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Permalink

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Journal

European Journal of Preventive Cardiology

ISSN

2047-4873

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Publication Date

2025-12-17

DOI

10.1093/eurjpc/zwaf771

Peer reviewed

The effect of urban heat island intensity on the rate of emergency department visits for acute myocardial infarctions

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Received 9 June 2025; revised 4 September 2025; accepted 20 October 2025; online publish-ahead-of-print 17 December 2025

Aims

This study investigates the effect of urban heat island exposure on clinically significant cardiovascular disease (CVD) and how this relationship changes when accounting for other environmental and social factors.

Methods and results

We used publicly available data from California urban areas on a census tract-level, including surface urban heat island intensity (SUHII), acute myocardial infarction (AMI) event rate, fine particulate matter pollution (PM_{2.5}), the Normalized Difference Vegetation Index (NDVI), racial and ethnic group percentages, and the Social Vulnerability Index (SVI). We created models to explore how these variables affect the predicted AMI event rate. We created census tract-level bivariate choropleth maps of urban areas in California counties. The models predict that residents in urban census tracts with median and high SUHII exposure have a 17 and 22% increased AMI event rate, respectively, compared with residents living in census tracts with low SUHII exposure. Increasing PM_{2.5} and SVI were associated with increasing predicted AMI event rates. Urban census tracts with a higher percentage of individuals who were identified as Hispanic, Black, and American Indian had higher predicted AMI event rates.

Conclusion

This study highlights the intersection of SUHII, AMI events, and various environmental and social factors within urban areas on a census tract-level. It emphasizes the need to implement mitigation strategies to decrease the urban heat island effect, which may reduce the rate of heat-related AMI events.

Lay summary

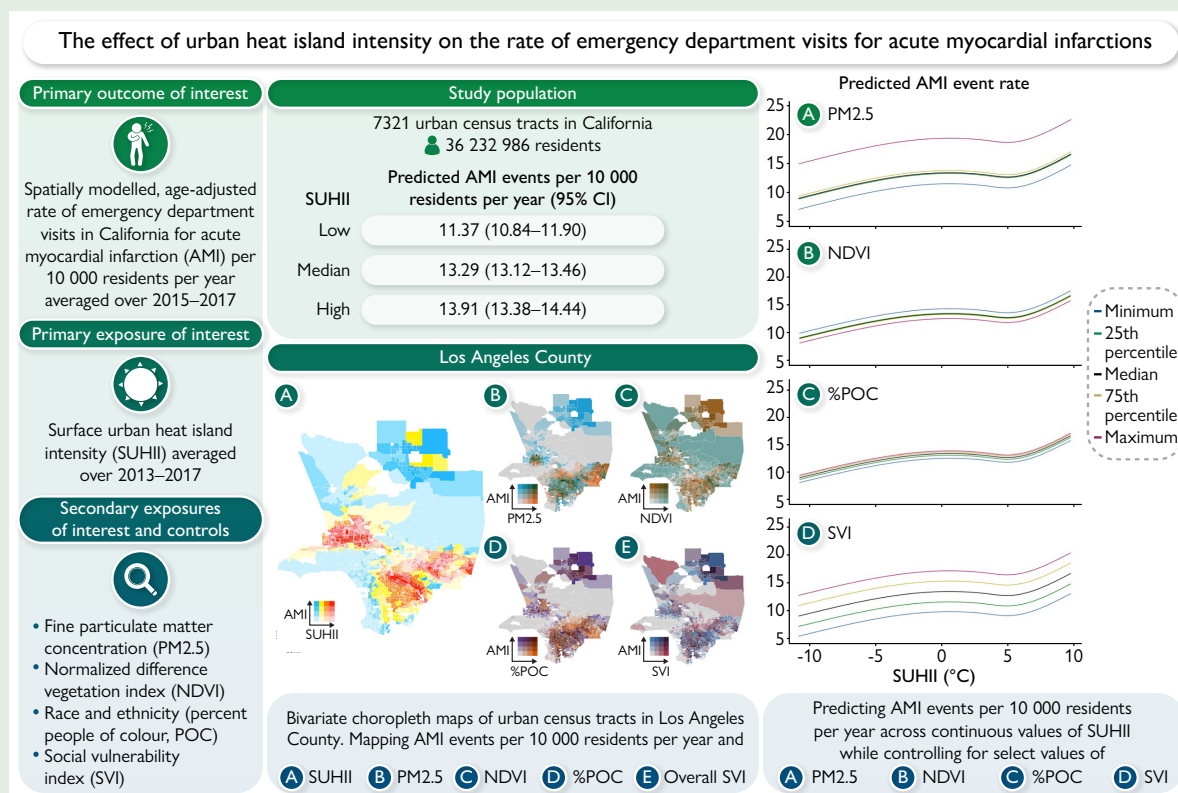
In a study of urban areas in California, the rate of heart attacks is predicted to be higher in census tracts with higher urban heat island intensity.

- Census tracts with greater exposure to air pollution and increased social vulnerability are also predicted to have higher rates of heart attacks.
- The rate of heart attacks is predicted to be higher in census tracts with higher representation of people of colour, specifically for people who were identified as Hispanic, Black, or American Indian.

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Graphical Abstract



Keywords

Myocardial infarction • Heart disease risk factors • Urban health • Hot temperature • Climate change • Health disparate minority and vulnerable populations

Introduction

Climate change has not only led to a gradual increase in global average temperature, but also increasing frequency, duration, and intensity of extreme heat events including heat waves.^{1,2} These extreme heat events have been associated with increased cardiovascular disease (CVD)-related morbidity and mortality.^{3–6}

Urban areas are particularly vulnerable, as they can develop higher temperatures compared with their rural counterparts, a phenomenon known as the urban heat island (UHI) effect. Urban heat islands are caused by increased heat-absorptive surfaces and heat-generating activities in combination with decreased evaporative cooling from vegetation.⁷ Heat waves are associated with higher UHI intensity compared with periods of cooler weather, which reciprocally augments heat stress in urban environments since UHIs locally exacerbate the effects of regional climates.⁸ During extreme heat events, urban areas with higher UHI intensity have been shown to have increased CVD-related morbidity and mortality.^{6,9}

Other factors that contribute to increased risk for CVD include race and ethnicity. Individuals who identified as Hispanic, non-Hispanic Black, and American Indian have higher rates of CVD or predisposing conditions such as hypertension, obesity, and diabetes.^{10,11} People of colour (POC, individuals who do not identify as non-Hispanic White) experience health disparities due to social determinants of health, which include unhealthy living conditions caused by the built environment.¹¹ Given the health risks associated with heat stress, living in an area with higher UHI exposure can be considered an unhealthy living

condition. Data have shown that both POC, regardless of socio-economic status, and people living below the poverty line live in areas with increased UHI exposure in the USA.¹² This may be due to prior redlining and/or under-investment in areas where historically marginalized communities live due to the White flight phenomenon.^{12,13}

As described above, CVD risk is influenced by various social, structural, and environmental factors. Since there is significant intra-city variation in these factors, including UHI intensity, it is important to analyse data on a geographic scale that is high-resolution, such as the census tract-level, to capture such intricacies.¹² Additionally, studies have not yet investigated how baseline UHI exposure, regardless of extreme heat events, impacts clinically significant CVD.

