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Land surface temperature and households' energy consumption: Who is affected and where?

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ABSTRACT

It is widely accepted that land surface temperature (LST) affects household energy consumption (HEC). There is, however, no previous study available that clarifies whether LST's impact is similar in each and every area, or if it varies from one location to another. Analysing the impact of LST on HEC of 2612 residential zones of the Netherlands in 2014, this study concludes that HEC of 50% of the zones is affected by LST, accounting for 0.8% of overall consumption on average. It is obtained that energy-intensive, high-income and large-size households are more likely to be affected by LST. The results show that the effect is likely to be significant in the zones with relatively milder air temperature, and higher levels of humidity and wind. It is obtained that the effect intensifies when the buildings are less compact and the zones are less urbanised. Ultimately, this study urges for a shift in the approach of the existing studies on the impact of LST by putting forward a proposition: the impact of LST on HEC could not be spatially generalised, and one cannot enhance the associations unless location-specific circumstances of the areas in question are taken into consideration.

1. Introduction

1.1. Land surface temperature and household energy consumption: a knowledge gap

Increase of land surface temperature (LST) is a known phenomenon in Dutch cities requiring urgent attention. Previous studies on the cities of Amsterdam and Rotterdam show that the heterogeneous distribution of water bodies and canals, building masses (that affect both solar radiation and the sky view factor, i.e. the ratio of visible sky at a given point in urban space), vegetated areas and types of vegetation, impervious surfaces (such as asphalt and paved surfaces), and disparate building materials have created a patchwork of heat islands in Dutch cities (van der Hoeven & Wandl, 2015a; Van der Hoeven & Wandl, 2015b). Although the circumstances that contribute to high level of LST are rigorously studied, the impact of LST on other societal aspects, among them energy consumption, is barely elaborated. In the next paragraphs two knowledge gaps in the existing literature on the associations between LST and household energy consumption (HEC) are introduced, and the objective and structure of this study is elaborated.

It is widely accepted that LST affect HEC. Ewing and Rong (2008, p. 1) conceptualised three frameworks for the effect of urban form on HEC: "electric transmission and distribution losses, energy requirements of different housing stocks, and space heating and cooling requirements associated with urban heat islands". Studies in a variety of cities and countries showed that increases in LST increase ambient temperatures around buildings, which is significantly associated with an increase in energy consumption for space cooling (see review by Santamouris, Cartalis, Synnefa, & Kolokotsa, 2015). Various studies (e.g. Hassid et al., 2000; Kolokotroni, Zhang, & Watkins, 2007; Santamouris et al., 2001) show that a higher LST decreases the amount of energy consumed for space heating in cold seasons.

Two knowledge gaps in previous studies are apparent. First, although the association between LST and HEC has been established, it is not clear how significant the contribution of LST is compared to other determinants of HEC such as socioeconomic factors, housing, urban form, outdoor temperature, humidity, and wind speed. There is no comprehensive empirical study on the impact of LST together with a range of other social and urban form factors on HEC. Second, previous empirical studies have tried to generalise the impact of LST on average HEC by estimation of a single rate. For example Santamouris et al. (2001) estimated that the heating load in the city centre of Athens is

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38% lower rather in than other areas. However, it is unclear whether such generalised rates could accommodate circumstances of different areas across a vast territory such as a country. Whether or not the impact of LST impact varies from one geographic context to another still needs to be studied. For instance, do the associations between LST and HEC differ in response to the quality and geometry of buildings? Could the effect be offset, or intensified, by the sociodemographic characteristics of the inhabitants of such buildings? Do higher, or lower, outdoor temperatures exacerbate, or alleviate, the impact of LST? This study aims to bridge the knowledge gap by analysing HEC across the residential zones of Netherlands in 2014. The article is divided in six main parts. In the first part, the objective and approach of the study is presented. In the second section, the method of study and the data sources are described. In the third and final parts the results of the study are presented and discussed, and conclusions and further studies are elborated.

1.2. Objective and approach of this study

This study aims to study the impact of LST on HEC in the residential zones of Netherlands. To do so three research questions are put forward. First, is the effect of LST spatially variant (i.e., is the effect specific to some zones) or spatially invariant (i.e., is the HEC of all the zones of the country affected by LST)? Second, compared to that of other determinants of HEC, how large is the impact of LST on HEC (i.e., for how many percentage points of HEC does LST account), and does the magnitude differ in different zones? Third, does the impact of LST differ in response to the geographic circumstances of a zone, i.e., the demography, quality of dwellings, local climate, and urban form?

Our analysis will be set out in two steps. The first step is to perform the geographical variability test (Nakaya, Fotheringham, Charlton, & Brunsdon, 2009), in order to identify spatially variant and spatially invariant determinants of HEC, among them LST. Subsequently, in the second step, two geographically weighted regression models (GWR) are developed, which allow for the estimation of spatially variant impacts. In the first GWR model, HEC is the dependent variable and LST as well as a variety of socioeconomic, housing, and climate indicators are the independent variables. In the second model, a similar regression analysis is carried out while LST is excluded from the independent variables. The comparison between the models indicates the impact of LST goodness-of-fit of estimation, as an indication of the percentage of HEC explained by LST, as well as the spatial variation of such an impact.

Nine types of control variable are used to control for the socioeconomic, housing, and climate characteristics of residential zones. The variables have previously been considered significant determinants of HEC in earlier studies:

1. Inhabitant income, as it is considered to be associated with a higher level of HEC (e.g. Druckman & Jackson, 2008; Joyeux & Ripple, 2007; Yun & Steemers, 2011);
2. Household size, as per capita consumption could decrease in larger households due to economies of scale (e.g. Fong, Matsumoto, Lun, & Kimura, 2007; Lenzen et al., 2006; Tso & Yau, 2003);
3. Building age, as a proxy for energy efficiency of dwellings (e.g. Druckman & Jackson, 2008; Mashhoodi, Stead, & van Timmeren, 2019; Tso & Yau, 2003);
4. The surface to volume ratio of the building as an indicator of the thermal loss of the building (e.g. Bernabé et al., 2015; Steemers & Yun, 2009; Mashhoodi, Stead, & van Timmeren, 2019);
5. Population density as an indicator of urbanisation (for instance York, 2007);
6. Outdoor temperature as it affects the thermal comfort of the residents (e.g. Zhang, 2004);
7. Humidity, as it affects the thermal environment and thermal sensation (Alfano, Palella, & Riccio, 2011; Chow, Fong, Givoni, Lin, & Chan, 2010);
8. Wind speed, as it affects the air infiltration and exfiltration of buildings, ambient temperature of dwellings, and felt temperature (Sanaieian, Tenpierik, van den Linden, Seraj, & Shemrani, 2014; Van Moeseke, Gratia, Reiter, & De Herde, 2005);
9. Land cover and vegetation index in the zones, as they significantly affect HEC (Letu et al., 2010; Mashhoodi & van Timmeren, 2018).

