0.01
Burkart 2016[b]	Daily UTCI	1 °C above the 95th %	All cause mortality	0–2	LST day (highest quartile vs others)	1.02, 1.02–1.02	153.1	< 0.01
Burkart 2016	Daily UTCI	1 °C above the 95th %	All cause mortality	0–2	LST day (quartiles)	–	211.6	< 0.01
Burkart 2016[a,b]	Daily UTCI	1 °C above the 99th %	All cause mortality	0–2	NDVI (lowest quartile vs others)	1.10, 1.08–1.13	59.5	< 0.01
Burkart 2016	Daily UTCI	1 °C above the 99th %	All cause mortality	0–2	NDVI (quartiles)	–	65.5	< 0.01
Burkart 2016	Daily UTCI	1 °C above the 95th %	All cause mortality	0–2	NDVI (lowest quartile vs others)	1.02, 1.01–1.03	74.7	< 0.01
Burkart 2016[b]	Daily UTCI	1 °C above the 95th %	All cause mortality	0–2	NDVI (quartiles)	–	18.9	< 0.01
Burkart 2016	Daily UTCI	1 °C above the 99th %	All cause mortality	0–2	Distance from water (> 4 km vs ≤ 4 km)	1.05, 1.04–1.06	56.2	< 0.01
Burkart 2016	Daily UTCI	1 °C above the 95th %	All cause mortality	0–2	Distance from water (> 4 km vs ≤ 4 km)	1.01, 1.01–1.02	41.8	< 0.01
Gronlund 2016[a]	Daily maximum temperature	> 97th% vs < 90th %	Hospitalizations for renal, heat, or respiratory causes	0–1	% non-green (25th vs 75th %)	1.02, 0.98–1.06	0.79	0.37
Gronlund 2016	Daily maximum temperature	> 97th% vs < 90th %	Hospitalizations for renal, heat, or respiratory causes	0–5	% non-green (25th vs 75th %)	1.01, 0.96–1.06	0.08	0.78
Ho 2016[a]	Daily mean humidex	1 °C increase	Non-accidental mortality	0	Humidex map, areas (> 34.4 °C vs < 34.4 °C)	1.06, 1.00–1.12	4.49	0.03

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Table 3 (*continued*)

Author	Heat definition	Units for heat contrast	Outcome	Lags	Categories for the stratification variable	RRR	Cochran's test	
							Chi square	p-value
Milojevic 2016	Daily mean temperature	> 22.3 °C vs ≤22.3 °C	All cause mortality	0–1	UHI anomaly (−0.5 °C vs +0.5 °C) relative to London mean	1.00, 0.96–1.06	0.03	0.87
Son 2016	Daily mean temperature	1 °C above the 90th %	All cause mortality except external causes	0–1	NDVI (low vs medium vs high)	–	1.38	0.50
Son 2016[a]	Daily mean temperature	1 °C above the 90th %	All cause mortality except external causes	0–1	NDVI (low vs medium and high combined)	1.01, 0.99–1.04	1.19	0.28

Abbreviations: RRR, ratio of the relative risks; UHI, urban heat island; UHII, Urban heat island index; NDVI, Normalized Difference Vegetation Index LST, land surface temperature.

[a] RRR estimate included in the primary meta-analysis.

[b] RRR estimate was calculated after dichotomizing a multi-category effect measure modifier using fixed effect meta-analysis.

[c] Exposure contrast was converted to one-degree Celsius increases.

mortality with one degree increases in mean daily apparent temperature were quantified. In both cases, higher risk of mortality was observed in the higher NDVI category (higher greenness and cooler category), which is contrary to expectations. Burkart et al. (2016) found evidence of differences in the association between temperature and mortality across categories of nighttime land surface temperature when they contrasted days with temperature above the 99th percentile of the distribution with those below this percentile (RRR: 1.08, 95% CI: 1.06–1.10). When days with temperatures above the 95th percentile of the distribution were contrasted with other days, differences across categories of nighttime land surface temperature were less substantial, although the RRR estimate remained elevated > 1, suggesting that there was higher risk of temperature related mortality in hotter areas (RRR: 1.02, 95% CI: 1.01–1.02). Goggins et al. (2013) ran models with temperature parameterized using linear terms (hot season temperature only), and also as two piecewise linear terms. The RRR estimates from both were nearly identical.