This study aims to investigate the relationships between UHI intensity and CVD on a census tract-level within urban areas in the state of California and how this relationship changes when controlling for other environmental and social variables.

Methods

We received IRB exemption from the University of California, Los Angeles for this study.

Study area

We chose the state of California within the USA as the area of interest since it has a high average number of clear-sky days during the summer months of June through August. While variable throughout the state, on average there

are 75–87% clear-sky days in June, 88–91% in July, and 90–91% in August.¹⁴ This is important to consider, as the surface urban heat island intensity (SUHII), as defined in the next section, is a clear-sky estimate and thus only valid in clear-sky conditions.

Additionally, according to the 2010 California Census of Population and Housing, 95% of the population in California lived in urban areas, allowing for a large number of urban census tracts to be included in this study.¹⁵ Counties are the largest legal and administrative subdivisions of most states within the USA, typically formed from geographic boundaries. Census tracts are subdivisions of a county, forming homogeneous units with stable boundaries that contain 1500–8000 people. A census tract is considered urban when there is a population of at least 5000 residents, or at least 2000 housing units.¹⁵

Surface urban heat island intensity

The primary exposure of interest was the SUHII, created by Chakraborty *et al.*¹⁶ The SUHII was calculated as the difference between land surface temperature in urban and rural areas, measured in degrees Celsius. We used the summer (June through August) daytime SUHII estimates. Land surface temperature mean estimates were derived from the Moderate Resolution Imaging Spectroradiometer 8-day land surface temperatures from NASA's Aqua satellite at 1000 m resolution from 2013 to 2017. Since the satellite sensors do not penetrate clouds, these are clear-sky estimates. The European Space Agency's Climate Change Initiative land cover data at 300 m resolution for 2015 were used to identify urban and rural areas to calculate the urban-rural differentials for each census tract. The rural references represent the non-urban, non-water pixels within the urbanized area.

Acute myocardial infarction event rate

The primary outcome of interest was the acute myocardial infarction (AMI) event rate, which was obtained from the 'Cardiovascular Disease' indicator in the CalEnviroScreen 4.0 dataset. CalEnviroScreen 4.0 defines this indicator as a spatially modelled, age-adjusted rate of emergency department visits in California for AMI per 10 000 residents per year averaged over 2015–17. It is a census tract estimate, derived from population-weighted 2010 census block estimates. The AMI data were obtained from Emergency Department and Patient Discharge Datasets from the State of California, Office of Statewide Health Planning and Development. CalEnviroScreen 4.0 included records of patients residing in California with a primary diagnosis of AMI coded for the emergency department visit. Also included were hospitalizations coded with a primary diagnosis of AMI if the hospitalization was described as originating from the hospital's own emergency department.¹⁷ In this study, we reference this 'Cardiovascular Disease' indicator as the AMI event rate, to more precisely represent the primary diagnosis of interest.

Fine particulate matter pollution (PM2.5)

Air pollution, especially particulate matter, has been shown to increase CVD-morbidity and mortality. Particulate matter exposure has been associated with increased mortality in individuals who have an AMI.¹⁷ Fine particulate matter (PM2.5) pollution was included as a secondary exposure of interest to address air pollution as a possible confounding environmental factor. We used the PM2.5 indicator from CalEnviroScreen 4.0, which is a census tract estimate of the annual mean concentration ($\mu\text{g}/\text{m}^3$) of fine particulate matter measuring 2.5 μm or less in diameter over 2015–17. The calculations were derived from data from the Air Monitoring Network and Satellite Remote Sensing Data from the California Air Resources Board.¹⁷

Normalized Difference Vegetation Index

To further address possible confounding environmental factors, we used an indicator for green space called the Normalized Difference Vegetation Index (NDVI) as a secondary exposure of interest. The NDVI is a value indicating the health and density of vegetation in an area, determined by measures of surface reflectance in the red and near-infrared bands. The NDVI census

tract estimates from Chakraborty *et al.*¹⁶ were used in this study, calculated using the Moderate Resolution Imaging Spectroradiometer 8-day surface reflectance product from NASA's Aqua satellite at 500 m resolution from 2013 to 2017. The NDVI ranges from –1 to 1; a high positive value corresponds to healthy, dense vegetation, whereas values close to zero represent barren areas, and negative values suggest a lack of dry land.

Race and ethnicity

To investigate social confounding factors, another secondary exposure of interest was race and ethnicity. The racial and ethnic population estimates were obtained from CalEnviroScreen 4.0 and were initially derived from the 2019 American Community Survey. Per cent POC (% POC) represents the sum of population estimate percentages of residents in a census tract who did not identify as non-Hispanic White. Per cent White (% White) is the population estimate of the per cent per census tract of those who were identified as non-Hispanic White. Per cent Hispanic (% Hispanic) is the population estimate of the per cent per census tract of those who were identified as Hispanic or Latino. Per cent Black (% Black) is the population estimate of the per cent per census tract of those who were identified as non-Hispanic Black or African American. Per cent Asian (% Asian) is the population estimate of the per cent per census tract of those who were identified as non-Hispanic Asian or Pacific Islander. Per cent American Indian (% American Indian) is the population estimate of the per cent per census tract of those who were identified as non-Hispanic American Indian or Native American. Per cent Multiple Races (% Multiple Races) is the population estimate of the per cent per census tract of those who were identified as non-Hispanic 'Other' or as multiple races.¹⁶

Social Vulnerability Index

The final secondary exposure of interest was the Social Vulnerability Index (SVI) created by the Agency for Toxic Substances and Disease Registry of the Centers for Disease Control and Prevention.¹⁸ The SVI is a place-based index designed to identify communities experiencing social vulnerability. The 2018 SVI database was used in this study as it was derived from 2010 census tracts and demographic variables from the 2014–18 American Community Survey. California data for overall SVI were used in the primary and secondary analyses as well as the choropleth maps. However, we explored the individual SVI Themes (Theme 1: Socioeconomic Status, Theme 2: Household Composition and Disability, Theme 3: Minority Status and Language, and Theme 4: Housing Type and Transportation) in the bivariate plots. The SVI is a percentile ranging from 0 to 1, where values closer to 1 represent greater social vulnerability.¹⁸ See [Supplementary material online, Table S1](#) for the demographic variables that were included in the 2018 SVI database.