2. Methods and data

2.1. Method

In order to estimate the impact of LST as well as that of the other control variables on HEC, first it is necessary to identify what are the determinants that affect the HEC of all zones at a similar rate, i.e., the spatially invariant determinants, and in which determinants does their effect vary across the zones, i.e., the spatially variant determinants. To do so, the geographical variability test of the GWR 4.0 tool is employed (developed by Nakaya et al., 2009). The test is based on the conduction of multiple geographically weighted regression models (GWR) and comparing their performance in terms of AICc (Akaike Information Criteria) – a measurement of the trade-off between the simplicity of a model and the amount of information that it provides (Akaike, 1981). In order to assess whether the impact of the one independent variable is spatially variant or invariant, two GWR models are developed: first, a model that treats all independent variables as spatially variant determinants; second, a model that holds all independent variables as spatially variant determinants, except the one certain variable in question, which is considered as a spatially invariant. The comparison between the AICc of the two GWR models determines whether that the exception variable is a spatially variant or invariant determinant: should the AICc of the latter model be lower than that of the former, it indicates that the latter model performs better, reflected by a negative value of the so-called "DIFF of Criterion" in the geographical variability test – if the independent variable in question is a spatially variant determinant. Otherwise the variable is a spatially invariant determinant. As suggested by Nakaya et al. (2009), the values of "DIFF of Criterion" smaller than +2, however, could be seen as weak evidence for spatial invariability, and thus are considered as an indication of spatial variability in this study. The initial GWR model used by the geographical variability test, i.e. the model that hold all independent variables as spatially variant determinants, is formulated as follows:

$$y_i = \beta_0(\mu_i, \nu_i) + \sum_k \beta_k(\mu_i, \nu_i) x_{ik} + \varepsilon_i \tag{1}$$

where y_i denotes the estimation of HEC at the zone in question – location i, (μ_i, ν_i) is the geographic coordinate of the location i, $\beta_0(\mu_i, \nu_i)$ shows the intercept of the model, and $\beta_k(\mu_i, \nu_i)$ denotes the estimated coefficient of the independent variables, including LST and other control variables. x_{ik} and ε_i denote the value of the independent variables and random error term in location i. The coefficients are calculated as follows:

$$\widehat{\beta}(\mu, \vartheta) = \left(X^T W(\mu, \vartheta) X\right)^{-1} X^T W(\mu, \vartheta) y \tag{2}$$

where $\widehat{\beta}(\mu, \vartheta)$ is the unbiased estimate of β, and $W(\mu, \vartheta)$ the spatial weight matrix specific to location i. The spatial weight matrices are adopted based on the adaptive gaussian formulation:

$$W_{ij} = \begin{cases} exp\left(-\dfrac{d_{ij}^2}{\theta^2}\right), & if\ d_{ij} < \theta \\ 0, & otherwise \end{cases} \tag{3}$$

W_{ij} is the weight of zone j in the GWR model adopted for the location i. d_{ij} denotes the geodesic distance between the two zones. θ is the bandwidth size of the spatial weight matrix. The bandwidth size is set at the

value which minimises the corrected AICc of the GWR model.

Subsequent to the identification of the spatially variant and invariant determinants, as the output of the geographical variability test, two geographically weighted models are developed. The first model estimates the impact of LST, as well as the control variables, on HEC:

$$y_i = \beta_0(\mu_i, \nu_i) + \lambda\beta_{LST}(\mu_i, \nu_i)LST_i + (1-\lambda)\gamma_{LST}LST_i + \sum_m \beta_m(\mu_i, \nu_i)x_{im} + \sum_n \gamma_n z_{ni} + \varepsilon_i \quad (4)$$

$$\lambda = \begin{cases} 1, & LST \text{ is identified as a spatially variant variable} \\ 0, & LST \text{ is identified as a spatially invariant variable} \end{cases} \quad (5)$$

where λ denotes whether LST is identified as a spatially variant or invariant determinant of HEC. $\beta_{LST}(\mu_i, \nu_i)$ is the estimated coefficient of LST when it is a spatially variant determinant, and γ_{LST} is the estimated coefficient when LST is identified as a spatially invariant determinant. $\beta_m(\mu_i, \nu_i)$ denotes the estimated coefficient of the mth spatially variant control variable, and γ_n is that of the nth spatially invariant control variable. The second model estimates only the impact of the control variables on HEC:

$$y_i = \beta_0(\mu_i, \nu_i) + \sum_m \beta_m(\mu_i, \nu_i)x_{im} + \sum_n \gamma_n z_{ni} + \varepsilon_i \quad (6)$$

The comparison between the performance of the two models is used to measure the impact of LST on the overall HEC of the zones. To do so, the difference between goodness-of-fit (expressed as adjusted R^2) of the two models (equation (5) and equation (6)) measures the impact of LST on HEC. Finally, the impact of LST in different geographic contexts is summarised and compared. To characterise a geographic context, the notion of a mean contextual value (Brunsdon, Fotheringham, & Charlton, 2002) – i.e. the average value of a certain variable in a zone and its adjacent zones, with regard to a spatial weight matrix – is adopted:

$$\text{Mean contextual value of variable } K \text{ at zone } i = \frac{\sum_j W_{ij}x_{jk}}{\sum_j W_{ij}} \quad (7)$$

2.2. Dependent variable

This study is conducted on residential zones in the Netherlands (Fig. 1) – the so-called *wijken* in Dutch, the institutional boundaries of which are defined by the Dutch central bureau for statistics (CBS). The study area comprises 2612 zones. The dependent variable of this study is annual energy consumption, in Joules, for gas and electricity combined, per capita aggregated at the zones in 2014. The data on the gas and electricity consumption of the zones is provided by the CBS (Centraal Bureau voor de Statistiek, 2014).

