The Spatial Dimension of Household Energy Consumption

Mashhoodi, Bardia

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The Spatial Dimension of Household Energy Consumption

Dissertation

for the purpose of obtaining the degree of doctor
at Delft University of Technology
by the authority of the Rector Magnificus, prof.dr.ir. T.H.J.J. van der Hagen
chair of the Board for Doctorates
to be defended publicly on
Wednesday, 12 June 2019 at 10.00 o'clock

by

Bardia MASHHOODI
Master of Science in European Postgraduate Master in Urbanism,
Delft University of Technology, the Netherlands
born in Tehran, Iran

This dissertation has been approved by the promotors.

Composition of the doctoral committee:

Rector Magnificus,	chairperson
Prof.dr.ir. A. van Timmeren	Delft University of Technology, promotor
Dr. D. Stead	Delft University of Technology, copromotor

Independent members:

Prof.dr.ir. E.S. van Leeuwen,	Wageningen University and Research
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To

Azar, Sohrab, Katayoun, Reza, Laura and Ava

Preface

In my undergraduate studies, I trained simultaneously as an architect and an engineer, by completing two BSc degrees: one in Architecture and one in Industrial Engineering, specializing in system analysis and programming. Since the completion of my undergraduate studies, my primary research approach and interest has been to bring these two disciplines together. In my postgraduate thesis in urbanism, I developed a computer based decision support system to facilitate planning processes in Cruquius area in Amsterdam by analysing different layers of spatial data. Since 2010, in a variety of research projects in the Department of Urbanism, I have adopted engineering methods, among them data mining, mathematical analysis, and decision making techniques for application in spatial studies, thus that supporting urban planners, social scientists and policy makers with decision making and research.

Application of quantitative methods and engineering approach for urban studies, however, appeared to be subjected to lot of resistance from a part of researchers in the field of urban studies, whereas it was welcomed from the other part. When I was defending my master thesis, for instance, I have received very mixed reactions from the jury. While I got score A from two of the jury members, the third member of committee believed that "this is a thesis suitable for the faculty of computer science and not for the faculty of urban planning," and the fourth member of committee believed "urban design is our job, not that of computers." During the first-year-review of my PhD, a respected professor from our faculty had only one comment to make: "I believe modelling means garbage in, garbage out." He, subsequently, refused to elaborate any further.

My PhD is the story of an endeavour to prove that urban studies can benefit from mathematical and probabilistic studies. It is the story of a 24/7 nine-years fight to show that in the era of big data urban planners and designers cannot pass the growing amount of information unnoticed, and to do so need to be equipped with appropriate methods. Since 2010, one must acknowledge, the approach to modelling and use of data has vastly altered in the faculty, as nowadays the use of such methods is more and more accepted. The fight, however, goes on. It is on all young researchers to try to break through old perspectives while learning from, discussing with and engaging with learned researchers from previous generations. As Sohrab Sepehri, a contemporary Iranian poet, says:

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One must wash eyes, look differently to things
One must wash the words
One must shut umbrellas
One must walk in the rain
One must carry the thought, the recollection in the rain
One must go walk in the rain with all the townsfolk
One must see friends in the rain

Acknowledgements

This work is dedicated to my beloved mother, to my *madar joon*, to my *Azar*, for her unconditional love, for all her sacrifices, for her eternal emphasise on learning, reading and reasoning, for all self-confidence that she gave to me, for all her acknowledgments of my achievements from the very first day of my life, for her unconditional faith in me whenever I failed, for 26 years of being there whenever I wanted to talk, and for our non-stop dialogue of the last 12 years. I forever love you *madar joon*. I hope I am the son you wanted me to be.

This book is dedicated to my father, my *pedar joon*, my *Sohrab*, the best father one can ever wish for, for being my first teacher of urbanism, politics, history and economy; for all the times that I sat on his shoulder when he was reading; for all the walks of the school boy with his father while he was explaining the clash and deal between Reagan and Gorbachev; for telling me in a simplified language what is Marxism, Capitalism, Liberalism, Conservatism, and how inflation grows when government's deficit is large; for telling me over his masterplans of Shoushtar, Parsoumash, Masjed Soleyman, etc; for being self-less and modest while he always has been the person who we all have been extremely proud of being his family.

This book is to my sister, my *Katayoun*, for being my defender, my friend, my supporter and my secret keeper, for knowing that Katayoun is always there, and for the pride of being "Katayoun's brother". I dedicate the book to *Dai Reza* for his life time of support and unconditional love. From the first day, when you bought me a basketball ball double of my size, I learned to think and to wish big. This book is also dedicated to my *Laura*. When I saw you the first time at the lake and opened up with a random joke, I could not possibly imagine what a life-time friend I have found. I could not possibly imagine how my life will turn into love, happiness, friendship, security and hope, and that you are the "one". To you, to us, to our future and to the melody of our life, *Ava*.

I thank all the colleagues, friends and teachers without whom I would never manage to complete this dissertation. To beloved Dr. Ina Klaasen. Without your help I could not manage to pass the hardest days and complete my studies. To Professor Han Meyer and Professor Arjan van Timmeren and Dr. Dominic Stead for all their support. To Dena Kasraeian, a friend/sister, Pirouz Nourian, a friend/brother, Samaneh Rezvani, Milan Zlatkov, Hans Larsson, Anke van Den Dries, Marios Kotsonis, Daniel

Garcia Bernal, Pourya Mortazavian, Yasi Mirfendereski, Andre Schaap, Akkie van Nes, Jorge Gil, Miguel Serra, Alex Wandl, Birgit Hausleitner, Claudiu Forgaci, Olgu Caliskan and all friends and colleagues who have helped and supported me in the last nine years.

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Summary

The vast majority of previous studies on household energy consumption (HEC) has presumed that the influencing factors of HEC are similar in each and every location regardless of the location-specific circumstances. In other words, they assume that some generalizable facts explain the level of HEC and energy poverty across all areas of a city, country, region, and/or continent. At the national scale, the Third National Energy Efficiency Action Plan for the Netherlands, regarding the reduction of household energy consumption has introduced a variety of policy measures and incentives for reduction of HEC among them energy tax, reduction on VAT rate on labour cost of renovation of dwellings, energy saving agreement for rental sector, etc. Furthermore, the policy document emphasise that the geographic scope of all policy measures is “the Netherlands”. In this respect, Third National Energy Efficiency Action Plan for the Netherlands, introduce an identical set of measures and instrument for all areas of the Netherlands regardless of their location-specific circumstances.. The objective of this thesis is to examine the validity of this presumption through five different studies four of which published as a scientific journal, and one of which is accepted for publication. To do so, the impact of a variety of the determinants of HEC of the Dutch neighbourhoods are studied and compared. The result of the studies shows that the impact of such determinants are spatially homogenous (i.e. similar across all neighbourhoods in question) or spatially heterogeneous (varies from one neighbourhood to another). The studies can be categorised in two groups: (i) three studies on HEC of all neighbourhoods of the Netherlands; (ii) two studies on the neighbourhoods of the Randstad region.