Statistical analysis

The datasets were organized by census tract Federal Information Processing Standard codes and filtered to only include urban census tracts that had values for SUHII, AMI event rate, PM2.5, NDVI, racial and ethnic group percentages, and SVI.

Bivariate plots

Bivariate plots were created to explore the bivariate relationship between the AMI event rate and each exposure of interest, which helped inform the type of functions to use for each variable in the primary analysis. Pearson's correlation coefficients were calculated for each bivariate relationship.

Primary analysis: Predicting acute myocardial infarction event rate

We determined the predicted AMI event rate for urban census tracts across California using the following model:

$$\hat{y}_c = \alpha + ns(\text{SUHII}_c) + ns(\text{PM2.5}_c, \text{df} = 3) + \text{NDVI}_c + \text{POC}_c + \text{SVI}_c \quad (1)$$

where $\hat{y}_c$ is the predicted AMI event rate for a given census tract and α is the intercept. The primary exposure–response association was defined using a natural cubic spline with three internal knots placed at the 10th, 75th, and 90th percentiles of SUHII. The model controlled for the secondary exposures of interest: PM2.5, where $ns(PM2.5_c, df = 3)$ is a natural cubic spline of PM2.5 for a given census tract with three degrees of freedom (df), NDVI ($NDVI_c$), % POC (POC_c), and overall SVI (SVI_c).

Sensitivity analyses were performed to assess the fit of the model, including using a simple linear term instead of a natural cubic spline for the primary exposure–response association, and variations in knot placement (33rd–66th, 10th–50th–90th, 25th–50th–75th, and 10th–25th–75th–90th percentiles instead of 10th–75th–90th). We also assessed the sensitivity to df used to control for PM2.5 (2, 4, and 5 instead of 3) vs. using a simple linear term, and using natural cubic splines with $df = 3$ when controlling for NDVI, % POC, and overall SVI instead of simple linear terms.

To investigate the effect of each secondary exposure of interest, the predicted AMI event rate was modelled across continuous values of SUHII while controlling for the minimum, 25th percentile, median, 75th percentile, and maximum values of a given secondary exposure of interest, while holding the others constant at their median values.

The predicted AMI event rate for urban census tracts across California was calculated for low (1st percentile), median, and high (99th percentile) SUHII while holding all secondary exposures of interest constant at their median values. The 1st and 99th percentiles were chosen to capture the effect of SUHII for residents living in urban census tracts at either end of the SUHII distribution.

Secondary analyses: Racial and ethnic subgroup analysis

Subgroup analyses were performed to explore subgroup-specific patterns for each racial and ethnic group. We used the same model (Equation 1) to predict the AMI event rate as in the primary analysis, except the specific racial or ethnic group percentage was used instead of % POC. The predicted AMI event rate was modelled across continuous values of SUHII while controlling for the minimum, 25th percentile, median, 75th percentile, and maximum values of the racial or ethnic group percentage while holding all other secondary exposures of interest constant at their median values.

The predicted AMI event rate was calculated for low, median, and high SUHII for each racial and ethnic group while holding all other secondary exposures of interest constant at their median values.

Secondary analyses: County analysis

To determine how the predicted AMI event rate varies for different California counties, we calculated the predicted AMI event rate for urban census tracts in selected counties. The 10 counties with the highest number of urban census tracts were selected. The model used in the primary analysis was adjusted to account for over-fitting due to the significantly lower number of urban census tracts in each county compared to all of California:

$$\hat{y}_c = \alpha + SUHII_c + ns(PM2.5_c, df = 2) + NDVI_c + POC_c + SVI_c \quad (2)$$

Sensitivity analyses were performed to assess the fit of the models, which were compared with variations such as keeping the natural cubic spline for the primary exposure–response association while using different knot placement, as well as using a simple linear term to control for PM2.5 or keeping the original natural cubic spline with $df = 3$.

The predicted AMI event rate for urban census tracts within selected counties was calculated for low, median, and high SUHII while holding all secondary exposures of interest constant at their median values.

All predictions are presented with a 95% confidence interval (CI). The primary and secondary analyses were performed in RStudio using the splines package.

Spatial correlation and regression

Moran's I was used to test for spatial autocorrelation for each variable. Moran's I was also used to test for spatial autocorrelation of the regression residuals of

the model used in the primary analysis. A spatial error model was used for spatial regression, aiming to correct the standard error estimates of regression coefficients when spatial autocorrelation is present. Unfortunately, the ability to predict the outcome of interest (response variable) using spatial regression models is limited, since the current software is unable to produce observations of the response variable being predicted.¹⁹ The spatial correlation and regression analyses were performed in RStudio using the spatialreg package.

Choropleth maps

For geographical visualization of the data, we created bivariate choropleth maps in RStudio using the biscale package. The 2010 census tract Shapefiles were downloaded from census.gov and converted to geoJSON files, which were imported as map boundaries into RStudio.

Results

Study characteristics

The study included 7321 urban census tracts across the state of California. Table 1 shows the census tract characteristics for all values of SUHII and SUHII quartiles (Q1–Q4). The median overall SUHII was 1.71°C. Within the SUHII quartiles, the median values are as follows: −1.64°C for SUHII Q1, 0.83°C for SUHII Q2, 2.62°C for SUHII Q3, and 4.72°C for SUHII Q4.

The median AMI event rate was lowest in SUHII Q1 (10.28 AMI events per 10 000 per year) and highest in SUHII Q4 (13.45 AMI events per 10 000 per year). The median AMI event rate was similar in SUHII Q2 and Q3 (12.65 and 12.59 AMI events per 10 000 per year, respectively).

