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Feminization of surface temperature: Environmental justice and gender inequality among socioeconomic groups

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A B S T R A C T

This study seeks answers to whether certain gender groups are overexposed to land surface temperature (LST) and whether or not the levels of such overexposure differ across socioeconomic groups and locations? The results of a geographically weighted regression model on 2400 Dutch residential zones show that LST is feminized. Gender composition alone explains about 10% of LST variations, regardless of other socioeconomic characteristics. For a 1% increase in women's population in a residential zone, LST increases by more than 0.1 °C. When socioeconomic characteristics are considered, the model explains more than 75% of variations. It shows that women living in low-value and relatively-old buildings are more exposed than men in 51% and 41% of the zones. Older-than-65-years and high-income women are more exposed than men in 24% and 22% of zones. Feminization of LST has a spatial pattern, too. It is more likely to occur in a moderate climate than in areas with extreme cold or warm climates. This study discusses the results and offers a series of possible explanations: Women's overrepresentation in urbanised areas, gender imbalance in economic sectors, suburbanisation of poverty, unequal access to green, different life expectancy among gender groups, and high variation of LST in moderate climates.

1. Introduction

1.1. Land surface temperature, environmental justice and gender inequality

Summer heatwaves are becoming more severe and frequent around the globe and in Europe. "The 2003 summer European heatwave alone caused up to 70,000 excess deaths over 4 months in central and western Europe" (Climate Adapt, 2021). In 2019, "soaring temperatures broke records in Germany, France, Britain and the Netherlands" (Reuters, 2019), and "several historical records at single locations in France, Switzerland, Austria, Germany, the Czech Republic and Spain" (World Weather Attribution, 2019). Different climate scenarios for 2050 indicate that a substantial increase in heatwaves in urban and rural areas is plausible (Molenaar et al., 2016).

The abundance of climate hazards and heatwaves raised awareness of climate and environmental justice. UN-Habitat, by a regional guide for climate-oriented policies, urges for climate justice, i.e. "[t]he concept that climate change is not caused by all population groups equally, and that its impacts affect different population groups differently" (UN Habitat, 2018, pp.44). European Environmental Agency calls for devoting to equality and justice of exposure to climate hazard the attention it deserves (European Environment Agency, 2018). Meanwhile, many environmental justice scholars believe that injustice in exposure to climate hazards could be a new

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face of inequalities between socioeconomic groups, including gender inequality. Notabaly, Geraldine Terry (2009) states that there is "[n]o climate justice without gender justice", arguing that gender-specific barriers and social constructs set the level to which gender groups are exposed to climate hazards.

This study examines environmental justice and gender inequality in exposure to land surface temperature (LST), a phenomenon with a significant impact on thermal comfort during heat waves (Offerle et al., 2006) and disproportionate spatial distribution across human settlements (Oreszczyn et al., 2006). This study seeks answers to whether certain gender groups are overexposed to LST and whether or not the level of such overexposure differs across socioeconomic groups and locations? In the following sections, first previous studies and a knowledge gap related to environmental justice and gender inequality are explained. Subsequently, the aim, method and data used in this study are described. Ultimately, the results of the analysis are presented and discussed.

1.2. Exposure to summer land surface temperature and gender inequality: A knowledge gap

A variety of previous studies shows that LST affects gender groups differently, particularly during heatwaves. A study on the heatwaves in Nanjing by Chen et al. (2015) shows that the mortality rate differs across gender, age, and education groups. The results show that during heatwaves, when the daily average temperature is above 98th percentile for more than four consecutive days, the mortality rate among women vastly outnumbers that among men, 30.3% compared with 18.4%. Studying 66 Chinese communities, Ma et al. (2015) find that heatwaves risk is 5.8% higher among females compared with males. A study on 31 major Chinese cities by Yang et al. (2019) estimates heatwave mortality risk is between 4% to 6% higher among women than men. Fouillet et al. (2006), studying excessive mortality of the 2003 heatwave in France, find that heatwave mortality is more than 15% higher among women older than 55 years old than men with a comparable age. The observed death to expected death during the heatwave is 1.8 for women older than 75 years, compared with 1.5 among men. However, the ratio is higher for males aged 33–44 years, 1.3 compared with 1. Considering all age groups, the ratio is respectively 1.7 and 1.4 among women and men. Son et al. (2016) study the impact of vegetation on mortality rate among demographic groups. The results show that in the areas with a low level of vegetation, the mortality risk is 3.8% among women, compared with 2.2% among men. In Medium vegetated areas, men are more at risk than women (2.8% compared with 2.3%). In highly-vegetated areas, women's risk outnumbers men's risk (1.9% compared with 1.3%). Bell et al. (2008), by a study on Latin American cities, show that in Santiago heatwave mortality is greater among men than women, 1.98% compared with 1.65%. Similarly, in São Paulo, men face more risk than women, 4.59% compared with 4.25%. However, in Mexico City, the heatwave risk is higher among women (1.75%) than men (0.78%). Toloo et al. (2014) find that the share of heat-related to non-heat-related visits to emergency departments is slightly higher among Australian men than women (1.09 compared with 1.08). A study by Donaldson et al. (2003) on heatwave and mortality in North Carolina, South Finland and Southeast England concludes that annual heatwave mortality per capita is greater among men than women. However, when heatwave mortality relative to the baseline mortality is considered, the risk is higher among women than men.

There is a knowledge gap in the previous studies on gender inequality and heatwaves. Although various studies have analysed and compared mortality among gender groups, it remains vastly unknown to what extent such gender inequalities are due to unequal exposures to LST. In the Netherlands, with a single exception, the previous studies on LST offer no insights into gender inequality. Five overlapping types of Dutch studies can be characterised. The first type maps LST and socioeconomic characteristics across cities (van der Hoeven and Wandl, 2015). The second type focuses on the impacts of urban morphology on LST (Jacobs et al., 2020; Taleghani et al., 2015; Steeneveld et al., 2011). The third type seeks the impact of LST on energy consumption in the residential sector (Mashhoodi et al., 2020) and energy poverty (Mashhoodi, 2020). The fourth type estimates the impacts of land cover on LST (Klemm et al., 2015; Steeneveld et al., 2014). The fifth type is the only type that studies exposure of gender groups to LST. The study shows that for 1 1% increase of women population compared with men, the LST increase for an average of 0.16 °C. The study, however, neglects the interaction between gender and other socioeconomic characteristics, e.g. age, income (Mashhoodi, 2021). In short, the previous studies do not offer a perspective on gender inequality in exposure to LST among socioeconomic groups.