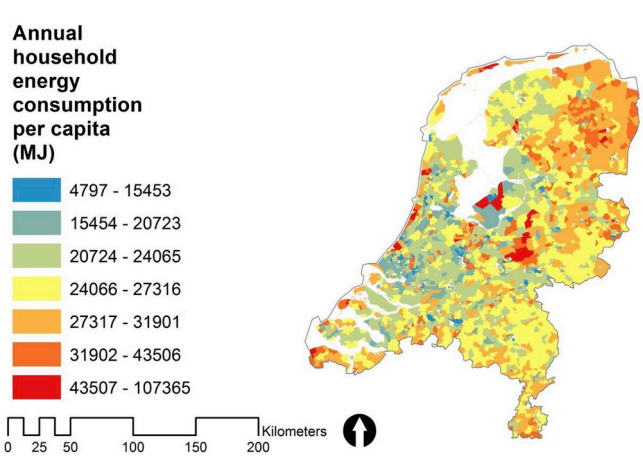

Fig. 1. Case study areas and dependent variable.

2.3. Independent variables

The independent variable of this study is land surface temperature (LST). Using MODIS/Terra Land Surface Temperature/Emissivity 8-Day L3 Global 1 km SIN Grid V006 (MOD11A2) data, average value of twelve images is calculated (Earthdata, 2019). Each of the images show the average daily LST of 8 days in 2014. In this respect, the average annual LST used in this analysis represent the average daily LST of 96 days in 2014. The reason for use of daily LST values, and excluding the data on LST during nights, is that the data on the latter is unreliable in many cells (according to Quality Assurance band of the satellite images). The twelve images are chosen based on three criteria: first, temporal intervals between the dates is roughly equal, and thus the twelve values provide a preview of annual LST; second, the satellite images cover all the study areas; third, according to the Quality Assurance band of the satellite images, all the cells have a valid LST value (Table 1).

The spatial resolution of the MOD11A2 is 1 km per 1 km, which is not as fine-grained as that of Landsat 8 and Landsta7 data. However, as the spatial units of this study are the zones and the LST data need to inevitably be aggregated at the zone level, the spatial resolution of MOD11A2 suffice for the purpose of this study. (Choice of zones as the spatial unit of the study is due to availability of energy consumption and socioeconomic data.) Fig. 2 show the average annual LST across the study areas.

2.4. Control variables

This study uses ten control variables (see Table 2). *Income* represents the average annual disposable income per capita in the zones. *Household size* is the average number of residents in a household. *Population density*, as a proxy for level of urbanity, shows the ratio of the population of a zone to its area (inhabitants per square kilometre). *Building age* is the median age of the buildings, which are solely or partially residential. *Surface to volume ratio* shows the ratio of the area of buildings' external surfaces – external walls plus roof area – to their volume. The data on *Income*, *Household size* and *Population density* are provided by the CBS (Centraal Bureau voor de Statistiek, 2014). *Building age* and *Surface to volume ratio* are calculated based on the building database of Netherlands – 3D BAG (Esri Netherlands, 2016).

In order to control for the climate conditions of the zones, climate

Table 1
The satellite data used in this study.

	Time period			Mean	Minimum	Maximum	SD
LST[a]	09/01/2014	to	16/01/2014	5,16	−9,49	8,53	1,27
	02/02/2014	to	09/02/2014	5,74	−0,93	8,59	0,83
	22/03/2014	to	29/03/2014	13,24	−1,81	21,11	1,81
	15/04/2014	to	22/04/2014	18,45	7,75	25,53	2,08
	17/05/2014	to	24/05/2014	24,79	13,47	33,61	2,17
	02/06/2014	to	09/06/2014	23,85	11,17	34,21	2,41
	12/07/2014	to	19/07/2014	27,45	12,57	38,13	2,32
	28/07/2014	to	04/08/2014	26,05	13,69	34,75	1,97
	29/08/2014	to	05/09/2014	21,78	13,69	29,93	1,43
	30/09/2014	to	07/10/2014	19,99	9,61	25,19	1,51
	01/11/2014	to	08/11/2014	13,67	1,31	18,81	1,08
	27/12/2014	to	31/12/2014	1,02	−14,17	8,03	2,20

[a] MOD11A2 weekly data.

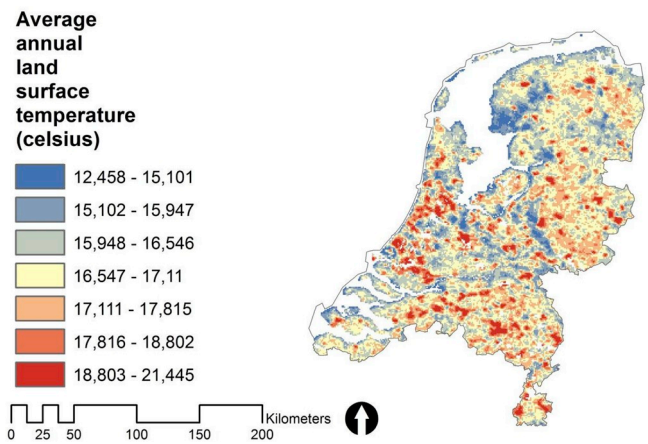

Fig. 2. Average annual Land surface temperature (LST).

Table 2
Descriptive statistics of control variables.