Studies on all neighbourhoods of the Netherlands

Local and national Determinants of Household Energy Consumption in the Netherlands

The policies of Third National Energy Efficiency Action Plan for the Netherlands, regarding the reduction of household energy consumption (HEC), were made based on the unwritten presumption that the stimuli of HEC are similar in each and every location of the Netherlands, and that it therefore is possible to formulate an identical set of incentives and regulations that are optimally suitable in all the locations of the country. The objective of this study is to examine the validity of this presumption

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by formulating two research questions: what are the global determinants of HEC, i.e. the stimuli that trigger the same response across the whole country? What are the local determinants of HEC, i.e. the stimuli which trigger different responses across the country? To identify local and global determinants of HEC, the impact of nine determinants of HEC in 2 462 neighbourhoods of the Netherlands is assessed by employing the geographical variability test. The results show that two of the determinants are global: (i) the number of frost-days, (ii) wind speed. The results indicate that seven of the determinants are local: (i) income, (ii) household size, (iii) building age, (iv) surface-to-volume ratio, (v) population density, (vi) number of summer days, and (vii) land surface temperature. By employing a semi-parametric geographically weighted regression analysis, the impact of the local and global determinants of HEC is estimated and mapped.

Urban heat islands and household energy consumption

It is widely accepted that urban heat islands affect household energy consumption (HEC). To verify the validity of this proposition, a variety of studies have examined the impact of land surface temperature (LST) on HEC. However, often the variation of LST's impact in different locations is not examined.. A number of questions arise: for how many percentage points of HEC does LST account? Furthermore, does LST's impact differ with regard to demography, housing, urban form, and urban microclimate of the neighbourhood in question? To study the impact of LST on the HEC of the urbanised neighbourhoods of the Netherlands in 2014, this study develops two semi-parametric geographically weighted regression models: first, estimating the impact of LST and nine control variables; second, estimating the impact of the control variables only. We conclude that: (i) the impact of LST varies from one neighbourhood to another; (ii) the impact of LST is significant in 31% of the neighbourhoods, where it accounts for 6% of HEC on average; (iii) the impact varies from one neighbourhood to another, and is vastly affected by geographic context of the neighbourhood in question.

Spatial homogeneity and heterogeneity of energy poverty in the Netherlands: a neglected dimension

Since the 1970s, a variety of studies has searched for the sociodemographic, housing, and economic determinants of energy poverty. A central question, however, has not been answered by any of the previous studies: what are the national-level determinants, i.e. the determinants that homogeneously provoke a high level of energy poverty in all areas of a country? What are the neighbourhood-specific determinants, i.e. the characteristics that have a heterogeneous impact across the neighbourhoods of a country? This study seeks to answer these questions by analysing the level of energy poverty, the percentage of households' disposable income spent on energy expenditure, in 2 473 neighbourhoods of the Netherlands in 2014. By employing a semi-parametric geographically weighted regression analysis, the effect of two of the determinants of energy poverty are found to be spatially homogeneous: (i) percentage of low income households; (ii) percentage of pensioners. The results indicate that the impact of four of the determinants are spatially heterogeneous: (i) household size; (ii) percentage of unemployment; (iii) building age; (iv) percentage of privately rented dwellings; (v) number of summer days; (vi) number of frost days. Subsequently, the effects of spatially homogeneous and heterogeneous determinants are estimated and mapped; the results are discussed and some policy implications are proposed.

Studies on the neighbourhoods of the Randstad region

Spatial Dynamics of Household Energy Consumption and Local Drivers in Randstad, Netherlands

This study is an attempt to bridge an eminent knowledge gap in the empirical studies on Household Energy Consumption (HEC): the previous studies implicitly presumed that the relationships between HEC and the geographic drivers is uniform in different locations of a given study-area, and thus have tried to disclose such everywhere-true relationships. However, the possible spatially varying relationships between the two remain unexplored. By studying the performance of a conventional OLS model and a GWR model – adjusted R2, randomness of distribution of residual (tested by Moran's I), AIC and spatial stationary index of the geographic drivers, ANOVA test of residuals – this study demonstrates that the GWR model substantially provides a better understanding of HEC in the Randstad. In this respect, the core conclusion of this study is: the relationships between HEC and geographic drivers are spatially varying and therefore needed to be studied by means of geographically weighted models. Additionally, this study shows that considering spatially varying relationships between HEC and geographic drivers, by application of hierarchical clustering, the areas of the Randstad can be classified in four clusters: building age and income impact areas, building density impact areas, population density and built-up impact areas, household size and income impact areas.

Local determinants of household gas and electricity consumption in Randstad region, Netherlands: application of geographically weighted regression

The previous studies on household energy consumption (HEC) are based on an implicit assumption: the impact of geographic determinants on HEC is uniform across a given region, and such impacts could be unveiled regardless of geographic location of households in question. Consequently, these studies have searched for global determinants which explain HEC of all areas. This study aims at examining validity of this assumption in Randstad region by putting forward a question regarding households' gas and electricity consumption: are the determinants global, stationary across all the areas of the region, or local, varying from one location to another? By application of geographically weighted regression, impact of socioeconomic, housing, land cover and morphological indicators on HEC is studied. It is established that the determinants of HEC are local. This result led to second question: what are the main determinants of gas and electricity consumption in different neighbourhoods of Randstad? The results show that variety of factors could be the most effective determinant of gas consumption in different neighbourhoods: building age, household size and inhabitants' age, inhabitants' income and private housing tenure, building compactness. Whereas, in case of electricity consumption the picture is more deterministic: in most of the neighbourhoods the most effective factors are inhabitants' income and private tenure.