1.3. Objective and approach of this study

This study aims to bridge the knowledge gaps in the previous studies on environmental justice and gender inequality, posing three research questions:

a) Is a certain gender group over- or underexposed to LST in the Netherlands?
b) Does such an overexposure follow a specific spatial pattern?
c) Does gender-based overexposure vary across socioeconomic groups -i.e. age, ethnicity, income, and housing tenure groups?

This study controls for four types of socioeconomic characteristics that are associated with LST exposure:

1. Ethnic background, regarding its associations with living environment of the households (Mitchell and Chakraborty, 2018; Jesdale et al., 2013);
2. Housing tenure, regarding the associations between the property value in different locations (Tan and Samsudin, 2017; Rosenthal et al., 2014);
3. Age groups, regarding the dissimilar lifestyle of different age groups which persuade them to dwell in different locations of a region (Vargo et al., 2016; Madrigano et al., 2015);

4. Income groups, regarding the income gap across regions and settlement with different levels of urbanity (Park and Guldmann, 2020; Nesbitt et al., 2019);

In the following sections, the method and data of this study are described.

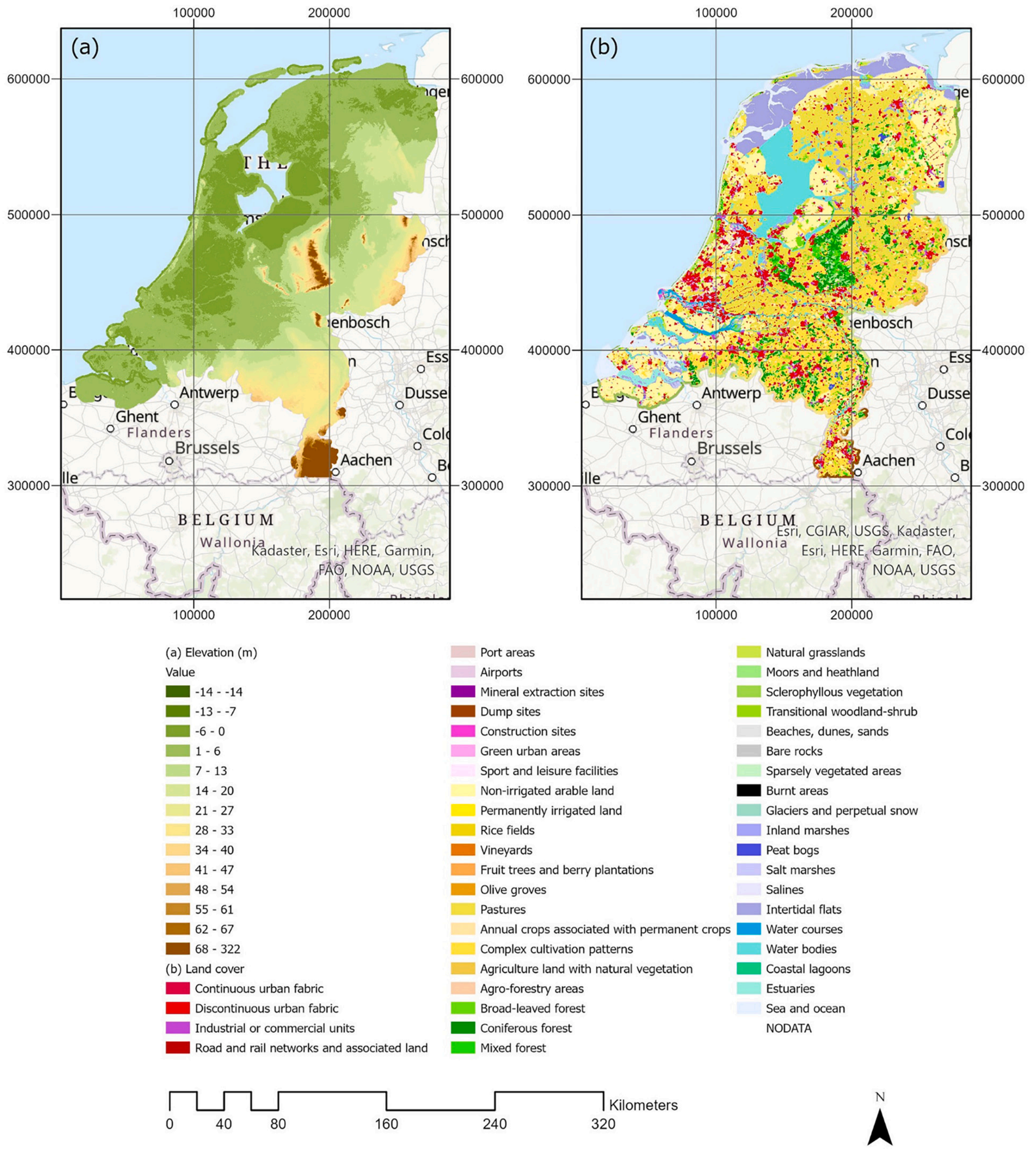

Fig. 1. (a) Elevation (mapped based on AHN, 2020), and (b) land cover (mapped based on Copernicus, 2018) in the Netherlands, the case study area.