Variable	Mean	Minimum	Maximum	SD
Income	23,20	12,00	66,30	4,05
Household size	2,35	1,20	4,00	0,31
Population density	1731,63	3	21656	2555,23
Building age	39,3200	0,0000	164,0000	14,9400
Surface to volume ratio	0,26	0	0	0,04
Number of summer days	23,0690	5,9844	37,6956	7,9593
Number of frost days	68,84	50	81	6,65
Humidity (%)	80,89	79	83	0,84
Wind speed	40,99	28,58	77,85	7,32
NDVI[a]	0,6270	0,2777	0,8041	0,0981

[a] average of monthly values retrieved from MOD13A3 monthly data.

observations at the 28 meteorological stations of the Royal Netherlands Meteorological Institute (KNMI) are used. The observed values of the stations are interpolated based on the guidelines on the most appropriate interpolation methods, provided by the KNMI scientific team (see Sluiter, 2012, pp. 1–71). The climate conditions of the zones are quantified by means of four variables. The first variable is the *Number of summer days*, the days in 2014 in which the maximum temperature exceeded 25 °C. The second variable is the *Number of frost days,* the days in 2014 in which the minimum was below zero. These variables are calculated based on the universal kriging interpolation of the KNMI stations observations, with external drift of log distance to the shore. The third value is the relative *Humidity*, which is calculated based on ordinary kriging interpolation of the humidity in the KNMI stations, with an exponential variogram. The measurement of humidity at the KNMI stations is made at height of 150 cm. *Wind-speed*, the speed of the wind blowing at a height of 10 m above ground level, is retrieved based on the two-layer model of the planetary boundary layer interpolation (for a detailed description see Stepek & Wijnant, 2011) of the observed values at the KNMI stations. To conduct the calculations the CORINE land-cover database (European Environment Agency, 2016) is used as the basis for the calculation of roughness length classifications, based on the classification methods of Silva et at. (2007). The last control variables is average monthly Normalized Difference Vegetation Index (NDVI) in 2014. The data is retrieved from MODIS/Terra Vegetation Indices Monthly L3 Global 1 km SIN Grid V006, and the average value of the twelve months is used as measurement of average annual NDVI (Earthdata, 2019).

Data on the observations of meteorological stations are extracted from KNMI database (KNMI, 2018).

3. Results

3.1. Identification of spatially variant impacts and development of GWR models

The first step is to apply the geographical variability test, in order to identify spatially variant and invariant impacts. The results of the test (Table 3) show that the DIFF of criterion of all eleven independent variables is in the range indicating a spatially variant impact on HEC (see Nakaya et al., 2009). On the basis of this results, two GWR models for estimation of the effect of LST are developed.

In the second step of the analysis, subsequent to the identification of the spatially variant and invariant independent variables, two GWR models are developed. The first model estimates the impact of the LST and the ten control variables on HEC. The second model tests the impact of the ten control variables only (Table 4). A comparison between the performance of the two models shows that the inclusion of LST in Model 1 increases the goodness-of-fit of the GWR by a 0,4 percentage point – which quantifies the overall impact of LST on HEC of all the zones of the Netherlands. Given that the Model 2 explains more than 49% of HEC variation, this result indicates that impact of LST is relatively small compare to that of the other ten determinants of HEC. The lower level of AICc in Model 1 compared to Model 2 shows that the inclusion of LST in the analysis contributes to form a more informative estimation. The lower level of Moran's I in Model 1 compared to Model 2 shows that the spatial distribution of residual in the former is more random, and therefore the estimates of Model 1 are more trustworthy.

3.2. The impact of LST compared to other determinants of HEC

The results of Model 1 shows that the coefficients of LST are significant (*p-value* < 0,05) in more than 50% of zones. In this case, the effect of LST is significant in lesser number of zones than five of the independent variables: *Income*, *Household size*, *Population density*, *Building age*, *Number of Frost days*. More number of zones are affected by LST than four micro-climate characteristics: *Number of summer days*, *Humidity(%)*, *Wind speed*, *NDVI*. Compared to the impact of the building geometry, assessed by *Surface to volume ratio*, the impact of LST is significant, by a wide margin, in more number of zones.

Should the impact of LST be significant in a zone, higher levels of LST contribute to lowering the level of HEC. In this respect, the impact of LST is comparable to that *Household size*, *Population density*, and *NDVI*, which also contribute to decreasing energy consumption. The impact of LST outweighs that of *NDVI* in most of the zones. The impact, however, is categorically smaller than the impact of *Population density*. Although the impact could be at the same range as the impact of *Household size* in some zones, however the latter has a larger impact on HEC in average. A property of LST impact, compared to the impact of other control variables is that, if significant, in the range its local coefficients is relatively small. In the other words, either LST has no impact on HEC, or the

Table 3
The results of the geographical variability test and identification of the spatially variant and invariant impact.

Variable	DIFF of Criterion[a]	Type of spatial impact
Income	−14,96	spatial variant
Household size	−56,70	spatial variant
Population density	−26,92	spatial variant
Building age	−28,27	spatial variant
Surface to volume ratio	−11,55	spatial variant
Number of summer days	0,34	spatial variant
Number of frost days	−7,86	spatial variant
Humidity (%)	−16,61	spatial variant
Wind speed	−12,14	spatial variant
Land surface temperature	−2,09	spatial variant
NDVI	−6,40	spatial variant

[a] result of the geographical variability test.

Table 4
Estimates of the GWR models.

	Model 1		Model 2	
Variable	β mean	β SD	β mean	β SD
Intercept	−0,3507	0,2308	−0,3509	0,2520
Income	0,3629	0,0728	0,3724	0,0773
Household size	−0,0681	0,1060	−0,0698	0,1073
Population density	−0,3806	0,1128	−0,4214	0,1262
Building age	0,2945	0,0682	0,2988	0,0673
Surface to volume ratio	0,0191	0,0514	0,0337	0,0525
Number of summer days	0,1909	0,2869	0,2131	0,3015
Number of frost days	0,0803	0,3395	0,0859	0,3474
Humidity (%)	0,0232	0,1909	0,0282	0,1990
Wind speed	0,0590	0,1068	0,1162	0,1263
NDVI	−0,0004	0,0813	0,0247	0,0714
LST	−0,1064	0,0653		
R-squared	51,90%		51,27%	
adjusted R-squared	49,58%		49,16%	
AICc	5683,831		5699,811	
residual Moran's I	0,0250		0,0257	
adaptive bandwidth	155		155	

β: standardized regression coefficient.

magnitude of the effect is quite homogenous, in terms of standardized coefficient (Fig. 3).