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Samenvatting

In eerder onderzoek naar huishoudelijk energieverbruik (*household energy consumption*, HEC) is er meestal van uitgegaan dat de factoren die van invloed zijn op het HEC overal ongeveer gelijk zijn, ongeacht plaatsgebonden omstandigheden. De aanname was met andere woorden dat een aantal te veralgemeniseren feiten de hoogte van het HEC en de energiearmoede kan verklaren in alle delen van een stad, land, regio of continent. Zo is ook het beleid van het Derde Nationale Energie Efficiëntie Actie Plan voor Nederland (2014), gericht op vermindering van het energieverbruik van huishoudens, gebaseerd op de onuitgesproken veronderstelling dat de oorzaken van het HEC op elke plaats in Nederland dezelfde zijn, en dat het mogelijk is één stelsel van stimuleringsmaatregelen en richtlijnen te formuleren dat overal in het land even goed toepasbaar is. Het doel van dit proefschrift is de geldigheid van deze veronderstelling te onderzoeken aan de hand van vijf verschillende studies, waarvan er vier zijn gepubliceerd in een wetenschappelijk tijdschrift en een is geaccepteerd voor publicatie. Met het oog op dit doel is de impact van een aantal determinanten van het HEC in Nederlandse buurten onderzocht en vergeleken. Uit de studies blijkt dat de impact van deze determinanten hetzij ruimtelijk homogeen (soortgelijk in alle onderzochte buurten), hetzij ruimtelijk heterogeen (van buurt tot buurt verschillend) zijn. De studies kunnen in twee groepen worden onderverdeeld: (i) drie studies over het HEC van alle buurten van Nederland; (ii) twee studies over de buurten in de Randstad.

Studies over alle buurten van Nederland

Lokale en nationale determinanten van huishoudelijk energieverbruik in Nederland

De beleidsregels van het Derde Nationale Energie Efficiëntie Actie Plan voor Nederland, gericht op vermindering van het HEC, zijn gebaseerd op de onuitgesproken veronderstelling dat de bepalende factoren van het HEC op elke plaats in Nederland dezelfde zijn, en dat het daardoor mogelijk is één stelsel van stimuleringsmaatregelen en richtlijnen te formuleren dat overal in het land optimaal toepasbaar is. Het doel van deze studie is de geldigheid van deze veronderstelling te onderzoeken door twee onderzoeksvragen te formuleren. Wat zijn de globale determinanten van het HEC, dat wil zeggen de stimuli die in het hele land dezelfde

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respons opwekken? Wat zijn de lokale determinanten van het HEC, dat wil zeggen de stimuli die op verschillende plaatsen verschillende responsen opwekken? Om de lokale en globale determinanten van het HEC te bepalen, is de impact van negen determinanten van het HEC in 2462 buurten in Nederland beoordeeld met behulp van de geografische variatietest. Uit de uitkomsten blijkt dat twee van de determinanten globaal zijn: (i) aantal vorstdagen en (ii) windsnelheid. Uit de uitkomsten blijkt dat zeven van de determinanten lokaal zijn: (i) inkomen, (ii) grootte van het huishouden, (iii) bouwjaar, (iv) oppervlakte-inhoudrelatie, (v) bevolkingsdichtheid, (vi) aantal zomerse dagen en (vii) aardoppervlaktemperatuur. Door toepassing van semiparametrische geografisch gewogen regressieanalyse wordt de impact van de lokale en globale determinanten van het HEC geschat en in kaart gebracht.

Stedelijke hitte-eilanden en huishoudelijk energieverbruik

De invloed van stedelijke hitte-eilanden op het HEC is algemeen aanvaard. Om de geldigheid van deze stelling te verifiëren, is in een aantal onderzoeken de invloed van de aardoppervlaktemperatuur (*land surface temperature*, LST) op het HEC bestudeerd. Er is echter geen eerder onderzoek bekend waarin wordt opgehelderd of de impact van de LST in elke buurt dezelfde is dan wel per locatie varieert. Hierbij komen verschillende vragen op. Voor welk aandeel van het HEC is de LST verantwoordelijk? En verschilt de impact van de LST met betrekking tot de demografie, de huisvesting, de stedelijke vorm en het stedelijke microklimaat van de buurt in kwestie? Om de impact van de LST op het HEC in de verstedelijkte buurten van Nederland in 2014 te onderzoeken, zijn in deze studie twee semiparametrische geografisch gewogen regressiemodellen ontwikkeld: het eerste om de impact van de LST en negen controlevariabelen te schatten, het tweede om uitsluitend de impact van de controlevariabelen te schatten. Onze conclusie is dat: (i) de impact van de LST van buurt tot buurt verschilt, (ii) de impact van de LST significant is in 31% van de buurten, waar de aardoppervlaktemperatuur verantwoordelijk is voor gemiddeld 6% van het HEC, en (iii) de impact in hoge mate wordt beïnvloed door de geografische context van de buurt in kwestie.

Ruimtelijke homogeniteit en heterogeniteit van de energiearmoede in Nederland: een verwaarloosde dimensie

Sinds de jaren 1970 is verschillende malen onderzoek gedaan naar de sociaal-demografische, huisvestingsgerelateerde en economische determinanten van energiearmoede. Een centrale vraag is echter niet in eerder onderzoek beantwoord: wat zijn de determinanten op nationaal niveau, dat wil zeggen de determinanten die op homogene wijze in alle regio's van een land tot een hoge mate van energiearmoede leiden? En ook: wat zijn de buurtspecifieke determinanten, dat wil zeggen de kenmerken die een heterogene impact hebben op de buurten in een land? In dit onderzoek proberen we deze vragen te beantwoorden door de energiearmoede (het percentage van het besteedbaar inkomen dat huishoudens aan energie uitgeven) in 2014 te analyseren in 2473 buurten in Nederland. Door toepassing van semiparametrische geografisch gewogen regressieanalyse wordt aangetoond dat het effect van twee van de determinanten van energiearmoede ruimtelijk homogeen is: (i) percentage huishoudens met een laag inkomen en (ii) percentage gepensioneerden. De uitkomsten geven aan dat de impact van vier van de determinanten ruimtelijk heterogeen is: (i) grootte van het huishouden, (ii) percentage werkloosheid, (iii) bouwjaar, (iv) percentage particuliere huurwoningen, (v) aantal zomerse dagen en (vi) aantal vorstdagen. Vervolgens worden de effecten van ruimtelijk homogene en heterogene determinanten geschat en in kaart gebracht, de uitkomsten besproken en enkele beleidsimplicaties geformuleerd.

Studies over de buurten in de Randstad

De ruimtelijke dynamiek van huishoudelijk energieverbruik en lokale factoren in de Randstad

Deze studie is een poging om een belangrijk kennistekort in het empirisch onderzoek naar het HEC op te heffen: in eerder onderzoek werd impliciet aangenomen dat de relatie tussen het HEC en de geografische factoren op verschillende plaatsen binnen een onderzocht gebied eenvormig zou zijn, en werd derhalve getracht dergelijke overal geldende relaties bloot te leggen. Mogelijke ruimtelijk gevarieerde relaties werden echter niet onderzocht. Door bestudering van de prestaties van een conventioneel OLS-model en een GWR-model -gecorrigeerde R2, aselecte verdeling van residuen (getest met Moran's I), AIC en ruimtelijke stationaire index van de geografische factoren, ANOVA-test van residuen- toont dit onderzoek aan dat het GWR-model een substantieel beter inzicht biedt in het HEC in de Randstad. In dat verband is de centrale conclusie van dit onderzoek dat de relatie tussen het HEC en de geografische factoren ruimtelijk variabel is en daarom moet worden bestudeerd met behulp van geografisch gewogen modellen. Bovendien toont dit onderzoek aan dat ten aanzien van ruimtelijk variabele relaties tussen het HEC en de geografische factoren de gebieden van de Randstad door toepassing van hiërarchisch clusteren kunnen worden onderverdeeld in vier clusters met een overheersende (1) impact van bouwjaar en inkomen, (2) impact van dichtheid van bebouwing, (3) impact van bevolkingsdichtheid en bebouwing en (4) impact van grootte van het huishouden en inkomen.