2. Method

The analysis consists of three steps. At the first step, an ordinary least square linear regression model (OLS) including only LST and gender imbalance at the residential zones is adapted. The model is used to examine whether there is a significant association between gender and LST (see Eq. (1)):

$$LST_i = \beta_0 + \beta_{WmM} WmM_i + \varepsilon_i \tag{1}$$

where LST_i, WmM_i are LST, and the percentage of women minus the percentage of men at residential zone i. β_{WmM} is the coefficients of WmN, and β_0 and ε_i are intercept and random error at residential zone i. At the second step, an OLS model including socioeconomic control variables and their interaction with gender imbalance is adapted (see Eq. (2)).

$$LST_i = \beta_0 + \beta_{WmM} WmM_i + \sum_k \beta_k x_{ik} + \sum_k \gamma_k WmM_i x_{ik} + \varepsilon_i \tag{2}$$

where x_{ik} is the socioeconomic control variable k at the residential zone i. β_k, and γ_k are the coefficients of the socioeconomic control variable k, and that of the interaction terms between the control variable and WmM_i. At the third step, adapting a geographically weighted regression model (GWR), the analysis accounts for spatial variation of the associations (Eq. (3)).

$$LST_i = \beta_0(\mu_i, \nu_i) + \beta_{WmM}(\mu_i, \nu_i) WmM_i + \sum_k \beta_k(\mu_i, \nu_i) x_{ik} + \sum_k \gamma_k(\mu_i, \nu_i) WmM_i x_{ik} + \varepsilon_i \tag{3}$$

where (μ_i, ν_i) shows the geographic coordinate of the centroid of zone i. $\beta_0(\mu_i, \nu_i)$, $\beta_{WmM}(\mu_i, \nu_i)$, $\beta_k(\mu_i, \nu_i)$, and $\gamma_k(\mu_i, \nu_i)$ are respectively intercept, the estimated coefficient of WmM and that of the control variable k and the interaction terms at the location i. The GWR coefficients are formulated as follows (Eq. (4)):

$$\widehat{\beta}(\mu, \vartheta) = \left(X^T W(\mu, \vartheta) X\right)^{-1} X^T W(\mu, \vartheta) y \tag{4}$$

where $\widehat{\beta}(\mu, \vartheta)$ is the unbiased estimate of β, and $W(\mu, \vartheta)$ is the spatial weight matrix calculated based on an adaptive Gaussian function (Eq. (5)):

$$W_{ij} = \begin{cases} \left(1 - \dfrac{{d_{ij}}^2}{\theta}\right)^2, & if\ d_{ij} < \theta \\ 0, & otherwise \end{cases} \tag{5}$$

where W_{ij} is the weight assigned to zone j in the regression model specific to zone i. d_{ij} is the bird-fly distance between the centre points of zones i and j. θ is the adaptive bandwidth, the number of nearest zones of zone i included in the location-specific regression model. Using the GWR 4.0 tool developed by Nakaya et al. (2009), the bandwidth size that minimises the GWR model's Corrected Akaike Information Criteria (AICc) is selected. Finally, a comparison between four performances of OLS and GWR models is conducted: adjusted R^2, AICc, and size and spatial pattern of the residuals.

3. Data

3.1. Case study area

The case study is the Netherlands, a country located in the so-called "temperate without dry season and warm summer" climate zone, according to the Köppen-Geiger classification (Kottek et al., 2006). The country is relatively flat, with most areas located below 5 m in height from sea level (Fig. 1a). More than 75% of the country is covered with agricultural, forests, grasslands, moors, marshes, dunes and sandy lands. The built-up areas, including urban fabrics, ports, industrial areas, roads, urban greens, etc., account for 13% of land covers. Inland water bodies and large-scale lakes account for almost 8% of lands, and 3% of the territory is seas and ocean waters (Fig. 1b). The spatial elements of the study are the residential zones of the Netherlands, the so-called *Wijk* in Dutch. The Dutch central bureau of statistics (CBS) defines the boundary of the zone. The zones are among the most fine-scale spatial units with socioeconomic data open to the public (CBS, 2014). This study includes 2400 out of 2835 zones, excluding non-residential zones and those with missing data in the CBS dataset or covered by cloud in satellite images.

3.2. Dependent variable

The dependent variable is average summertime - June, July, August- LST. The average LST value represents day and night temperature in five time periods. Each of the periods summarizes satellite observations of eight days and nights. In this respect, the average summertime LST accounts for 40 days and nights in total. Using MODIS satellite images (Earthdata, 2020), LST of four different overpassing local times at each of the periods are retrieved: MODIS Terra day (10:30 a.m.), MODIS Terra night (10:30 p.m.), MODIS Aqua day (1:30 p.m.), and MODIS Aqua night (1:30 a.m.). The spatial resolution of the satellite images is 1 km per 1 km. The satellite images are selected based on three criteria: reliable values of LST, based on the Quality Assurance band; roughly regular time intervals between the images; maximizing the number of cells that are not covered by clouds in any of the images. Table 1 represents the satellite images used for the calculation of average summertime LST.

Fig. 2 illustrates the variation of LST in the summer of 2014 in the Netherlands. It points out gradual warming from June to the peak in the third week of July and a gradual cooling afterwards.

Finally, the average summertime LST at the scale of residential zones are retrieved. The spatial resolution of satellite images and residential zones are compatible, i.e. most satellite cells fall only within one zone. However, given the irregular geometry of the residential zones, some of the cells overlap with more than one residential zone. Therefore, every satellite cell is split into 400 cells with the spatial resolution of 50 m per 50 m, using the Resample function in ArcGIS Pro, which are subsequently aggregated at the scale of residential zones. Given the gaps in satellite images due to clouds, the residential zones that overlap with no cells are excluded from the study. Fig. 3 shows the average summertime LST at the residential zones.

3.3. Independent variables

The study's independent variable is the gender imbalance at the residential zones, *Women minus men* (%), calculated by subtracting the percentage of men registered in a zone from the percentage of women (CBS, 2014). Fig. 4 maps the distribution of the independent variable across the residential zones of the Netherlands.

3.4. Control variables

This study uses nine control variables (Table 2). Two control variables represent residents' ethnicity: *Western immigrants* (%) and *Non-Western immigrants (%)*. CBS defines an immigrant as a person with one or two none-Dutch parents and accounts for two generations of immigrants. In this respect, a person born in the Netherlands and possessing Dutch nationality may also be considered an immigrant. Western ethnicity refers to the European, Northern American and Oceanian countries, and Japan and Indonesia. Non-Western ethnicity includes the rest of the countries (CBS, 2014).