3.8. Meta analysis

Fig. 2 shows results from a random effects meta-analysis of the primary RRR estimates. The pooled RRR estimate was slightly further from the null for localized temperature indicators (RRR: 1.06, 95% CI: 1.03–1.09) than for vegetation (RRR: 1.05, 95% CI: 1.00–1.11). RRR estimates from studies that evaluated vegetation as EMMs were more inconsistent ($I^2 = 87.2\%$) than those that evaluated localized temperature indicators as EMMs ($I^2 = 59.4\%$). For the most part, the sensitivity analyses did not change the pooled estimates substantially (Supplemental Figs. 1–7). Also, removing the individual effect estimates did not substantially change the pooled RRR estimates (Supplemental Table 2). We did not observe evidence of publication bias when we evaluated the RRR estimates ($p = 0.905$ for Egger's test for small-study effects) or examined the funnel plot (Supplemental Fig. 8).

4. Discussion

In this systematic review and meta-analysis, we identified and summarized the epidemiologic literature that investigated indicators of microclimates as EMMs of the association between ambient temperature and morbidity and mortality. We calculated RRR estimates to characterize differences in the association between temperature and mortality or morbidity across categories of microclimate indicators. The use of this ratio lessened the influence of the different temperature contrasts used in the individual studies. The meta-analyses served to summarize the RRR estimates and indicated, overall, that those living in hotter or less vegetated areas had higher risk of mortality/morbidity in association with high ambient temperatures than those living in cooler or more vegetated areas.

We conducted separate meta-analyses for vegetation and localized temperature indicators. We made this decision because, while the presence of vegetation may contribute to lower localized temperatures, other landscape characteristics may also have cooling effects (van Hove et al., 2014). Nevertheless, the meta-RRR estimates for both microclimate indicator categories were similar in magnitude (1.05 vs 1.06). This is intuitive when one considers the strong relationship between vegetation and localized temperature. For example, the NDVI has shown to be negatively correlated with land surface temperature during the warm months (Sun and Kafatos, 2007).

The meta-RRR estimates should be interpreted as general indicators of the magnitude of differences of the association in hot/less vegetated areas versus cool/more vegetated areas. Papers differed in terms of temperature measures and parameterizations, microclimate indicator definitions and assessment, and lags. These between paper differences might reflect, at least in part, the fact that the relationship between temperature and health, and especially mortality, has been shown to be climate- and place-specific (Davis et al., 2016). Because the various