Median PM2.5 was lowest in SUHII Q1 (9.52 µg/m³) and highest in SUHII Q4 (11.53 µg/m³). Median NDVI was highest in SUHII Q1 (0.30) and lowest in SUHII Q4 (0.26). Median overall SVI was lowest in SUHII Q1 (0.29) and highest in SUHII Q4 (0.62).

Median % POC was lowest in SUHII Q1 (45.01%) and highest in SUHII Q4 (82.47%). Reciprocally, median % White was highest in SUHII Q1 (55.00%) and lowest in SUHII Q4 (17.53%). Median % Hispanic was lowest in SUHII Q1 (18.86%) and highest in SUHII Q4 (47.78%). Median % Black was lowest in SUHII Q1 (2.27%) and highest in SUHII Q2 (3.42%). Median % Asian was lowest in SUHII Q1 (12.87%) and highest in SUHII Q3 (18.27%). Median % American Indian was 0.00% for all SUHII quartiles. Median % Multiple Races was highest in SUHII Q1 (3.58%) and lowest in SUHII Q4 (2.24%).

Bivariate plots

Supplementary material online, Figures S1–S15, shows the bivariate relationships between the AMI event rate and each exposure of interest. Supplementary material online, Table S2 lists the correlation coefficients for these relationships. Determining the strength of the correlation using the Chan YH method,²⁰ there were poor positive correlations between the AMI event rate and SUHII (0.21), % Black (0.25), and SVI Theme 4 (0.21). There were fair positive correlations for PM2.5 (0.28), % POC (0.43), % Hispanic (0.53), overall SVI (0.52), SVI Theme 2 (0.45), and SVI Theme 3 (0.41). There was a moderately strong positive correlation for SVI Theme 1 (0.59). There was a poor negative correlation for % Multiple Races (−0.23) and fair negative correlations for NDVI (−0.27), % White (−0.43), and % Asian (−0.29). There was no correlation for % American Indian (0.07), most likely due to a low population of individuals who were identified as American Indian living in California urban census tracts.

Table 1 Characteristics of urban census tracts across California for all surface urban heat island intensity and by surface urban heat island intensity quartiles

Characteristic	All SUHII	SUHII Q1	SUHII Q2	SUHII Q3	SUHII Q4
Urban census tracts, #	7321	1831	1830	1830	1830
SUHII, °C					
Range	−10.74 to 9.77	−10.74 to −0.22	−0.22 to 1.71	1.71–3.49	3.49–9.77
Median (Interquartile Range, IQR)	1.71 (3.70)	−1.64 (2.08)	0.83 (0.96)	2.62 (0.85)	4.72 (1.58)
AMI event rate ^a					
Range	2.86–35.47	2.86–32.35	3.95–32.56	4.27–35.47	4.21–27.88
Median (IQR)	12.30 (7.01)	10.28 (6.38)	12.65 (7.60)	12.59 (6.79)	13.45 (6.40)
PM2.5, µg/m ³					
Range	5.17–16.39	5.17–15.74	5.19–16.39	5.22–15.50	5.17–15.45
Median (IQR)	10.62 (3.29)	9.52 (3.04)	10.16 (3.23)	11.25 (3.16)	11.53 (3.38)
NDVI					
Range	−0.28 to 0.80	−0.28 to 0.80	−0.07 to 0.73	−0.05 to 0.68	−0.05 to 0.53
Median (IQR)	0.28 (0.12)	0.30 (0.15)	0.29 (0.12)	0.27 (0.11)	0.26 (0.09)
POC, %					
Range	0.00–100.00	0.00–100.00	6.79–99.82	6.19–100.00	13.97–100.00
Median (IQR)	64.99 (44.65)	45.01 (37.08)	61.42 (40.51)	72.83 (41.80)	82.47 (33.56)
White, %					
Range	0.00–100.00	0.00–100.00	0.18–93.21	0.00–93.81	0.00–86.02
Median (IQR)	35.01 (44.66)	55.00 (37.09)	38.58 (40.51)	27.16 (41.81)	17.53 (33.56)
Hispanic, %					
Range	0.00–100.00	0.00–98.62	0.7–99.00	1.36–98.97	0.74–100.00
Median (IQR)	31.66 (42.68)	18.86 (25.10)	32.06 (39.24)	36.08 (42.52)	47.78 (51.33)
Black, %					
Range	0.00–84.71	0.00–82.16	0.00–84.71	0.00–80.64	0.00–61.07
Median (IQR)	2.80 (6.07)	2.27 (4.64)	3.42 (7.51)	3.22 (8.28)	2.68 (4.98)
Asian, %					
Range	0.00–94.55	0.00–94.55	0.00–81.93	0.00–83.88	0.00–87.55
Median (IQR)	9.56 (15.79)	8.19 (12.87)	8.10 (13.80)	11.18 (18.27)	11.23 (17.66)
American Indian, %					
Range	0.00–19.52	0.00–9.14	0.00–19.52	0.00–7.41	0.00–13.83
Median (IQR)	0.00 (0.31)	0.00 (0.32)	0.00 (0.32)	0.00 (0.30)	0.00 (0.29)
Multiple races, %					
Range	0.00–17.07	0.00–17.07	0.00–15.53	0.00–15.76	0.00–13.62
Median (IQR)	2.90 (3.34)	3.58 (3.20)	3.06 (3.35)	2.76 (3.40)	2.24 (3.30)
Overall SVI, %ile					
Range	0.00–1.00	0.00–0.99	0.00–1.00	0.00–1.00	0.01–1.00
Median (IQR)	0.49 (0.51)	0.29 (0.40)	0.49 (0.51)	0.59 (0.51)	0.62 (0.42)

^aSpatially modelled, age-adjusted rate of emergency department visits in California for AMI per 10 000 residents per year averaged over 2015–17.

Primary analysis

Predicting acute myocardial infarction event rate: All urban census tracts

The predicted AMI event rate increased with increasing SUHII within the low range of the SUHII distribution, plateaued in the mid-range, and then increased again within the high range (Figure 1). When controlling for different values of the secondary exposures of interest, increasing values of PM2.5 (Figure 1A), % POC (Figure 1C), and overall SVI (Figure 1D) increased the predicted AMI event rate. Increasing values of NDVI (Figure 1B) decreased the predicted AMI event rate.

There was a statistically significant difference between the predicted AMI event rate for low SUHII (11.37, 95% CI 10.84–11.90) and median SUHII (13.29, 95% CI 13.12–13.46), as well as low SUHII and high SUHII

(13.91, 95% CI 13.38–14.44) (Table 2, Figure 2). While the predicted AMI event rate was higher for high SUHII compared with median SUHII, the difference was not statistically significant.