Three variables control for the real estate market in the residential zones. *Rental dwelling (%)* is the percentage of the dwellings rented out. *Property value* is the average value of properties in the past five years. *Building age* is the median age of the buildings with residential function (entirely or partially). The two former variables are retrieved from the CBS database (2014). The latter is computed using the Dutch GIS database of buildings (Esri Netherlands, 2016).

Three variables control for the age of residents: *Population age 65 or older (%)*, *Population age 15–24 (%)* and *Population age 14 or younger (%)*. The last control variable represents annual net income per capita: *Income* per capita. The source of age and income variables is CBS (2014). Table 2 shows descriptive statistics of the control variables.

4. Results

4.1. The results of the statistical model and the selection of the best model

Fig. 5 illustrates the results of the first statistical model, i.e. the OLS model including only LST and *Women minus men* (%). The figure illustrates the ranges of the two variables that include most of the zones. The regression line, however, is base on the complete range of the variables. The result shows that there is a significant association between the gender composition of residential zones and LST ($F(1, 2616) = 278.3$, *p-value* < 0.001). It indicates that gender composition alone explains about 10% of LST variations. For a 1% increase in *Women minus men (%),* LST increases by more than 0.1 °C, *p-value* < 0.001 (Fig. 5).

Subsequently, two statistical models including control variables and interaction terms are developed. One of the models does not account for spatial variation (OLS), and one accounts for it (GWR). Table 3 summarizes the results of the OLS and GWR models. The results of the OLS model show that including the control variables and the interaction terms improves goodness-of-fit, adjusted R-squared, from 10% to more than 54%. The model is also used for measuring the level of collinearity between the independent variable, control variables and interaction terms. It shows that the variance inflation factor (VIF), the measurement of collinearity, is at the commonly accepted range in all the cases.

The performances of the OLS and GWR models indicates that accounting for spatial variation in the GWR model produces a better estimation of the associations. Adjusted R-square shows that the GWR model explains more than 75% of variations, which is 21% higher than that of the OLS model. The GWR model's AICc is significantly smaller than the OLS model, implying that the former is a more informative model. The ANOVA test of residuals shows that GWR's residuals are significantly smaller than those of the OLS

Table 1
The satellite images used for the calculation of the average LST in the summer of 2014.

Satellite	Local overpassing time	Date
	10:30 a.m.	**Time period #1**: 02 June 2014–09 June 2014
	10:30 p.m.	**Time period #2**: 26 June 2014–03 July 2014
MODIS/Terra (MOD11A2)		**Time period #3**: 20 July 2014–27 July 2014
	1:30 a.m.	**Time period #4**: 05 August 2014–12 August 2014
MODIS/Aqua (MYD11A2)	1:30 p.m.	**Time period #5**: 29 August 2014–05 September 2014

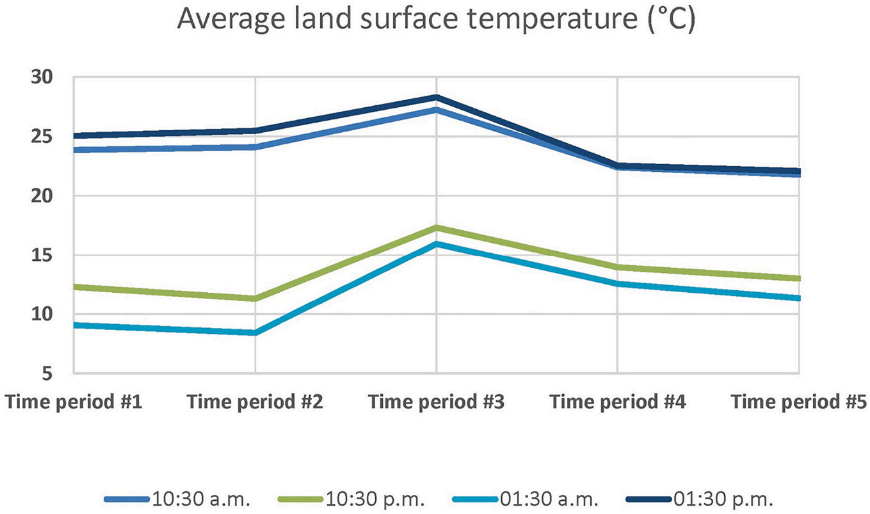

Fig. 2. Average LST value in the Netherlands in the summer of 2014.

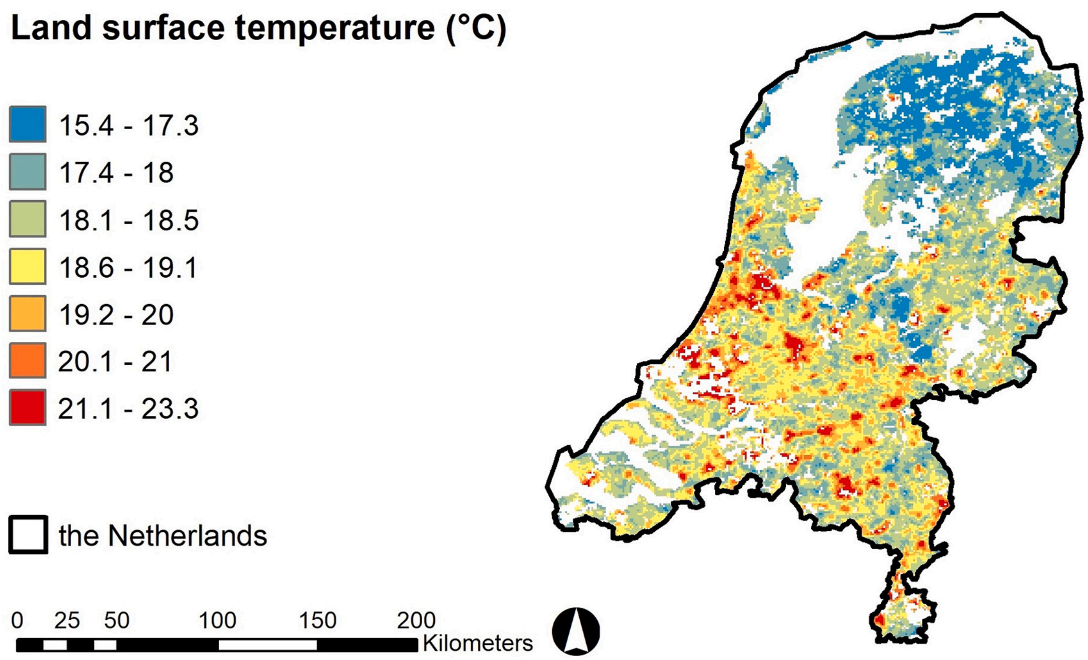

Fig. 3. Average summertime LST at residential zones in summer 2014.

model. The Moran's I test of the spatial distribution of the residuals shows that residuals of the GWR model are more randomly distributed (Table 3).