Lokale determinanten van huishoudelijk gas- en elektriciteitsverbruik in de Randstad: toepassing van geografisch gewogen regressie

Eerdere onderzoeken naar het HEC waren gebaseerd op de impliciete veronderstelling dat de impact van geografische factoren op het HEC binnen een bepaalde regio eenvormig zou zijn, en dat die impact aan het licht kon worden gebracht ongeacht de geografische locatie van de huishoudens in kwestie. Als gevolg hiervan werd in deze onderzoeken gezocht naar globale determinanten als verklaring voor het HEC in alle gebieden. Deze studie is bedoeld om de geldigheid van de veronderstelling in de Randstad te onderzoeken met een vraag naar huishoudelijk gas- en elektriciteitsverbruik: zijn de determinanten globaal en dus stationair in alle delen van de Randstad, of zijn ze lokaal en dus verschillend van plaats tot plaats? Met behulp van geografisch gewogen regressieanalyse is de impact van sociaaleconomische, huisvestingsgerelateerde, bebouwingsgerelateerde en morfologische indicatoren op het HEC onderzocht. Daarbij is vastgesteld dat de determinanten van het HEC lokaal zijn. Deze uitkomst leidde tot een tweede vraag: wat zijn de voornaamste determinanten van gas- en elektriciteitsverbruik in verschillende buurten in de Randstad? De resultaten laten zien dat verschillende factoren in verschillende buurten de invloedrijkste determinant van het gasverbruik kunnen zijn: bouwjaar, grootte van het huishouden en leeftijd van de bewoners, inkomen van de bewoners en particulier woningbezit, compactheid van de bouw. Bij het elektriciteitsverbruik is het beeld eenduidiger: in de meeste buurten zijn de invloedrijkste factoren het inkomen van de bewoners en particulier woningbezit.

1 Introduction

1.1 Climate change, GHG emission, and energy consumption: a global outlook

1.1.1 Global Warming

Global Warming, an agreed-upon fact among almost all environmental scientists around the world, is something that can be quantified by variety of measurements. The most accepted measurements of Global Warming come from the Intergovernmental Panel on Climate Change (IPCC), a research body that is affiliated to the United Nations (UN). Global Warming technically refers to the increase in Global Mean Surface temperature (GMST), which has been recorded for decades, starting from the pre-industrial period of human development (IPCC, 2017). A variety of methods for the measurement of GMST have been proposed and applied during the recent years – among them include finding the weighted average of the near-surface temperature (Hartmann et al., 2013; Morice et al, 2012) and the changes of temperature over land and sea surface (Stocker et al., 2013). According to a study by Cowtan et al. (2015), although the application of different methods has resulted in different measurements of GMST since the difference between measurements remains below 0.2°C. In short, this change of temperature confirms that the earth is becoming warmer. An estimation of average global land-sea temperature by NASA (Figure 1.1), for example, shows that the increase in temperature is in fact significant.

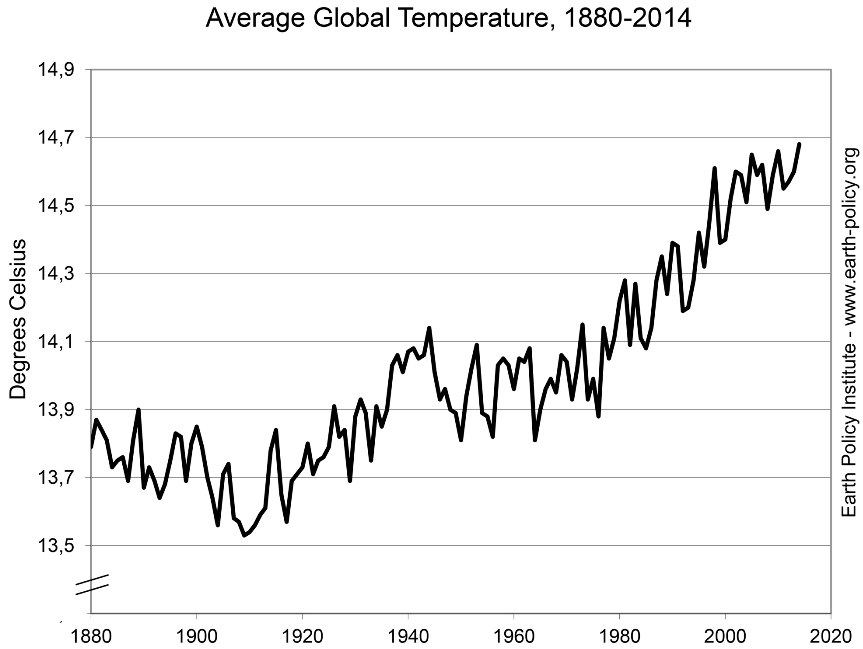

FIG. 1.1 Average global temperature 1880-2020 (Earth Policy Institute, 2015)

Continued Global Warming in the next couple of decades will pose a great risk to humankind, in terms of both economic growth and overall health. Simulation models that measure the impact of global change on economic growth developed by the Organisation for Economic Co-operation and Development (OECD – an organization of mostly developed countries) show that if no specific action to mitigate the climate change is taken, the global annual GDP will shrink between 1.0% to 3.3% by 2060. Should global temperatures rise up to 4.0°C above the pre-industrial level (as projected if the current trend carries on), the damage to global GDP could amount up to 10%. According to the OECD, the agriculture sector would bear the most damage in the global economy, due to expected decreases in crop yields and reductions of labour productivity. If the current trends in warming continue, the projected production of fruits and vegetables such as sugar cane, beets, oil seeds, plant fibres, rice, wheat and other grains would sharply decrease in the most of the areas of the world by 2050. In India, for example, the production of sugar cane and beets are expected to decline by 50%, while China and Korea are supposed to see declines in the 20 to 30 percent ranges. The yield of rice in Mexico and North America, as well as the production of vegetables and fruits in ASEAN 9 countries, is estimated to drop around 30%. The expected rise of sea levels consequent to Global Warming is expected to damage the economy of many coastal regions, subsequent to the loss of land and capital caused by flooding and the destruction of property. This type of damage could account for severe GDP loss in many regions of the world. The places which are expected to feel the highest amounts of contraction include India (0.63%), China (0.86%), Canada (0.47%), the Middle East (0.35%), and Europe (0.37%) by the year 2060 - when compared to year 2000 (OECD, 2015).