Secondary analyses

Racial and ethnic subgroup analysis

When controlling for individual racial and ethnic groups, increasing % White (see Supplementary material online, Figure S16), % Asian (see Supplementary material online, Figure S19), and % Multiple Races (see Supplementary material online, Figure S21) decreased the predicted AMI event rate. Increasing % Hispanic (see Supplementary material online, Figure S17), % Black (see Supplementary material online,

Figure S18), and % American Indian (see [Supplementary material online, Figure S20](#)) increased the predicted AMI event rate.

The AMI event rate was predicted to be lowest in urban census tracts with low SUHII and highest in urban census tracts with high SUHII for all racial and ethnic groups. There was a statistically significant difference between the predicted AMI event rate for low SUHII and median SUHII as well as low SUHII and high SUHII for all racial and ethnic groups. The difference between the predicted AMI event rate for median SUHII and high SUHII was statistically significant for % Black, % Asian, % American Indian, and % Multiple Races, though not for % POC, % White, or % Hispanic (see [Supplementary material online, Figure S22](#)).

County analysis

The AMI event rate was predicted to be lowest in urban census tracts with low SUHII and highest in urban census tracts with high SUHII for 80% of the selected counties (Los Angeles, San Diego, Orange, Santa Clara, Alameda, Sacramento, Contra Costa, and San Francisco) ([Table 2, Figure 2](#)). Of these, there was a statistically significant difference between the predicted AMI event rate for low SUHII and median SUHII, except for Sacramento and Contra Costa, and a statistically significant difference between low SUHII and high SUHII, except for Contra Costa alone. There was a statistically significant difference between median SUHII and high SUHII in Los Angeles, San Diego, Santa Clara, and Alameda. Riverside and San Bernardino were the only counties where low SUHII was associated with a higher predicted AMI event rate, though in Riverside the differences in predicted AMI event rate for low and high SUHII compared with median SUHII were not statistically significant.

Spatial correlation and regression

The primary outcome of interest and the primary and secondary exposures of interest were positively autocorrelated with Moran's I testing for spatial correlation, with $P < 0.01$ for all correlations. The Moran's I statistics were the following: 0.82 for AMI event rate, 0.88 for SUHII, 0.99 for PM2.5, 0.79 for NDVI, 0.84 for % POC, and 0.69 for overall SVI. This suggests that each variable is spatially clustered within urban areas in California. Moran's I testing of the regression residuals of the primary model ([Equation 1](#)) demonstrated spatial autocorrelation as well (0.69, $P < 0.01$).

The spatial error model used to perform spatial regression of the primary model ([Equation 1](#)) had a lambda of 0.89 ($P < 0.01$), also indicative of spatial autocorrelation. The coefficients of the spatial error model are presented in [Supplementary material online, Table S3](#). When comparing these coefficients to the primary model ([Equation 1](#)), which is an ordinary least-squares model, there was no change in the direction of the estimated effects, though there were changes in the magnitude. There were also changes in the P -values, particularly for the natural cubic spline estimate for SUHII 3.49–5.05°C.

Choropleth maps

Bivariate choropleth maps were created for the state of California (see [Supplementary material online, Figure S23](#)), to demonstrate the urban areas involved in the study, and selected California counties for increased granularity. The county choropleth maps illustrate the bivariate relationships between AMI event rate and SUHII, PM2.5, NDVI, % POC, and overall SVI. [Figure 3](#) demonstrates the choropleth maps of Los Angeles County. Other county maps are presented in [Supplementary material online, Figures S24–S32](#).

Sensitivity analyses

[Supplementary material online, Table S4](#) and [Figures S33–S35](#) show the sensitivity analyses for the primary analysis. When using a simple linear term, the primary exposure–response association was under-fitted compared with using a natural cubic spline. The tails of the model were sensitive to the number of knots; however, the model was insensitive to knot placement when using three knots (10th–50th–90th, 25th–50th–75th, or 10th–75th–90th percentiles of SUHII) (see [Supplementary material online, Figure S33](#)). The model varied slightly with different df in the natural cubic spline used to define PM2.5, and when using a simple linear term instead (see [Supplementary material online, Figure S34](#)). The model was insensitive to using natural cubic splines to define NDVI, % POC, and overall SVI instead of simple linear terms (see [Supplementary material online, Figure S35](#)).

[Supplementary material online, Table S5](#) and [Figures S36](#) and [S37](#) show the sensitivity analyses for the county analysis, using Los Angeles County as an example. The model did not change substantially when using a natural cubic spline to define SUHII instead of a simple linear term, particularly with three knots placed at 10th–75th–90th percentiles (see [Supplementary material online, Figure S36](#)). All county models were insensitive to different df in the natural cubic spline used to define PM2.5 (see [Supplementary material online, Figures S37–S46](#)). The majority were also insensitive to using a simple linear term to define PM2.5 instead; however, there were significant changes in the models for Riverside, Santa Clara, and San Bernardino Counties, particularly in Riverside and San Bernardino where the direction of the effect changed (see [Supplementary material online, Figures S40, S41, and 43](#)).

Discussion

In California urban areas, the AMI event rate was predicted to be lowest for residents living in census tracts in the low end of the SUHII distribution and highest for those in the high end of the SUHII distribution. There was a predicted 17% increased AMI event rate for residents living in urban census tracts with median SUHII exposure compared with low SUHII exposure, and a predicted 22% increased AMI event rate for those living in urban census tracts with high SUHII exposure compared with low SUHII exposure. A similar trend was observed for 8 out of 10 California counties with the highest number of urban census tracts. For the counties that did not follow this trend under the final model parameters (Riverside and San Bernardino), sensitivity analyses showed that when using a different function to define PM2.5, increasing SUHII was associated with increasing predicted AMI event rates. This suggests that PM2.5 may have a strong effect on the predicted AMI event rate in these counties.