In Short, the comparison between the diagnosis of the GWR and the two OLS models shows that there is a significant spatial variation that needs to be accounted for. In this respect, this study uses the GWR model as the primary model for analysis (Table 3).

4.2. Estimates of the gender inequality among socioeconomic groups

Fig. 6 shows the percentage of significant (*p-value* $\leq$ 0.05) local coefficients in the GWR model. Gender represents the local coefficients of *Women minus men (%)*, i.e. over-or underexposure of women regardless of other socioeconomic, possibly due to latent societal impacts not reflected in the dataset. Other variables show the interaction of *Women minus men (%)* with a socioeconomic variable. The results show that women are overexposed to LST in more than half of the residential zones, regardless of their socioeconomic characteristics. Additionally, four socioeconomic characteristics are associated with women overexposure to LST: low

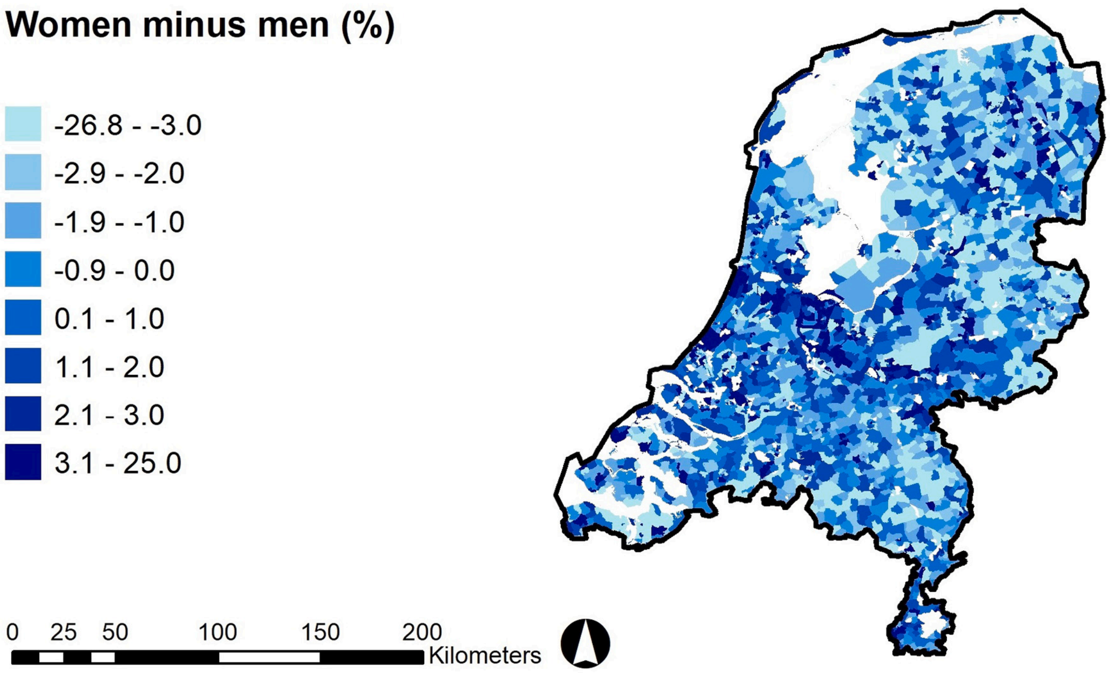

Fig. 4. Independent variable of the study, *Women minus men (%)*, calculated by subtracting the percentage of men registered in a zone from the percentage of women.

Table 2
The descriptive statistics of the control variables.

Variable	Mean	SD	Percentiles		
			25	50	75
Western immigrants (%)	9.66	4.76	7.00	9.00	11.00
Non-Western immigrants (%)	8.81	8.24	3.00	6.00	11.00
Rental dwelling (%)	43.69	15.98	32.00	42.00	54.00
Building age (median)	44.07	16.42	36.00	42.00	50.00
Population age 65 or older (%)	23.59	9.21	19.00	22.00	26.00
Population age 15–24 (%)	10.85	3.26	10.00	10.00	12.00
Population age 14 or younger (%)	15.33	3.81	14.00	16.00	17.00
Income per capita (× 1000 €)	24.64	5.63	21.30	23.40	26.24
Property value (× 1000 €)	233.46	102.44	168.00	210.00	264.00

property value, high building age, high income, and the presence of the age group older than 65 years. Two of the socioeconomic variables affect overexposure of gender groups to LST, with a negligible impact on gender inequality, as they affect both men and women in different locations: *Western immigrants* (%), *Non-Western immigrants* (%). Three socioeconomic characteristics have negligible impact on exposure of a gender group to LST: *Rental dwellings* (%), *Population age 15–24* (%), *Population age 14 or younger* (%) (Fig. 6).

Fig. 7 illustrates the five characteristics associated with high gender inequality and maps the residential zones where such inequalities are observed. The maps have a spatial pattern in common: the areas with gender inequality are not located at the Southeast or Northwest corners of the country, i.e. the warmest and coldest areas of the Netherlands. Fig. 7a shows that gender per se, i.e. without interaction with socioeconomic characteristics accounted for in this study, is the reason for overexposure of women in more than half of the residential zones. The areas spread all over the country, except in the Northeast and Southwest. In more than 40% of the zones, women living in relatively older buildings are overexposed to LST, including those located in the most urbanised areas of the West and Southeast of the country (Fig. 7b). The women aged 65 years old or older (Fig. 7c) are overexposed in the Western areas with a mix of agricultural and urbanised lands, i.e. provinces of Zeeland and northern parts of the Noord Holland. High-income women (Fig. 7d) are overexposure to LST in the Eastern provinces with moderate climate. Women living in low-value properties (Fig. 7e) are overexposed to LST in almost all residential zones, except in Southwest and Northeast areas.