The predicted increase in the frequency and amount of intense climate events such as large scale hurricanes, floods in the urban areas, and out of control wildfires would further damage many national economies. In the long run, Global Warming is also expected to decrease the demand for tourist related activities. This prediction is formulated by the so-called Hamburg Tourism Model (Bigano et al., 2007), which is an econometric simulation model of domestic and international tourism. This model shows that the impact of climate change (i.e. the increase in the average temperature) on the income per capita and the plausibility of tourist destinations, which combined could estimate the posed risks to the economic revenues of the tourism sector.

The health issues caused by the continued increase in the global temperature are amplified in urbanized areas due to the consequences of the urban heat island effect. This phenomenon poses a risk of increased premature mortalities in the warm seasons caused by heat stress in regions which are densely populated (e.g. India and China) and the regions with a high concentration of senior citizens who are particularly vulnerable to heat waves (e.g. Europe and Japan). Changes in the global climate also pose other health risks, such as the increase in the occurrence of diseases such as Schistosomiasis, Malaria, Dirrohoea, and other cardiovascular and respiratory problems (Bosello and Parrado, 2014; Bosello et al., 2012).

In addition to all the previously mentioned risks that a continued trend of Global Warming could pose, there are many other natural, managed, and human systems which can see a significant impact (Figure 1.2). Article 2 of the United Nations Paris Agreement on Climate Change (Paris Agreement, 2015, p.3) states that “holding the increase in the global average temperature to well below 2°C above pre-industrial levels” is an essential action that must be undertaken by all member states. It also recommends that “pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels would significantly reduce the risks and impacts of climate change.”

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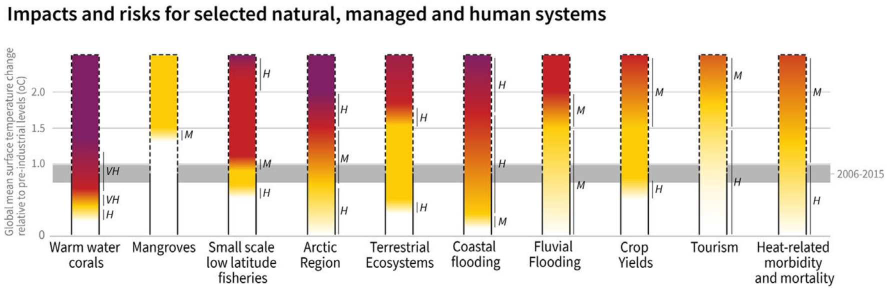

FIG. 1.2 Risk assessment of global warming in three categories: Very high (VH), High (H), Moderate (M) (IPCC, 2017. pp. SPM-13)

1.1.2 Global Warming and greenhouse gas emission

According to a report by the World Meteorological Organization, greenhouse gas emissions (GHG) in general, and long-lived greenhouse gases (LLGHGs) in particular, has caused a 33k higher surface temperature when compared to a situation in which the gasses would be absent (WMO, 2015). This increased effect is caused by a phenomenon produced by GHG called "Radioactive Forcing," which is defined as the difference between the amount of solar radiation absorbed by the Earth surface and the amount of energy that is radiated back by the Earth. The concentration of GHG causes higher levels of surface temperature because it alters the equilibrium of Radioactive Forcing. The concentration of GHG creates a situation in which the amount of energy absorbed by the Earth increasingly exceeds the energy reflected back to space (Shindell et al., 2013). The WMO report shows that the Radiative Forcing created by the three main LLGHGs (i.e. CO_2, CH_4, N_2O), together with the gasses CFC-12 and CFC11, account for 96% of the imbalance in the Radioactive Forcing (CO_2 alone causes 65% this imbalance).

The association between Global Warming and the amount of global atmospheric CO_2 has been quantified by a variety of studies, such as the investigation into Equilibrium Climate Sensitivity (ECS). The study of ECS refers to the changes in the global surface temperature consequent to a 100% increase in atmospheric CO_2. The report on climate change by the IPPC (2007) states that there is a 90% likelihood that the temperature difference in ECS will increase more than 1.5°C, while there is a 66% likelihood that the increase will be between 2.0°C to 4.5°C. In the most likely of scenarios, the report estimates that the ECS will end up being around 3.0°C. In comparison, the OECD report on the economic impacts of climate change states that ECS is likely to range from 1.5°C to 4.5°C (2015). According to a review by

Rogelj et al. (2012), all previous studies have concluded that ECS is almost certainly to increase more than 1.5°C, with a probability ranging from 82% to 100% - past the minimum threshold set by the Paris agreement to limit the damages of Global Warming. Furthermore, according to the estimations of the most of the previous research, the likely value of ECS will be higher than the alarming 2.0°C threshold also set by Paris Agreement (Figure 1.3).

Study	Probability			Most likely value
	Above 1.5 °C	**Between 2.0 °C and 4.5 °C**	**Above 4.5 °C**	
Illustrative individual studies (non-exhaustive)				
Hegerl *et al.*[33]	87%	44%	34%	2.0 °C
Forster *et al.*[34]	82%	46%	20%	1.6 °C
Annan and Hargreaves[35]	98%	88%	5%	2.9 °C
Forest *et al.*[36] ('no expert priors' case)	100%	90%	6%	2.8 °C
Knutti *et al.*[37]	95%	71%	20%	3.2 °C
Murphy *et al.*[38]	100%	86%	14%	3.2 °C
Piani *et al.*[39]	99%	72%	24%	3.2 °C
Frame *et al.*[40]	100%	85%	12%	2.8 °C
Multiple lines of evidence				
IPCC FAR[41], SAR[42], TAR[43]	-	1.5–4.5 °C (no probability)	-	-
IPCC AR4 (ref. 1)	> 90%	> 66%	Not excluded	About 3 °C
This study's representative climate sensitivity distribution	95%	76%	14%	3.0 °C
Minimum-maximum values in this study's 10,000-member ECS ensemble	90 to > 99%	66–96%	< 1–33%	2.6–3.6 °C

FIG. 1.3 Selected previous studies on Equilibrium Climate Sensitivity (ECS) - the change in the global surface temperature consequent to 100% increase in the atmospheric CO_2 (Rogelj et al., 2012, pp. 249).