This study suggests that there are additional factors that may exacerbate the risk for AMI events. Increasing particulate matter exposure, as measured by PM2.5, and increasing social vulnerability, as determined by overall SVI, were associated with increasing predicted AMI event rates. The subgroup analyses showed that urban census tracts with a higher percentage of individuals who were identified as Hispanic, Black, and American Indian had higher predicted AMI event rates. While increasing % POC was associated with increasing predicted AMI event rates in the primary analysis, this finding was largely driven by the population of individuals who were identified as Hispanic in California urban census tracts. The analyses also identify factors that may be protective. Increasing vegetation, as measured by NDVI, was associated with decreasing predicted AMI event rates. Additionally, urban

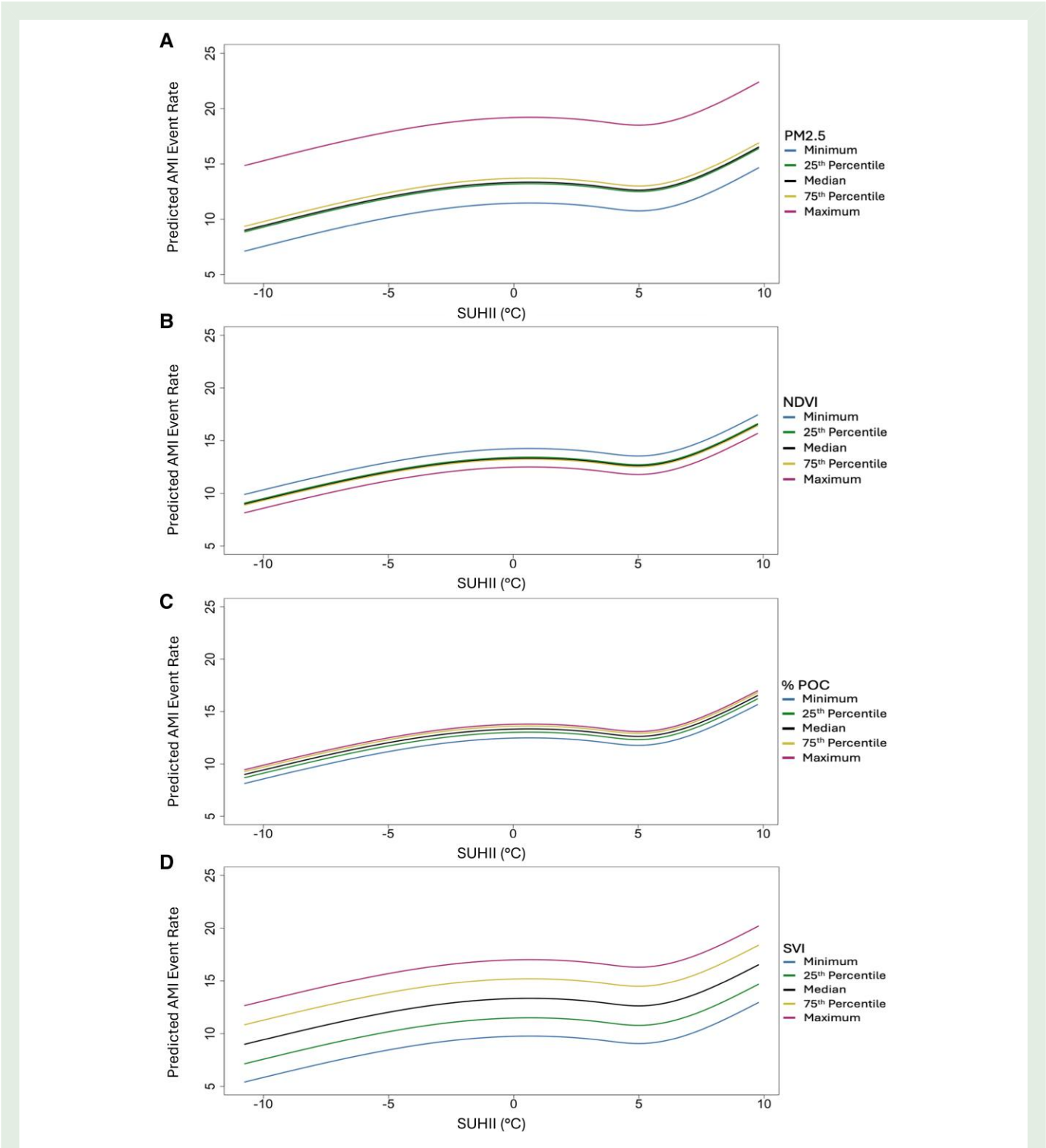


Figure 1 Predicting acute myocardial infarction events per 10 000 residents per year (acute myocardial infarction event rate) across continuous values of surface urban heat island intensity while controlling for selected values of the secondary exposures of interest. Selected values include the minimum (blue), 25th percentile (green), median (black), 75th percentile (yellow), and maximum (purple) values of PM2.5 (A), Normalized Difference Vegetation Index (B), per cent people of colour (C), and overall Social Vulnerability Index (D), while holding all other secondary exposures of interest constant at their median.

census tracts with a higher percentage of individuals who were identified as White, Asian, and either Other or Multiple Races had lower predicted AMI event rates.

Several studies have investigated the effect of extreme heat events on CVD. A systemic review and meta-analysis found a positive relationship between increasing temperature and CVD-related morbidity and

Table 2 Predicted acute myocardial infarction events per 10 000 residents per year (acute myocardial infarction event rate) for low, median, and high surface urban heat island intensities for all urban census tracts in California and selected counties

County	Urban census tracts, #	Population	SUHII	Predicted AMI event rate (95% CI)
All counties	7231	36 232 986	Low	11.37 (10.84–11.90)
			Median	13.29 (13.12–13.46)
			High	13.91 (13.38–14.44)
Los Angeles	2303	10 020 629	Low	12.50 (11.85–13.15)
			Median	14.45 (14.27–14.63)
			High	15.32 (14.99–15.65)
San Diego	605	3 223 113	Low	7.77 (7.22–8.32)
			Median	9.45 (9.25–9.65)
			High	10.57 (10.11–11.03)
Orange	581	3 168 011	Low	8.79 (8.05–9.54)
			Median	10.42 (10.18–10.66)
			High	10.99 (10.51–11.47)
Riverside	428	2 332 928	Low	21.85 (20.39–23.31)
			Median	20.42 (19.87–20.97)
			High	19.45 (18.53–20.37)
Santa Clara	372	1 927 470	Low	6.99 (6.17–7.81)
			Median	9.03 (8.80–9.26)
			High	9.78 (9.39–10.16)
Alameda	360	1 656 754	Low	10.01 (8.90–11.12)
			Median	12.71 (12.35–13.07)
			High	14.49 (13.78–15.20)
San Bernardino	318	1 945 972	Low	18.93 (17.62–20.24)
			Median	17.31 (16.80–17.82)
			High	15.01 (13.44–16.58)
Sacramento	307	1 483 372	Low	15.13 (13.88–16.38)
			Median	16.76 (16.33–17.19)
			High	17.75 (16.87–18.62)
Contra Costa	203	1 124 115	Low	11.83 (10.41–13.25)
			Median	12.53 (11.94–13.12)
			High	12.82 (11.95–13.69)
San Francisco	195	874 961	Low	6.69 (5.89–7.50)
			Median	7.94 (7.66–8.23)
			High	8.58 (8.07–9.09)