3.3. The spatial variation of LST's impact on HEC

The impact of LST is significant (*p-value*≤0,05) in 50% of the zones. The estimated magnitude of this impact varies spatially across the zones. As estimated in section 3.1, the overall impact of LST (i.e. impact of LST on the overall HEC of Dutch residential zones) is estimated at around 0,4%. Focusing on the areas where the LST has a significant impact, the results show that this magnitude is around 0.8% on average – with a standard deviation of 0.4%. In extreme cases the magnitude is as small as 0.2%, and as large as 2%. Generally speaking, the areas with significant impact of LST are distributed closer to the North Sea, Woddenzee, Ijsselmeer and Markermeer. There are some exceptions to this general pattern: the areas in vicinity of Westland, biggest concentration of glass houses in the Netherlands, and the Northern province of Friesland, with large area of lakes and farms (Fig. 4a). Should the estimated coefficient of LST be significant, the higher levels of LST are associated with lower levels of HEC. The smallest magnitude of impacts is observed around some of the urbanised areas such as the Lelystad, where one degree increase in LST is associated with less than 600 MJ decrease in HEC. This impact, however, can be as large as 1400 MJ in Amsterdam, Utrecht and Groningen (Fig. 4b).

3.4. Identification of the geographic contexts in which LST's impact on HEC is significant

Given the spatial pattern of LST's impact on HEC (Fig. 4a), the question is what the geographic contexts are – in terms of the level of HEC, intensity of LST, demography, housing and urban form, microclimate – in which LST significantly affects HEC. To answer this question, the geographic contexts of the zones where the impact of LST is significant are compared with those of the zones where the impact of is not significant. In order to quantify the geographic context of a zone, the status of HEC, LST, and the other control variables in the zone in question, as well as the status of those in its 155 closest zones, the bandwidth of the GWR models, are summarised (see the formulation of *Mean contextual value of variable K at location i* in section 2.1), and compared by means of one-way analysis of variance, ANOVA (Table 5).

As indicated by the F ratio of the ANOVA test, the result shows that status of micro climate illustrates the most remarkable characteristics of the zones affected by LST. The result of ANOVA test show that significant impact of LST is observed in zones with milder temperature, i.e. lesser number of *Summer days* and *Frost days*. The impact of LST is, however, likely to be more significant in zones where *Humidity (%)* and *Winds speed* are higher. The significant effect of LST is appeared to be more related to the geometry of the buildings rather than building age. It is found that households that are significantly affected by LST have a higher Income and HEC level than households who are not affected by LST. The impact of LST is significantly greater in the zones with larger households than in those with smaller household size.

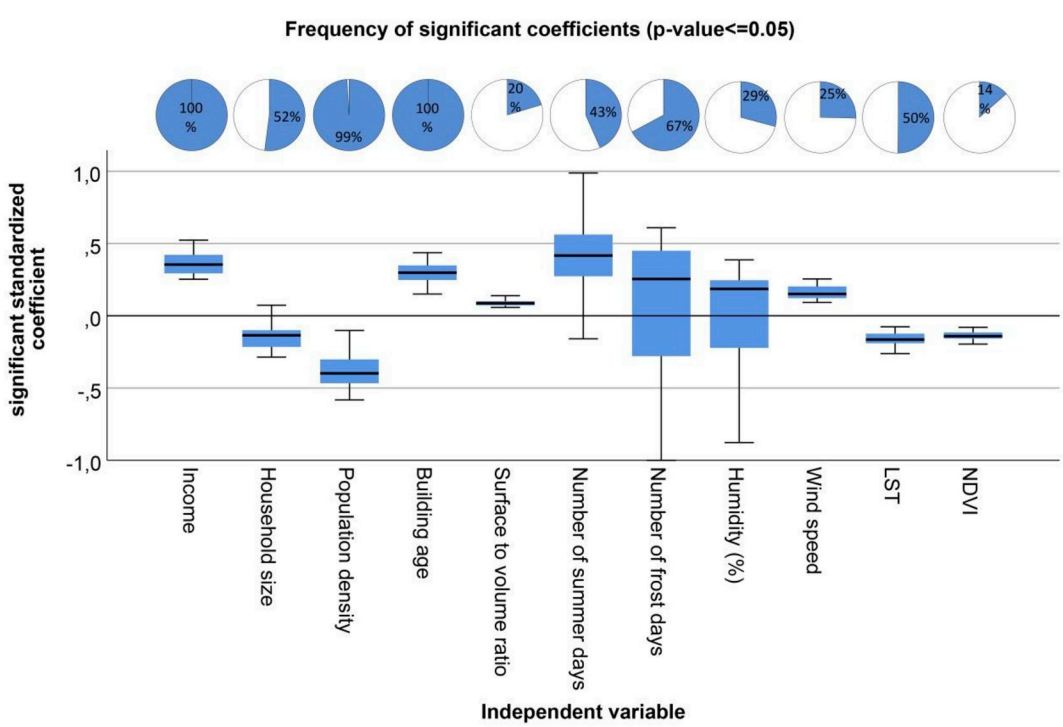

Fig. 3. The variation of significant (*p-value* < 0,05) standardised local coefficients (box plots). Pie charts show the frequency of significant impacts across the zones.

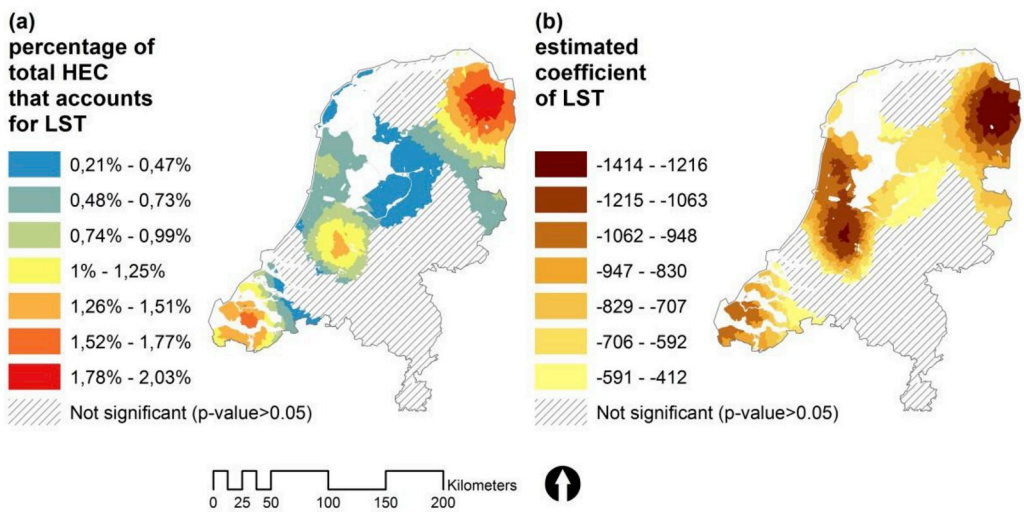

Fig. 4. The estimated impact of LST, i.e. the percentage of total HEC of a zone that accounts for LST (a), estimated coefficient of LST (b).