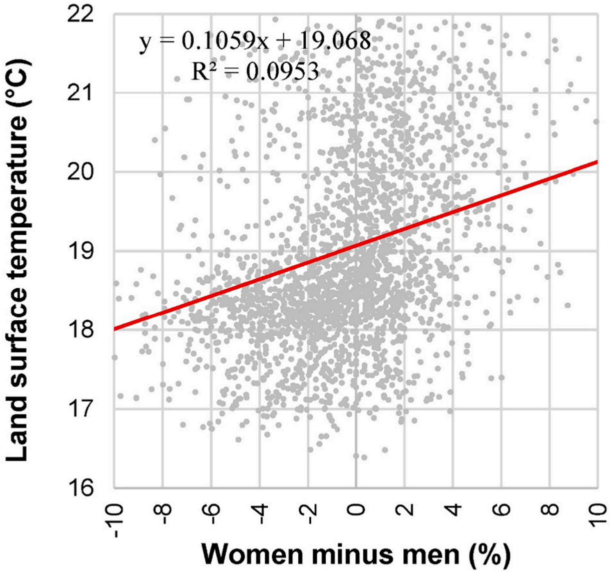

Fig. 5. The OLS model with LST as the dependent variable and *Women minus men* (%) as the independent variable shows a significant association between the two.

Table 3
Diagnosis of the OLS and GWR models accounting for the independent variable, control variables and interaction terms.

Variable	OLS results		GWR results			
	β	VIF	β mean	β SD	Positive significant (%)	Negative significant (%)
Intercept	0.00		0.087	0.427	60.4	20.8
Dependent variable						
Women minus men (%)	0.20	2.26	0.147	0.142	54.3	0.0
Control variables						
Western immigrants (%)	0.11	1.74	0.154	0.264	34.2	2.2
Non-Western immigrants (%)	0.35	2.32	0.357	0.210	90.5	0.0
Rental dwelling (%)	0.20	2.98	0.025	0.122	18.5	10.4
Building age (median)	−0.01	1.27	0.002	0.060	11.1	7.1
Population age 65 or older (%)	−0.25	3.75	−0.126	0.164	0.0	41.2
Population age 15–24 (%)	0.07	2.04	0.036	0.077	20.3	0.6
Population age 14 or younger (%)	−0.05	2.86	−0.025	0.110	7.6	18.0
Income per capita (× 1000 €)	0.29	3.38	0.185	0.182	55.9	0.0
Property value (× 1000 €)	−0.11	3.43	−0.226	0.190	0.0	65.6
Interaction terms						
Women minus men (%) * Western immigrants (%)	−0.08	1.76	−0.044	0.131	3.5	16.7
Women minus men (%) * Non-Western immigrants (%)	−0.01	2.04	−0.038	0.156	14.2	24.2
Women minus men (%) * Rental dwelling (%)	−0.04	3.04	−0.001	0.046	1.6	2.8
Women minus men (%) * Building age (median)	0.08	1.44	0.086	0.118	40.6	0.0
Women minus men (%) * Population age 65 or older (%)	0.10	5.75	0.101	0.221	23.8	0.2
Women minus men (%) * Population age 15–24 (%)	−0.04	2.53	0.013	0.072	8.4	3.3
Women minus men (%) * Population age 14 or younger (%)	0.01	4.02	0.027	0.120	9.1	2.6
Women minus men (%) * Income per capita (× 1000 €)	0.05	3.52	0.081	0.168	24.8	2.8
Women minus men (%) * Property value (× 1000 €)	−0.18	3.33	−0.166	0.186	0.0	50.9
R-square	0.544		0.797			
Adjusted R-square	0.541		0.752			
AICc	4963.104		3784.155			
Residual Moran's I	0.3477		0.0976			
Bandwidth	NA		299			
GWR ANOVA Table	**SS**	**DF**	**MS**	**F**		
Global Residuals	1091.9	2380.0				
GWR Improvement	606.1	418.6	1.4			
GWR Residuals	485.7	1961.5	0.2	5.8		

β: standardized regression coefficient.
OLS coefficients significant at the *p-value* < 0.05 level are marked underlined.
The percentage of the GWR positive and negative significant coefficients (%) calculated at *p-value* < 0.05.

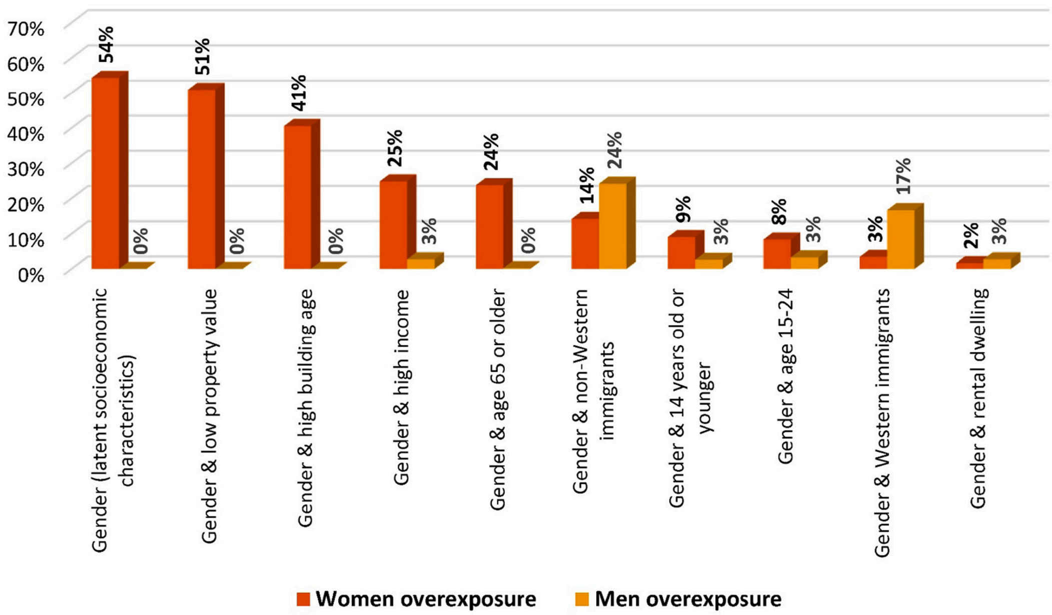

Fig. 6. Gender inequality in exposure to LST among socioeconomic groups.