In order to achieve the goals set by the Paris agreement, the IPCC report states that the amount of CO_2 parts in atmosphere (among the other factors) need to be decreased by 20% by the year 2030 (IPCC, 2007). Despite of some seasonal fluctuations in the amount of growth between 1988 and 1994, a study by NASA shows that not only has the amount of global CO_2 has been increased every year since the 1970s, but also every year during this period has shown an upward trend in the additional amount of CO_2 that enters the atmosphere (see Figure 1.4). The most recent report by the WMO (2015) states that the amount of the three main LLGHGs in the atmosphere has drastically increased since the pre-industrial era: an 143% increase in CO_2, an 254% in CH_4, and an 121% in N_2o.

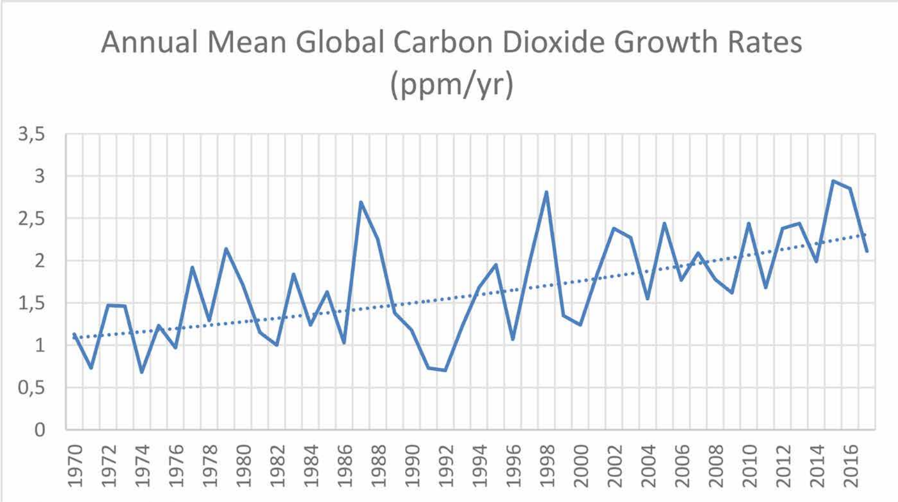

FIG. 1.4 Increase in concentration of CO_2 in atmosphere 1970-2016 (National Oceanic and Atmospheric Administration, 2018).

1.1.3 GHG emission and energy consumption

A report on the global trends of greenhouse gas emissions by the PBL Netherlands Environmental Assessment Agency (Olivier et al., 2017) shows that the level of GHG emissions is strongly associated with global energy consumption. A large share of CO_2 emissions, which account for 72% of global GHG emission, is created by energy consumption within country boundaries (i.e. excluding international aviation and shipping). In 2016, the amount of energy consumed in the more than five of the largest emitting countries (China, United States, India, Russia, Japan, and European Union) accounted for 68% of total global CO_2 emissions, and 63% of the world's total GHG emissions. One quarter of methane (CH_4) emissions, which account for 19% of the global GHG emissions are related to oil, natural gas, coal production, and distribution. One fifth of all fluorinated gases emissions, which account for 3% of global GHG emissions, is largely produced by processes involving refrigeration and air conditioning. Given the similar impact of energy consumption on N_2O emissions, the main determinant of most global GHG is the consumption of energy (Figure 1.5).

Global greenhouse gas emissions, per type of gas and source, including LULUCF

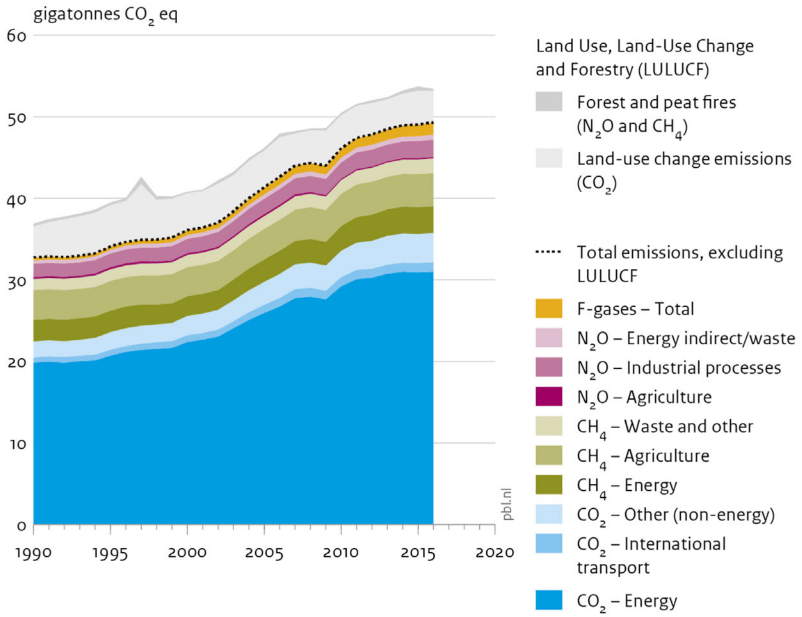

FIG. 1.5 Substantial share of energy consumption and production amongst the sources of global GHG emissions (Olivier et al., 2017, pp. 9).

The so-called Kaya Identity Method (Peters et al., 2017; Van Vuuren et al., 2007; Kaya, 1990) establishes causal links of GHG emissions, more specifically CO2 and its relation to energy consumption. This method analyzes three energy-related drivers of CO2 emission: (i) Gross domestic product (GDP), (ii) energy intensity of an economy (i.e. the average units of energy used per unit of GDP), and (iii) average CO2 emission produced per unit of energy use. The graph in Figure 1.6 illustrates the association between changes in the three components of the Kaya Identity Methods from 1990 and 2016, with the changes in global CO2 emissions that are also being measured within the same time frame. In this period, the global economy had grown by 3.3% (see the blue bars as the measurement of Purchasing Power Parity, PPP). In addition to this growth, the global energy use had also increased by 2% (1.3% less than global GDP – illustrated by negative green bars), while the CO2 emission per unit of energy use (illustrated by the purple bars) had decreased during most of the years. Also within this time frame, China experienced rapid growth, which had been stimulated by the vast consumption of coal, causing the average emission per unit of energy use to soar (especially during the years between 2003-2007). Since 2011, multiple factors have influenced the average emission per unit of CO2 to drop. This reduction is due in part to an increase in use of low-pollution energy sources (among them hydropower), the expansion in the use of renewable sources and nuclear energy, and the replacement of coal consumption with oil and natural gas (particularly in the emerging economies). The combined trajectories of the three components coincides with changes in the level of global CO2 emissions, demonstrated by the fact that the concentration of CO2 in the atmosphere has largely increased between 1990 and 2008 caused by massive growth in global GDP. In addition to this, the increase of CO2 in the atmosphere is more modest since 2008, due in part to the decline in energy intensity of both GDP growth and CO2 emission per unit of energy use.