Table 5
Characterising the impact of LST in relation to the geographic context of zones by one-way analysis of variance (ANOVA). The significantly larger values are marked bold-underlined.

	Mean		ANOVA			
	No significant effect of LST	Significant effect of LST		Sum of Squares	Mean Square	F
HEC	24508,44	**25118,34**	Between Groups	2,43E+08	2,43E+08	57,12*
			Within Groups	1,11E+10	4,25E+06	
			Total	1,13E+10		
Income	23,01	**23,52**	Between Groups	1,68E+02	1,68E+02	53,97*
			Within Groups	8,14E+03	3,12E+00	
			Total	8,31E+03		
Household size	2,3408	**2,3548**	Between Groups	1,28E-01	1,28E-01	12,16*
			Within Groups	2,76E+01	1,06E-02	
			Total	2,77E+01		
Population density	**1913,4968**	1688,59	Between Groups	3,30E+07	3,30E+07	21,50*
			Within Groups	4,01E+09	1,54E+06	
			Total	4,04E+09		
Building age	39,16	39,27	Between Groups	7,43E+00	7,43E+00	0,676
			Within Groups	2,87E+04	1,10E+01	
			Total	2,87E+04		
Surface to volume ratio	0,2608	**0,2646**	Between Groups	9,14E-03	9,14E-03	45,59*
			Within Groups	5,23E-01	2,01E-04	
			Total	5,33E-01		
Number of summer days	**27,01**	19,18	Between Groups	4,00E+04	4,00E+04	944,15*
			Within Groups	1,11E+05	4,24E+01	
			Total	1,51E+05		
Number of frost days	**69,70**	68,16	Between Groups	1,54E+03	1,54E+03	40,45*
			Within Groups	9,95E+04	3,81E+01	
			Total	1,01E+05		
Humidity (%)	80,52	**81,23**	Between Groups	3,30E+02	3,30E+02	695,67*
			Within Groups	1,24E+03	4,74E-01	
			Total	1,57E+03		
Wind speed	38,04	**43,33**	Between Groups	1,83E+04	1,83E+04	680,07*
			Within Groups	7,02E+04	2,69E+01	
			Total	8,85E+04		
LST	**17,4096**	17,0924	Between Groups	6,57E+01	6,57E+01	452,00*
			Within Groups	3,80E+02	1,45E-01	
			Total	4,45E+02		
NDVI	0,6233	**0,6317**	Between Groups	4,61E-02	4,61E-02	17,06*
			Within Groups	7,05E+00	2,70E-03	
			Total	7,10E+00		

* The mean difference is significant at <0.001 level

The results of the ANOVA test show that significant impact of LST is more likely to be observed in the zones where *Surface to volume* ratio is larger. There, however, is no significant difference between *Building age* in the zones with significant effect of LST and those without such an effect. The impact of LST is likely to be significant in zones with a lower levels of population density, or more less urbanised, and higher level of vegetation (NDVI). In a counter-intuitive way, therefore, it is observed that in average LST is larger in the areas where HEC is not significantly affected by LST. In the other words, the result of the comparison between means shows that the significant impact of LST is more related to the geographic context rather than magnitude of LST per se.

4. Discussion

The results of this study show that the effect of LST on HEC is spatially variant. Such an impact, in other words, could not be generalised for all zones of the Netherlands. On the contrary, the impact varies from one zone to another. The impact of the LST on HEC is significant in half the of zones – where it accounts for 0.8% of total HEC on average, and is often outnumbered by the impact of other determinants of HEC. In this respect, while studies and policies regarding HEC ought to acknowledge the impact of LST, it should be noted that this impact is only meaningful if it is studied alongside other socioeconomic, housing, urban form and climate factors.

The location-specific impact of LST is presumably due to the local status of other determinants of HEC: the impact of LST on the felt temperature is affected by the microclimate of the zones in question; the association between indoor and outdoor temperature varies across the zones, due to variation of geometry of the buildings; and inhabitants with different socioeconomic characteristics, and thus different energy behaviours, react differently at different levels of felt temperature. The location-specific impact of LST could be presumably be related to the interdependencies between determinants of HEC, which vary from one location to another. It must be acknowledged that not only do the determinants, among them LST, affect HEC, but they also affect one another in one way or another. For instance, the properties of urban form, such as typology of dwellings and presence of green surfaces, affect the level of LST as well as the association between indoor and outdoor temperature. The above-mentioned properties, meanwhile, attract households with a particular socioeconomic characteristics (Bayoh, Irwin, & Haab, 2006), and thus a certain type of energy behaviour. In this respect, the impact of the determinants of HEC, among them LST, are highly intermingled with one another.

The result of the study show that should LST has a significant impact on HEC, it contributes to lower level of consumption. This presumably is related to the particular circumstances of the Netherlands, where use of appliances for space cooling is not common. The result leads to the conclusion that the impact of the LST on HEC is not a function of LST intensity per se. However, the impact is related, to a large extent, to the level of HEC, demography, housing and urban form, and microclimate of the zones in question. A discussion of the circumstances under which the impact of LST on HEC is likely to be significant follows below.