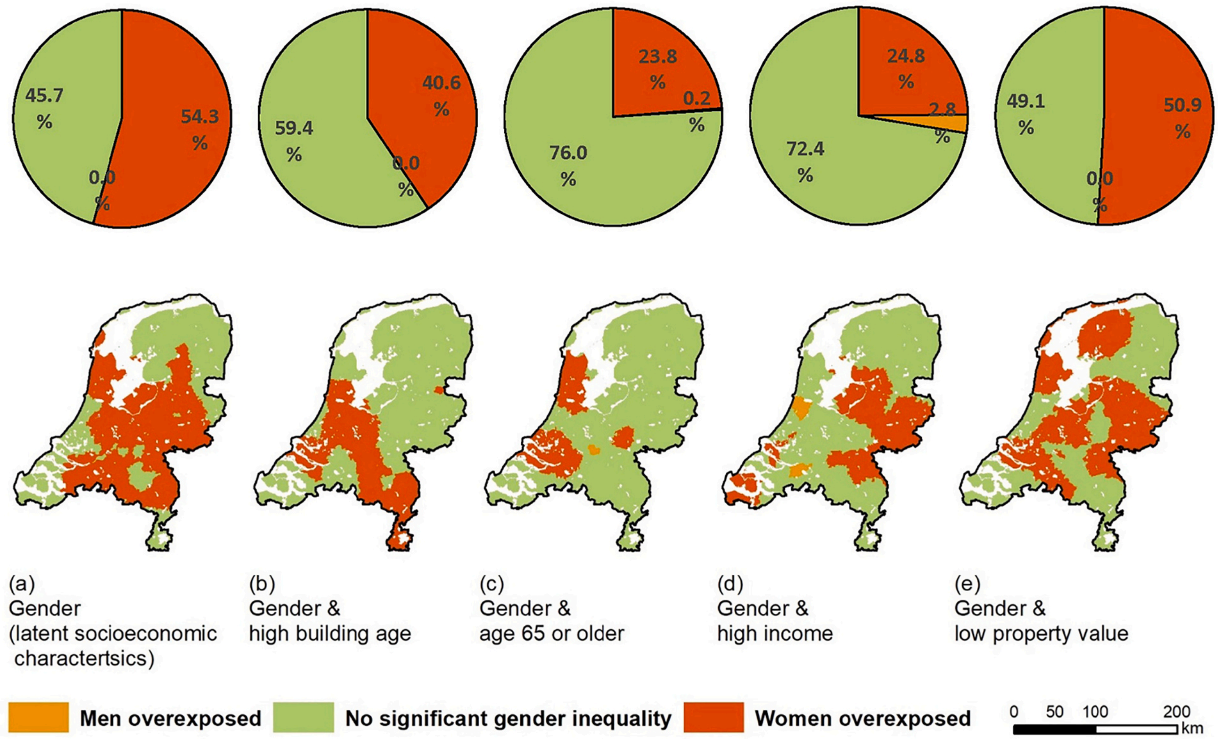

Fig. 7. Spatial distribution of the socioeconomic groups with significant gender inequality in LST overexposure.

5. Discussion

This study shows that overexposure to LST has significant gender, socioeconomic, and spatial dimensions. It appears that being a woman, regardless of other socioeconomic characteristics, is associate with overexposure to LST in more than half of the zones. Given her socioeconomic characteristics, a woman could be overexposed to LST in particular zones of the country. A woman is more likely to experience overexposure in a moderate climate than an extremely warm or cold climate. These results could be discussed from three points of view: overall overrepresentation of women in urbanised areas; societal issues affecting the spatial distribution of socioeconomic groups; the more significant impact of LST in a moderate climate. In the following paragraphs, these points of view are further elaborated.

In more than half of the zones, women are overexposed to LST, regardless of their socioeconomic characteristics. This is presumably due to the imbalance distribution of women and men across the urban and rural areas. CBS defines five levels of urbanity based on the density of dwellings. In 2014, women outnumbered men in the three most urbanised zones – the so-called "very highly urbanised", "highly urbanised", "moderately urbanised" - by 1.39%, 1.93%, 0.66%. Oppositely, in the two least urbanised zones – the so-called "barely urbanised", "no urbanisation" - men outnumbered women by 0.70% and 2.70% (own computation based on CBS, 2014). The gender imbalance between urban and rural areas is presumably related to the gender imbalance across economic sectors. The Gender Data Portal of The World Bank reported that in 2019 the industry sector employed almost 25% of Dutch working men. The corresponding number for Dutch working women was 6%. The percentage of working men with a job in the agricultural sector is two and a half times larger than that of working women (3% compared to 1.2%). The service sector, however, offers a different picture. In 2019, more than 92% of Dutch working women were employed in the service sector. The corresponding percentage of Dutch working men was less than 73% (The World Bank Group, 2020). The overrepresentation of men in the industry and agricultural sectors and women in the service sector presumably explains the overrepresentation of the former in less urbanised areas and that of the latter in the more urbanised ones.