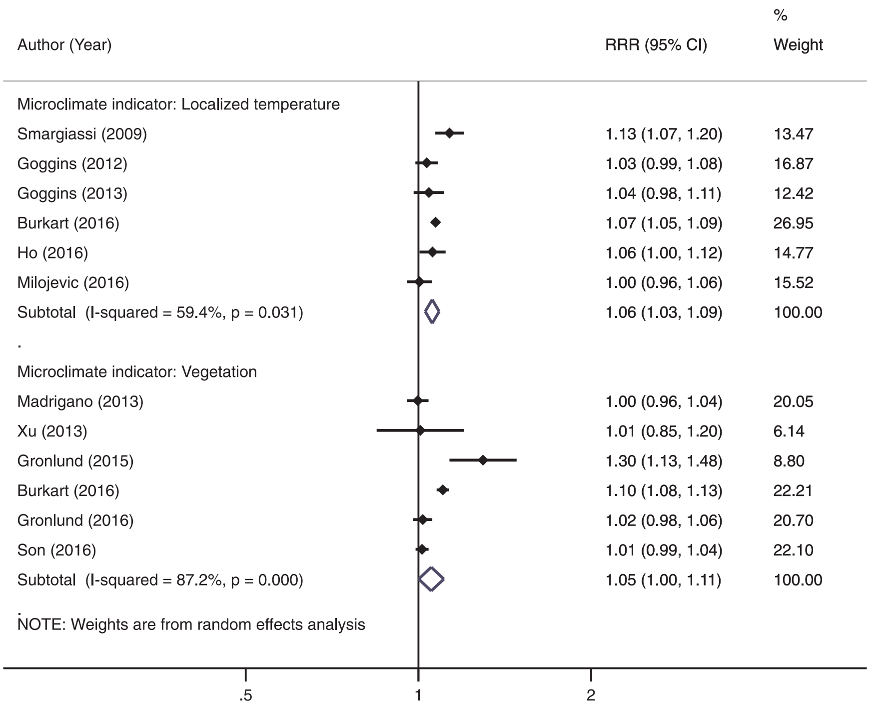

Fig. 2. Results from the meta-analysis of the ratio of the relative risks of the association between ambient temperature and morbidity or mortality for hot versus cold strata of microclimate indicators.

studies were conducted in different locations with different climates and infrastructure, the different temperature parameterizations and lags investigated from place to place might be appropriate.

Similarly, definitions of "hot" versus "cool" categories of localized temperature and vegetation varied across papers. Again, some of these different cut-points were driven by differences between cities and the relevant categories for each. To some extent, we were able to investigate the impact of alternative cut-points by exploring, in sensitivity analyses, multiple ways of combining categories, when contrasts were made across more than two categories (eg. contrasting hottest category with the coolest categories combined, the coolest category with the hottest categories combined, or dichotomizing the categories at the middle). Even after conducting the analysis with alternative categories, the meta-estimates remained the same. Nevertheless, this limits interpretation, speaks to the importance of clarity in defining the reasons that cut-points have been selected and raises the question of whether standard definitions for high versus low vegetation categories, in particular, should be developed and used.

Evidence of EMM in the temperature/mortality literature has been shown to depend on the temperature contrast examined (eg. > 95th percentile vs 50th percentile, or risk associated with 1 degree increases above a threshold) (Benmarhnia and Kaufman, 2016). By examining differences in RRR estimates within papers that used several temperature parameterizations, we were able to observe the influence of the temperature contrast used. In most cases, more extreme temperature comparisons (categorical) and more extreme thresholds led to more extreme RRR estimates. To address the potential that inferences about differences across hot/cold strata were influenced by the temperature contrast measure, we restricted the pooled analysis to estimates associated with one-degree increases in temperature above a threshold temperature value. The meta-RRR estimate remained unchanged (1.06).

Our objective was to characterize and quantitatively summarize the epidemiologic evidence of a modification of the association between daily temperature and daily mortality/morbidity outcomes by microclimate indicators. We excluded papers that did not have a time varying component (Belanger et al., 2016; Harlan et al., 2013; Heaviside et al., 2016; Jenerette et al., 2016; Johnson et al., 2009, 2012; Laaidi et al., 2012; Loughnan et al., 2011; Rosenthal et al., 2014; Scherber et al., 2013; Smoyer, 1998; Susca, 2012; Uejio et al., 2011; Vandentorren et al., 2006; Wu et al., 2008), and that could not be included in our quantitative summary. These papers are methodologically distinct from the papers included in the current review. Nevertheless, their presence in the literature is noteworthy. This body of research contributes to evidence of spatial variability in both temperature distributions and in adverse health effects of high ambient temperatures within cities. A summary of these papers in a separate systematic review would be an important contribution to the literature.