Households with a high level of energy consumption are more likely to be affected by LST than households with low levels of consumption. Presumably, the overall LST impact, which is negligible compared to other determinants of HEC, can disappear at the lower levels of consumption, due to behavioural adaptation, i.e. the circumstances under which an individual deals with climate conditions by adapting behaviours other than consuming extra energy units. LST has a greater impact on the HEC of households with relatively higher income levels. Presumably, as low-income households are more likely to use less energy, the negligible impact of LST, therefore, is becoming insignificant. The impact of LST on HEC is more significant in larger households. This is presumably related to the co-presence of a greater number of children within a dwelling, and a greater demand for space- and water heating. It is found that in the zones where outdoor temperatures is more extreme, i.e. where days with a maximum temperate higher than 25 and a minimum temperature of less than zero degrees Celsius are more frequent, the impact of the LST on HEC is less likely to be significant. Whereas in the zones with relatively mild temperatures –and higher levels of humidity and wind, which intensifies the so-called felt temperature – the impact is more likely to be significant. In this respect the following conclusion can be drawn: felt temperature has a great impact on exacerbating, or alleviating, the impact of LST on HEC, and such an impact could outweigh the effect of absolute outdoor temperature.

Considering the level of urbanisation, measured by population density, the results show that the impact of LST on HEC is overshadowed in more urbanised areas. Presumably, in urbanised and heterogeneous geographic contexts, a variety of socioeconomic and housing related factors are intermingled and do outnumber the effect of LST. This observation presumably is also related to compactness of the buildings in the urbanised areas. The results show that should the Surface-to-volume ratio of the buildings be higher, it is more likely that the effect of LST is significant, presumably due to stronger association between indoor and outdoor temperature when greater portions of the dwelling is exposed to the outdoor environment. The latter circumstances is more prominent in the rural areas, and so does the impact of LST. This effect also overshadow the age of the buildings, and the level of vegetation in the zones. In short, when it comes to the impact of LST on energy consumption of households, the impact of geometry of the buildings is more prominent than the quality of the buildings and the integration of green land cover in the public spaces.

5. Conclusion

The results of this study urges for a shift in the approach of the existing studies on the impact of LST on HEC by putting forward a central proposition: the impact of LST on HEC could not be spatially generalised. One cannot enhance the associations between the two unless location-specific circumstances of the areas in question are taken into consideration, i.e. level of HEC, demography, housing and urban form, and microclimate. The studies in this field need to seek answers to the question of "in which geographic context has LST a significant impact on HEC?" rather than simplifying the impact by estimation of a single rate. In this line, two detailed reflections upon the previous studies could be made.

First, recording a high level of LST is not an enough argument for a stronger impact of LST on HEC in an area. A seminal study by Santamouris et al., for instance, suggests that "[due to] higher temperatures in the city centers […] the heating load of urban buildings may be reduced up to 30–50% compared to buildings located in suburban areas" (2001, pp. 216). The results of this study suggest that such propositions do not necessarily hold, as the impact of the LST on HEC is not a function of LST magnitude per se: a relatively low level of LST could significantly affect HEC of households in an area - given their particular its particular geography, whereas a higher level of LST could be ineffective in another area. The studies in this field need to break through the narrow perspective of urban micro climate, by adopting a broad geographical perspective accounting for all determinants of HEC.

Second, the impact of LST on HEC needs to be acknowledged, however not to be exaggerated. Following the seminal publication of Ewing and Rong (2008), it is widely assumed that such impact exists, typically short of offering empirical evidences. The result of this study shows that such impact exist in only half of Dutch residential zones and is widely outnumbered by other determinants of HEC, accounting for less than 1% of overall consumption. The studies in this field need to adopt evidence-based approaches to compare the impact of LST with that of other determinants of HEC, and build upon the fact that these impacts vary from one location to another.

6. Further studies

While impact of LST on overall annual HEC could be negligible, in extreme situations such as during heat waves, it can cause a sudden increase in the level of HEC. This can result in city- or national-wide blackouts in electricity supply, and indirectly endanger the health of elderlies and children (Wolf & McGregor, 2013). Further studies need to analyse the level of LST at high temporal and spatial resolutions, and to elaborate on the associations between LST and spatiotemporal variation of HEC in course of a year. Preparing an extensive LST dataset – by conducting missing pixels recovery methods (see Cheng, Liu, Shen, Wu, & Zhang, 2017; Shen, Huang, Zhang, Wu, & Zeng, 2016; Zeng, Shen, & Zhang, 2013), further studies could additionally search for the longitudinal associations between LST and HEC across multiple years.

Declaration of competing interest

The authors declare that they have no conflict of interest.

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Appendix A. Supplementary data