The higher representation of women than men in the service sector, the phenomenon which presumably bound them to the most urbanised areas, corresponds to the so-called as feminization of labour trend. In her influential book on the change of women's societal role, Hanna Rosin foresees that women would dominate 12 out of 15 growing occupations in the 21st century, including jobs in the service sector such as health services (Rosin, 2012). Reporting on the future of the European labour market, the International Monetary Fund (IMF) forecasts that the service sector will employ a substantial portion of working women (Christiansen et al., 2016). The service sector is the engine for women's labour participation in the EU regions (Guisan and Aguayo, 2013), the gender gap in the highly-educated jobs is significantly closed (Evertsson et al., 2009), and the labour market in "digital" occupations is significantly "feminized" (Duffy and Schwartz, 2018). Feminization of service sectors presumably explains the overrepresentation of women in the most urbanised zones, which overexpose them to LST.

In addition to the overall gender imbalance between urban and rural areas, the socioeconomic characteristics of a woman have a significant impact on her overexposure to LST. Women's overexposure to LST in the older residential zones, measured by the median building age, presumably reflects the difference between old compact settlements and modernist, post-war neighbourhoods with large open, green spaces (Wagenaar, 2011). In the areas with a high mix of urbanised and rural areas, women with higher income levels are overexposed to LST. This presumably reflects the trend of the so-called suburbanisation of poverty, i.e. the growing income gap between urban and suburban areas (van Ham et al., 2020) in various metropolitan areas, among them Paris (Sarkar and De Ridder, 2011), New York (Gedzelman et al., 2003), London (Kolokotroni and Giridharan, 2008). In the Netherlands, low- and middle-income households were gradually moving from the core areas of the two major cities toward other areas of urban regions between 2004 and 2013 (Hochstenbach and Musterd, 2018), and the income gap between the urban core and the rest of the region has widened (Hochstenbach and Van Gent, 2015). Between 1999 and 2014, the income of the households living in the central areas of the four major Dutch cities has grown faster than that of the rest of the metropolitan region by 5% to 9% (Modai-Snir and Van Ham, 2020).

The overexposure of women living in low-value properties reflects the lack of water bodies, green spaces and trees in a zone. In the Netherlands, the value of a house with a garden and facing water can appreciate up to 28%, specifically, if the water body is "connected to a sizeable lake" (Luttik, 2000, pp. 161). Adjacency to a park or water significantly impacts property value (Visser et al., 2008). In Amsterdam, for instance, houses closer than 250 m to parks are up to 9% more expensive than their direct vicinity (Daams et al., 2019). The value of houses located within 0.5 to 7 km from attractive green spaces is higher between 16% and 1.6% (Daams et al., 2016). Street trees are an appreciating factor of the property value (Siriwardena et al., 2016; Pandit et al., 2013).

Women aged 65 years or more are overexposed to LST in 24% of the residential zones. A possible reason for such observation is that senior women outnumber senior men and are more likely to live in urbanised areas. The CBS data shows that in 2019 life expectancy of women was more than 3.5 years longer than men, 83.03 compared to 79.47 (CBS, 2020). A study on 40,000 elderlies in the Netherlands shows that 24.1% of women aged between 65 and 69 are widowers, whereas only 7% of men are. The corresponding number for the age group of 70–74 is respectively 37.2% compared with 10.7% (Kalwij et al., 2013). Ultimately, Dutch senior women are more likely to live in a metropolitan region than Dutch senior men, 50.9% compared with 49.1% (Houttekier et al., 2010). Such demographic trends cause a significant gender inequality in exposure to LST in the age group of 65 years and older.

Overexposure of women to LST has a spatial pattern, too. This study shows that women overexposure occurs in regions with moderate climates, and gender inequality is not observed in the warmest and coldest areas of the Netherlands. Presumably, LST is more variant across the areas with a moderate climate, whereas it is homogenously high or low in extreme climate conditions. Mashhoodi et al. (anonymised for review) found a similar pattern in the impact of LST on household energy consumption in the Netherlands. The authors observed that LST exert a significant impact only in a moderate climate, and its impact fades in extremely cold or warm climate conditions (Mashhoodi et al., 2020).

6. Conclusion

The findings of this study show that LST during warm seasons is, in effect, a spatial manifestation of gender inequality. Land surface temperature is feminized. In the majority of the Dutch residential zones, being a woman is associated with overexposure to LST.

Women with particular socioeconomic characteristics, in addition, are more likely to experience higher levels of LST. Feminization of land surface temperature is coupled with various social and spatial factors: imbalanced gender representation in economic sectors, suburbanization of poverty, different life expectancy between gender groups, the inequality in access to green spaces, and exacerbated impact of LST in moderate climates.

In the last decades, the gender gap has narrowed in many cases. Most notably, the employment ratio of women has increased from 62% in 2000 to 74% in 2019 in the Netherlands (OECD, 2019). Such improvements must be celebrated. They, however, should not be the reason for turning a blind eye to new forms of gender inequality, particularly those caused by climate change. The danger is that while one form of gender inequality pales, another form of gender inequality grows. Émilie du Châtelet, the natural philosopher and mathematician from the 18th century, in her commentary on the works of Isaac Newton, formulated the law of energy conversation: energy will not be destroyed; it only transforms from one form to another. Is there a law of gender inequality conversion?

7. Further studies

To elaborate on the findings of this study on the associations between gender inequality and LST, further studies need to elaborate on three issues. First, This study uses 1 km per 1 km satellite images for measuring LST and excludes the residential zones covered by clouds from the study. Further studies need to employ Filling Gap techniques to estimate LST at the polluted cells (see Yao et al., 2021) and benefit from downscaling methods for retrieving data at higher spatial resolutions (Oriani et al., 2020). The high-resolution LST data can be used to study micro-scale demographic data at the building block level. Second, this study analyses a single year and does not offer an insight into the temporal trajectory of environmental gender inequality. Further studies need to develop and analyse panel data on spatiotemporal changes of LST (Yao et al., 2017) and demography. Third, this study analyses the exposure to LST at the living location of different socioeconomic groups. Further studies need to offer complementary insights into LST exposure in public spaces, workplaces, and educational and recreational land uses. To do so, further studies can benefit from travel surveys (see Creemers et al., 2015) and use the geo-tagged data from social media (see Zhang et al., 2016).

Declaration of competing interest

The author declares that there is no conflict of interest regarding the publication of this article.

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