mortality.³ A USA county-level longitudinal analysis showed that each additional day of extreme heat was associated with a 0.12% increased monthly CVD-related mortality rate.⁴ A systematic review and meta-analysis revealed that exposure to heat waves was associated with an increased risk of AMI.⁵ A time series analysis across USA urban areas demonstrated that extreme heat increased the risk of CVD-related hospitalization by 1.5%.⁶ Additionally, other studies have illustrated the impact of UHIs on CVD during periods of extreme heat: in USA urban areas, the risk of CVD hospitalization due to extreme heat was greater in areas with higher UHI intensity, and in Beijing, hotter temperatures caused by the UHI effect were associated with increased CVD mortality.^{6,9}

This study further supports the association between heat exposure and increased risk of CVD, specifically AMI. It also offers a novel perspective by focusing on the effect of the baseline difference in temperature attributed to UHIs and does not fixate on periods of extreme heat.

This study suggests that even outside of extreme heat events, SUHII exposure may impact AMI event rates.

One of the strengths of this study was using census tract-level data, underscoring the range of the AMI event rate, SUHII, and the secondary exposures of interest across urban areas, which can be masked with city or county-level data. The choropleth maps highlight this variation and offer a visual representation of intra-urban heat islands, which studies have shown are remnants of prior redlining from the 1930s.^{21,22}

Extreme heat events are becoming more frequent and intense with climate change.^{1,2} Not only do heat waves augment UHI intensity, but the UHI effect itself has been shown to cause additional hot days and heat waves in urban areas.^{8,23} This study further supports the idea that increasing UHI intensity may increase heat stress and CVD in urban areas.⁴ The data also suggest that this burden is unequal—social factors such as a person's race, ethnicity, and socioeconomic status may make them even more vulnerable to CVD.

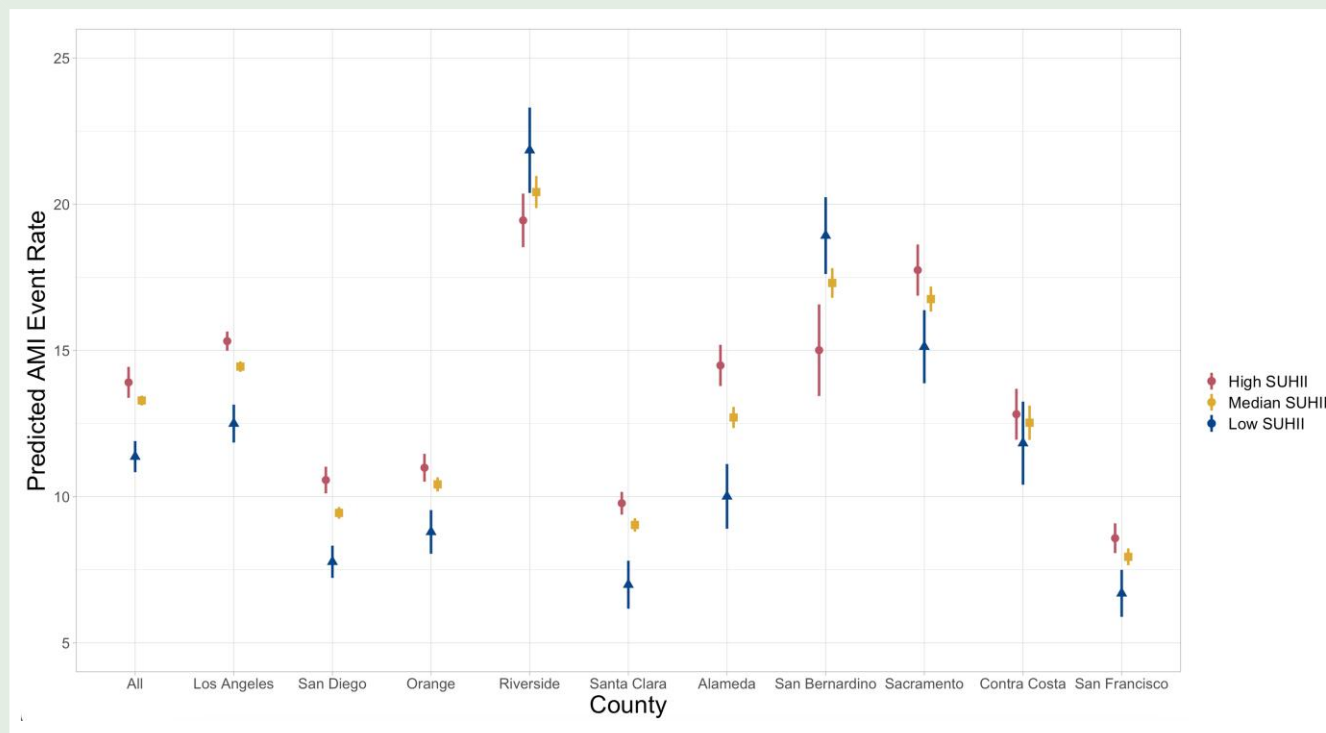


Figure 2 Predicted acute myocardial infarction events per 10 000 residents per year (acute myocardial infarction event rate) across all urban census tracts in California and selected counties. Predicted acute myocardial infarction event rates are shown for low (blue), median (yellow), and high (red) surface urban heat island intensity.

There are several limitations to this study. Foremost, the spatial regression analysis showed that there is spatial autocorrelation. This implies that there are likely other spatially structured variables that attribute to the unexplained variation in the ordinary least-squares model used in the primary analysis. As discussed in the Methods section, due to current limitations in software to calculate predictions from the spatial regression model, we are unable to determine the predicted AMI event rates, their significance, or how they may differ from the ordinary least-squares model after accounting for spatial autocorrelation. However, spatial regression can guide future studies that incorporate additional variables into the model that may reduce unexplained variation. Further research should include data on comorbidities that are known to increase the risk of AMI. It is possible that individuals who live in areas with higher SUHI also have a higher incidence of comorbidities. Unfortunately, such data were not included in the publicly available datasets used in this study.