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References

Akaike, H. (1981). Likelihood of a model and information criteria. *Journal of Econometrics, 16*(1), 3–14.
Alfano, F. R. D. A., Palella, B. I., & Riccio, G. (2011). Thermal environment assessment reliability using temperature—humidity indices. *Industrial Health, 49*(1), 95–106.
Bayoh, I., Irwin, E. G., & Haab, T. (2006). Determinants of residential location choice: How important are local public goods in attracting homeowners to central city locations? *Journal of Regional Science, 46*(1), 97–120.
Bernabé, A., Bernard, J., Musy, M., Andrieu, H., Bocher, E., Calmet, I., et al. (2015). Radiative and heat storage properties of the urban fabric derived from analysis of surface forms. *Urban Clim., 12*, 205–218.
Brunsdon, C., Fotheringham, A. S., & Charlton, M. (2002). Geographically weighted summary statistics—a framework for localised exploratory data analysis. *Computers, Environment and Urban Systems, 26*(6), 501–524.
Centraal Bureau voor de Statistiek. (2014). *Wijk- en buurtkaart 2014*. https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/geografische%20data/wijk-en-buurtkaart-2014/. (Accessed 8 March 2018).
Cheng, Q., Liu, H., Shen, H., Wu, P., & Zhang, L. (2017). A spatial and temporal nonlocal filter-based data fusion method. *IEEE Transactions on Geoscience and Remote Sensing, 55*(8), 4476–4488.
Chow, T. T., Fong, K. F., Givoni, B., Lin, Z., & Chan, A. L. S. (2010). Thermal sensation of Hong Kong people with increased air speed, temperature and humidity in air-conditioned environment. *Building and Environment, 45*(10), 2177–2183.
Druckman, A., & Jackson, T. (2008). Household energy consumption in the UK: A highly geographically and socio-economically disaggregated model. *Energy Policy, 36*(8), 3177–3192.
Earthdata. (2019). https://earthdata.nasa.gov/. (Accessed 22 July 2019).
Esri Netherlands. (2016). *3D BAG*. http://www.esri.nl/nl-NL/news/nieuws/sectoren/nieuw-in-arcgis-voor-leefomgeving. (Accessed 9 March 2017).
European Environment Agency. (2016). https://www.eea.europa.eu/data-and-maps/data/clc-2012-raster. (Accessed 8 March 2018).
Ewing, R., & Rong, F. (2008). The impact of urban form on US residential energy use. *Housing Policy Debate, 19*(1), 1–30.
Fong, W. K., Matsumoto, H., Lun, Y. F., & Kimura, R. (2007). Influences of indirect lifestyle aspects and climate on household energy consumption. *Journal of Asian Architecture and Building Engineering, 6*(2), 395–402.
Hassid, S., Santamouris, M., Papanikolaou, N., Linardi, A., Klitsikas, N., Georgakis, C., et al. (2000). The effect of the Athens heat island on air conditioning load. *Energy and Buildings, 32*(2), 131–141.
van der Hoeven, F., & Wandl, A. (2015). Amsterwarm: Mapping the landuse, health and energy-efficiency implications of the Amsterdam urban heat island. *Building Service Engineering Research and Technology, 36*(1), 67–88.
Joyeux, R., & Ripple, R. D. (2007). Household energy consumption versus income and relative standard of living: A panel approach. *Energy Policy, 35*(1), 50–60.
KNMI. (2018). http://www.sciamachy-validation.org/climatology/daily_data/selection.cgi. (Accessed 8 March 2018).
Kolokotroni, M., Zhang, Y., & Watkins, R. (2007). The London heat island and building cooling design. *Solar Energy, 81*(1), 102–110.
Lenzen, M., Wier, M., Cohen, C., Hayami, H., Pachauri, S., & Schaeffer, R. (2006). A comparative multivariate analysis of household energy requirements in Australia, Brazil, Denmark, India and Japan. *Energy, 31*(2), 181–207.
Letu, H., Hara, M., Yagi, H., Naoki, K., Tana, G., Nishio, F., et al. (2010). Estimating energy consumption from night-time DMPS/OLS imagery after correcting for saturation effects. *International Journal of Remote Sensing, 31*(16), 4443–4458.
Mashhoodi, B., Stead, D., & van Timmeren, A. (2019). Spatial homogeneity and heterogeneity of energy poverty: a neglected dimension. *Annals of GIS, 25*(1), 19–31.
Mashhoodi, B., Stead, D., & van Timmeren, A. (2019). Local and national determinants of household energy consumption in the Netherlands. *GeoJournal*, 1–14.
Mashhoodi, B., & van Timmeren, A. (2018). Local determinants of household gas and electricity consumption in Randstad region, Netherlands: application of geographically weighted regression. *Spatial Information Research, 26*(6), 607–618.
Nakaya, T., Fotheringham, A. S., Charlton, M., & Brunsdon, C. (2009). *Semiparametric geographically weighted generalised linear modelling in GWR 4.0*.
Sanaieian, H., Tenpierik, M., van den Linden, K., Seraj, F. M., & Shemrani, S. M. M. (2014). Review of the impact of urban block form on thermal performance, solar access and ventilation. *Renewable and Sustainable Energy Reviews, 38*, 551–560.
Santamouris, M., Cartalis, C., Synnefa, A., & Kolokotsa, D. (2015). On the impact of urban heat island and global warming on the power demand and electricity consumption of buildings—a review. *Energy and Buildings, 98*, 119–124.
Santamouris, M., Papanikolaou, N., Livada, I., Koronakis, I., Georgakis, C., Argiriou, A., et al. (2001). On the impact of urban climate on the energy consumption of buildings. *Solar Energy, 70*(3), 201–216.
Shen, H., Huang, L., Zhang, L., Wu, P., & Zeng, C. (2016). Long-term and fine-scale satellite monitoring of the urban heat island effect by the fusion of multi-temporal and multi-sensor remote sensed data: A 26-year case study of the city of Wuhan in China. *Remote Sensing of Environment, 172*, 109–125.
Silva, J., Ribeiro, C., & Guedes, R. (2007). May. Roughness length classification of corine land cover classes. In *Proceedings of the European wind energy conference, milan, Italy* (Vol. 710, p. 110).
Sluiter, R. (2012). *Interpolation methods for the climate Atlas. KNMI technical rapport TR–335*. De Bilt: Royal Netherlands Meteorological Institute.
Steemers, K., & Yun, G. Y. (2009). Household energy consumption: A study of the role of occupants. *Building Research & Information, 37*(5–6), 625–637.
Stepek, A., & Wijnant, I. L. (2011). *Interpolating wind speed normals from the sparse Dutch network to a high resolution grid using local roughness from land use maps*. Technical Report TR-321. Koninklijk Nederlands Meteorologisch Instituut.
Tso, G. K., & Yau, K. K. (2003). A study of domestic energy usage patterns in Hong Kong. *Energy, 28*(15), 1671–1682.
Van Moeseke, G., Gratia, E., Reiter, S., & De Herde, A. (2005). Wind pressure distribution influence on natural ventilation for different incidences and environment densities. *Energy and Buildings, 37*(8), 878–889.
Van der Hoeven, F. D., & Wandl, A. (2015). Hotterdam: Hoe ruimte Rotterdam warmer maakt, hoe dat van invloed is op de gezondheid van inwoners, en wat er aan te doen is. *TUDelft Boukunde*.
Wolf, T., & McGregor, G. (2013). The development of a heat wave vulnerability index for London, United Kingdom. *Weather Clim. Extrem., 1*, 59–68.
York, R. (2007). Demographic trends and energy consumption in European Union Nations, 1960–2025. *Social Science Research, 36*(3), 855–872.
Yun, G. Y., & Steemers, K. (2011). Behavioural, physical and socio-economic factors in household cooling energy consumption. *Applied Energy, 88*(6), 2191–2200.
Zeng, C., Shen, H., & Zhang, L. (2013). Recovering missing pixels for Landsat ETM+ SLC-off imagery using multi-temporal regression analysis and a regularization method. *Remote Sensing of Environment, 131*, 182–194.
Zhang, Q. (2004). Residential energy consumption in China and its comparison with Japan, Canada, and USA. *Energy and Buildings, 36*(12), 1217–1225.