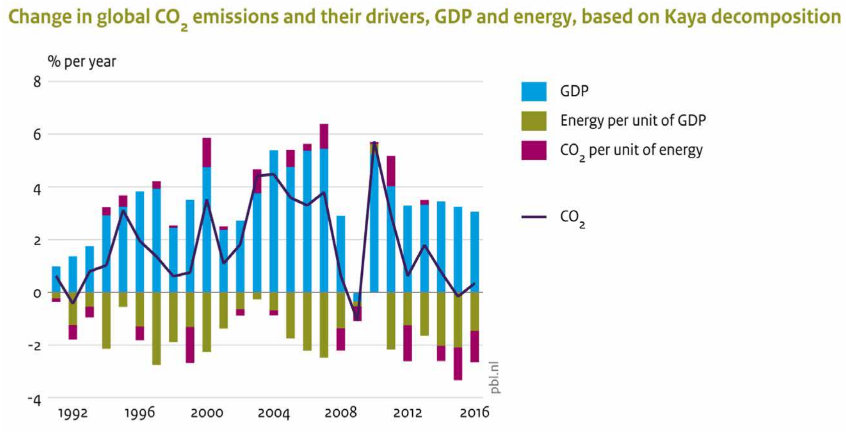

FIG. 1.6 Global changes in the three components of KAYA Identity model in associations with changes in CO2 emission (Olivier et al., 2017, pp. 14).

In contrast to the rest of the globe, the Kaya Identity Model of the European Union exhibits energy use and CO_2 emissions which illustrate a rather different picture. This is due in part to the increasing use of energy sources which are less carbon intensive between 1990 and 2016. The changes in the levels of CO_2 has been negative or near zero in most of the years between 1990 and 2016, mostly in response to phasing out the use of coal in regions like the Czech Republic, Eastern Germany, Romania, and the UK; as well as the growing use of solar and wind energy in Germany, UK, and Italy. Coupled with the general lower energy intensity demanded by EU economies, the decline in the carbon intensity of energy use set the EU and Japan apart from the six other large global emitters, due in part to the relatively low production of new CO_2 emissions (Figure 1.7).

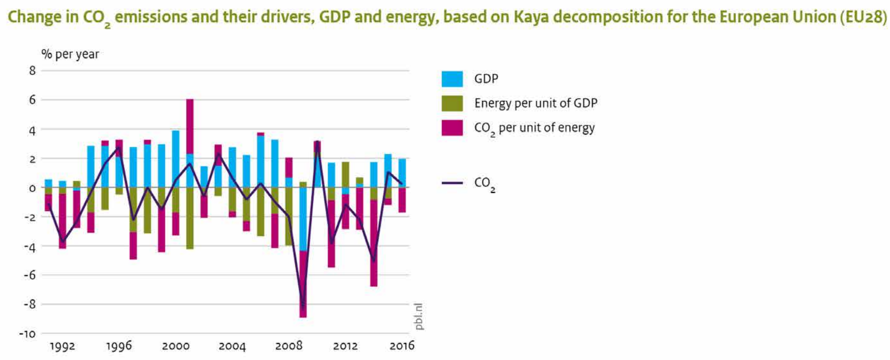

FIG. 1.7 Changes in the three components of KAYA Identity model in associations with changes in CO_2 emission in EU28 countries (Olivier et al., 2017, pp. 29).

1.1.4 Energy consumption and households

Around the globe, household energy consumption (HEC) accounts for a substantial share of both total energy consumption and the GHG emission associated with it. However, the share of HEC can vary across different countries and continents due to diverse levels of development, types of energy sources available, and access to gas and electricity grids. For example, the impact of HEC on CO_2 emissions in China is found to be highly variable across different regions, urban districts, and rural areas. In the case of rural areas, CO_2 emission per unit of energy use is higher than that in urban districts. This is due to the high dependency on coal consumption in rural areas, combined with their low to almost non-existent access to electricity and natural gas (Feng et al., 2011). A study of ten different rural areas across Africa, for instance, shows that on average 99% of households use fuelwoods for one purpose or another, while the access to electricity grid in these same areas is below 10% (Adkins et al., 2012). In summary, a substantial share of HEC emissions created around the globe is an established fact between scholars. The magnitudes of this share of emissions, however, vary from one location to another.

In the EU, the share of the residential sector in total energy consumption is substantial, and will continue to be substantial over the next three decades, according to a projection by the EU commission, also known as the EU Reference Scenario (European Commission, 2016). Presuming that the EU Commission policies targeting energy efficiency are well adhered to with efforts such as the Energy Efficiency Directive (EED) and the Energy Performance of Buildings Directive (EPBD). Because of these mandates, the total amount of energy consumption in the EU countries is supposed to start dropping after 2020. However, the share of residential sector is expected to stay around 27% of total energy consumption. Due to the expected growth of income in the coming decades, the demand for energy in the residential sector of the EU is set to grow. The absolute amount of energy use in the residential sector, however, will slightly decline due in part to both the rise of energy efficiency in appliances and buildings, combined with the increase in use of renewable energy such as solar panels (Figure 1.8).

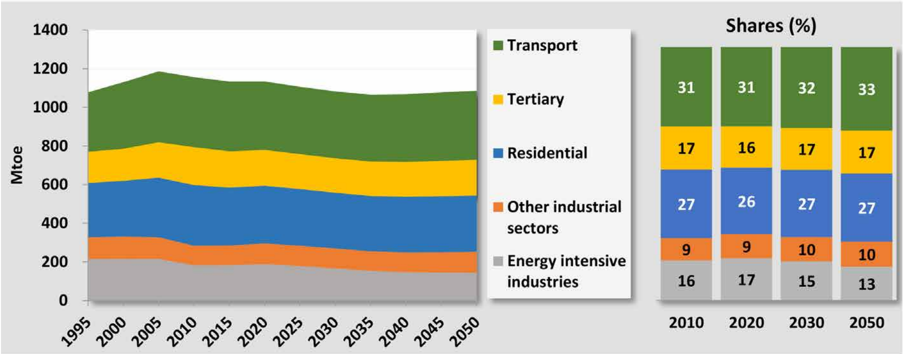

FIG. 1.8 Share of household energy consumption from total energy consumption will expectedly continue to persist over the next couple of decades (European Commission, 2016. pp. 50).

The increased share of the HEC from total energy consumption is supposed to continue until at least the year 2050. This trend is influenced by the impact of residential sector on the production of GHG emissions over the coming decades. In the EU-27 countries during 2015, the residential sector accounted for 25.3% of the total final energy consumption. The direct energy consumption by households, let alone their indirect consumption, created 19% the of GHG emissions in the EU (Eurostat, 2018a) (see Figure 1.9).