Additionally, the AMI event rate data were derived from emergency department visits, which may not include the full extent of AMI events. Given that the severity of symptoms associated with AMIs would cause most people to present to the emergency department, this should still capture most AMI events. Furthermore, since California data were used in this study, it is unclear if these conclusions can be applied to other areas of the USA or more globally, where there are differences in the number of clear-sky days and per cent of the population living in urban areas. This study also does not consider that individuals spend time outside of their home census tract, where they may be exposed to different SUHIs, or even the variation in SUHI within census tracts. It also

does not address the amount of time individuals spend indoors vs. outdoors, and if they have access to indoor cooling measures such as air-conditioning. Of note, this study used summer daytime SUHI estimates in the analyses, thus the results should only be interpreted in this context, as SUHI varies by time of day and year.¹⁶

This study emphasizes the need for change in clinical practice and public health in the pursuit of environmental justice. It is important for clinicians to be aware of the impact of the UHI effect on health and risk for CVD. Practitioners should consider asking their patients about their living and work environments and if they have access to cooling measures. On a public health-level, these data can be used to identify urban census tracts that may carry a higher heat stress burden. Strategies to mitigate heat stress that have been shown to decrease mortality, such as distribution of home air-conditioners or access to cooling centres, can be implemented in vulnerable communities.²⁴ However, these are not long-term solutions, since air-conditioning causes harm by generating heat outdoors, thereby increasing the UHI effect.¹

More emphasis needs to be placed on preventative interventions that aim to decrease UHI intensity. These include implementing reflective roofing and pavement to decrease heat absorption and creating urban green spaces, green roofs, and vertical green walls with vegetation to augment shade and evaporative cooling.^{25,26} While increased vegetation offers many benefits, newly planted trees may take decades to create adequate shade, and some urban areas are limited by water availability. It may be necessary to pair such long-term strategies with the installation of shade structures—preferentially with materials that minimize heat absorption—to reduce heat stress from mean radiant temperature.^{27,28}

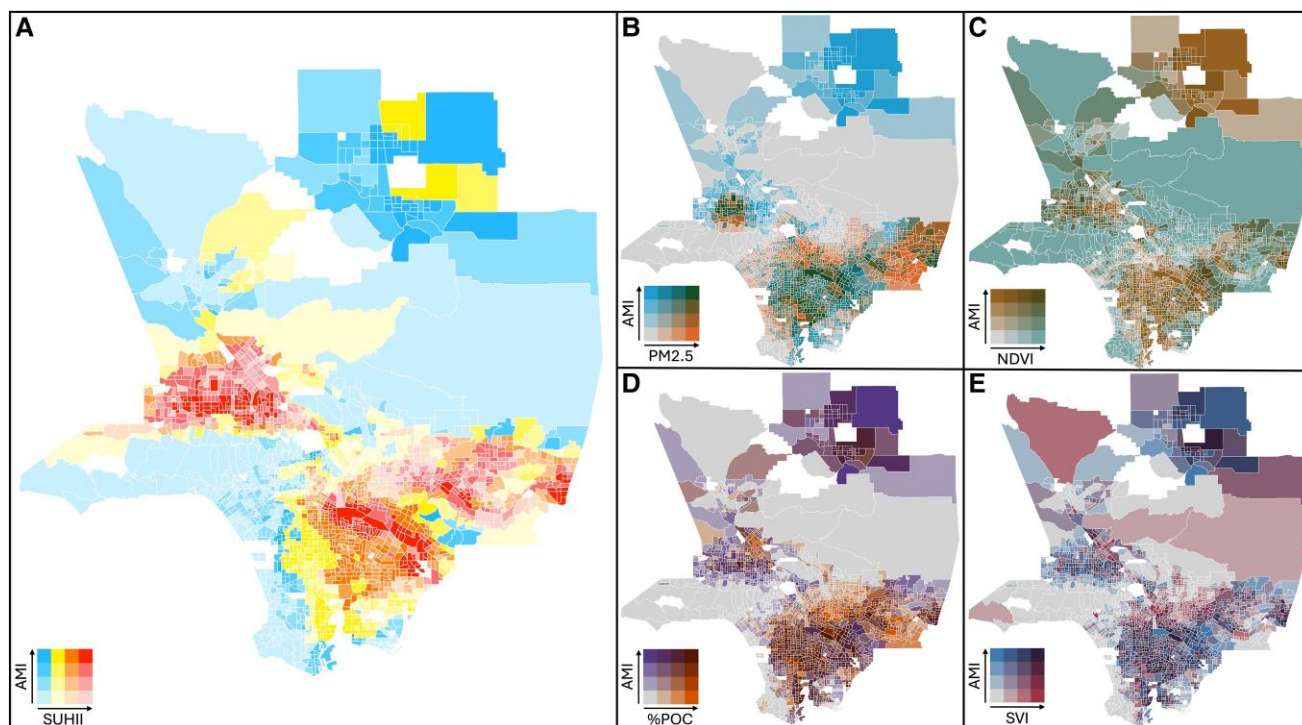


Figure 3 Bivariate choropleth maps of urban census tracts in Los Angeles County. Mapping acute myocardial infarction events per 10 000 residents per year (acute myocardial infarction event rate) and surface urban heat island intensity (A), PM_{2.5} (B), Normalized Difference Vegetation Index (C), per cent people of colour (D), and overall Social Vulnerability Index (E), respectively.

Supplementary material

Supplementary material is available at *European Journal of Preventive Cardiology*.

Acknowledgements

The authors would like to thank Dr Nicholas Jackson for his statistical consultative contribution to this study.

Author contribution

B.L., O.A., and B.Z. contributed to the conceptualization and methodology of the work. B.L. contributed to the data curation, analysis, and visualization of the work. B.L. drafted the manuscript. O.A. and B.Z. critically revised the manuscript. All gave final approval and agreed to be accountable for all aspects of the work in ensuring its integrity and accuracy.

Funding

No funding was required.

Conflict of interest: The authors declare they have no conflicts of interest related to this work to disclose.

Data availability

The datasets were derived from sources in the public domain: SUHII and NDVI (<https://data.mendeley.com/datasets/x9mv4krnm2/1>), AMI event rate, PM_{2.5}, and racial and ethnic group percentages (<https://calenviroscreen-oehha.hub.arcgis.com/#Data>), SVI (https://www.atsdr.cdc.gov/place-health/php/svi/svi-data-documentation-download.html?CDC_AAref_Val=https://

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