There are several ways by which investigators can build upon the area of research covered in the current meta-analysis. First, a valuable contribution would be investigation of the joint relationship between physiologic adaptation to extreme temperatures and landscape characteristics. Past studies have shown that there is regional variability in the temperature value at which mortality rates are lowest (Leone et al., 2013). In addition, scientists have demonstrated that, within the same location, the minimum mortality temperature has become hotter over time, which suggests either physiologic or behavioral adaptation to changes in temperature (Astrom et al., 2016). The literature identified in this review used varying temperature metrics (eg. maximum temperature, apparent temperature), temperature contrasts, and microclimate indicators. Because evidence of EMM is dependent upon the exposure metric used (Benmarhnia and Kaufman, 2016), and because human adaptation to temperature may be location dependent, multicity studies that attempt to utilize the same statistical methods, metrics, and microclimate indicators would be a valuable contribution by allowing consistency across locations while accommodating place based differences, such as different minimum mortality temperature thresholds.

Future work might also consider the combined effect of microclimate indicators, outdoor ambient temperature, indoor temperature, and personal behaviors and physiology on personal temperature experiences and the associated health responses. In a study of 16 homes in one city, indoor and outdoor temperature were shown to be highly correlated (Nguyen et al., 2014). However, there is evidence that personal temperature experiences are largely influenced by factors such as time spent indoors, the home thermal environment, and individual-level physiological characteristics (Bernhard et al., 2015). In addition, factors such as crime and noise may affect window opening behaviors, building ventilation and indoor temperatures (Gronlund, 2014). Since most people spend the majority of their time indoors (Anderson et al., 2013), it is important to consider the relationship of landscape characteristics and outdoor temperatures with indoor temperatures and health.

With a few exceptions, aside from vegetation, the epidemiologic literature we reviewed was largely lacking in its assessment of individual landscape characteristics that could potentially modify the association between temperature and health. Future epidemiology case-crossover and time series analysis should fill this gap. Literature from other fields has already started to distinguish between various types of vegetation. In Germany, the cooling effects of urban forests were shown to be more important than urban parks (Jaganmohan et al., 2016). A review paper from 2007 discusses the concept of health urbanization, and urban design choices, such as building insulation, that may impact energy consumption and risk of mortality from both cold and hot temperatures (Campbell-Lendrum and Corvalan, 2007). Roofing surfaces (green or cool) may have important urban heat island reduction effects (Saiz et al., 2006). Some of these factors are likely to be represented in measures like the NDVI (green roofs) or localized temperature indicators. However, it would be an important contribution to evaluate the independent contribution of these characteristics to differences in health effects of temperature exposures.

Also, differences in wind-velocity have been shown to be strong determinants of intra-urban variability in human thermal comfort level (van Hove et al., 2014). Future studies should better characterize and consider landscape characteristics that affect wind velocity, such as the height of trees and buildings. Other urban characteristics that could be evaluated as modifiers include spacing of buildings, surface albedo, the ratio between building height and street width, and sky view factor (the amount of visible sky at a given location). All of these factors impact radiation and air flow and might be important determinants of local climates (van Hove et al., 2014). Also, studies could be designed to consider the impact of landscape characteristics on humidity, which is an important determinant of thermal comfort and is also be influenced by vegetation, such as trees (Hass et al., 2016). The spatial resolution of many of the modification variables was relatively coarse (250+ m in many cases). This could lead to misclassification. For example, one study showed that the mean and median measurable cooling effects of parks in London were 125 and 99 m, respectively (Doick et al., 2014). In other fields, finer spatial resolution of these microclimate indicators is already being measured and used (Jenerette et al., 2016).

5. Conclusion

We observed compelling evidence that microclimate indicators within cities modify the association between temperature and morbidity/mortality within cities. This review also demonstrates that the body of epidemiologic literature focusing on this topic is relatively small. It is well worth the effort to pursue more research on this topic, considering its public health importance. This research area provides important information about the complex relationship between the urban landscape, ambient temperature, and human health, all of which should be considered within the context of urban design conversations. With appropriate planning, urbanization processes can be optimized to promote health.

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Conflicts of interest

The authors have no conflicts of interest to report.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.envres.2017.11.004.

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