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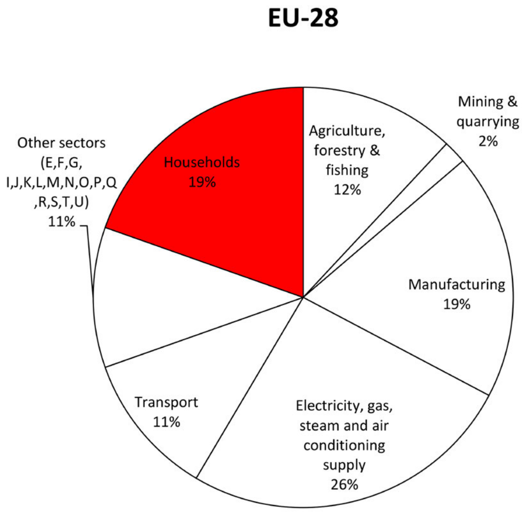

FIG. 1.9 Greenhouse gas emissions by economic sector, 2015 (Source: Eurostat, 2018a)

1.2 GHG emission and household energy consumption in the Netherlands

The energy sector in the Netherlands is highly dependent on fossil fuels. According to the National Energy Outlook (PBL, 2017), the trends and future projections of the primary energy sources in the Netherlands (i.e. the direct sources of energy before any conversion or transformation process) shows that in the year 2000, fossil fuels accounted for more than 90% of the primary energy sources used. Similar observations had been made by PBL in regards to the various types of fossil fuels during 2015. During this time period, oil has stayed relatively stable (36% in 2000 and 37% in 2015), while the share of natural gas has reduced about 10 % (moving down to 27% in 2015), and the share of coal has increased about 6% (moving up to 16% in 2015). In contrast, PBL energy projections indicate a rise in the share of renewable resources (up to 9% in 2020, and 17% 2035). The share of the fossil fuels, however, is not expected to decline below 83% until the year 2035 (Figure 1.10).

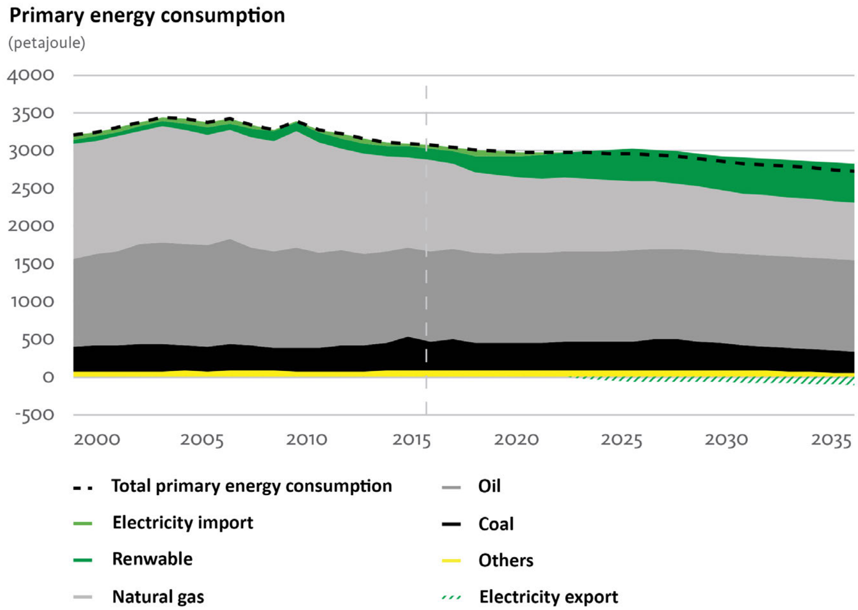

FIG. 1.10 Primary energy sources in the Netherlands (source: PBL, 2017b, pp.81)

The per capita amount of emissions in Netherlands are higher than the average emissions per head within the EU-28 countries. Since 1990, per capita emissions in both the Netherlands and Eu-28 countries have continuously declined. The rate of decline in the Netherlands, however, is slower than the overall average of the EU. In 1990, per capita emissions in Netherlands was 24% higher than the EU average. The corresponding number in 2016 was 37% higher than the EU average (Figure 1.11).

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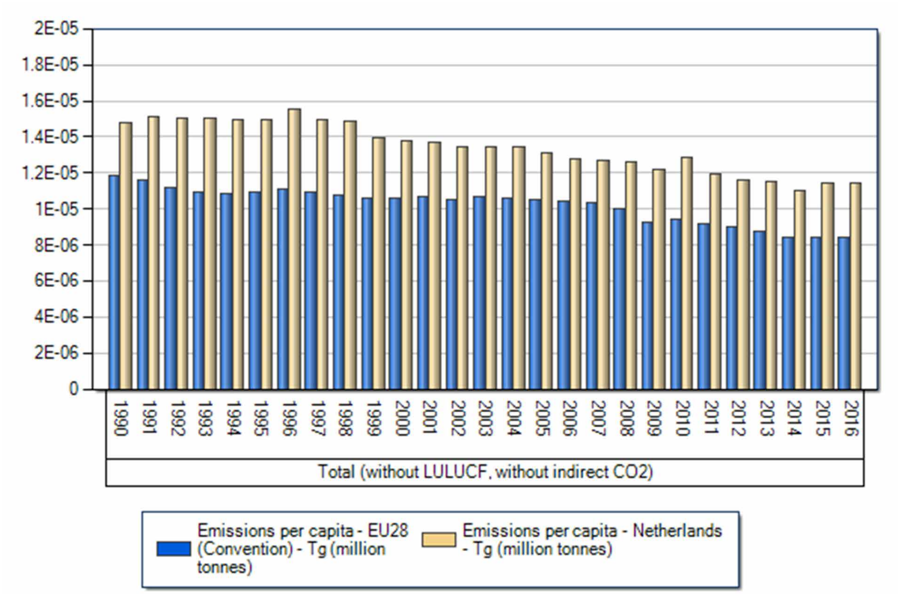

FIG. 1.11 Emission per capita in Netherlands compared to that of the EU member states (Source European Energy Agency, 2018)

The Netherlands is among the most energy intensive countries of the EU, and it is expected it will continue to be for the foreseeable future. According to the projection done by the EU commission, also known as the EU Reference Scenario (European Commission, 2016), the energy intensity of the EU countries (i.e. energy consumption compared to national GDP, particularly that of the Western member states and that of the countries with stronger economies) will continue to improve until the year 2030. Alongside Belgium, the Netherlands is the exception to this rule. According to the projection, by 2030 both countries will have significantly higher energy intensive economies when compared to their neighbouring countries, among them being Germany, France, and the UK (Figure 1.12).

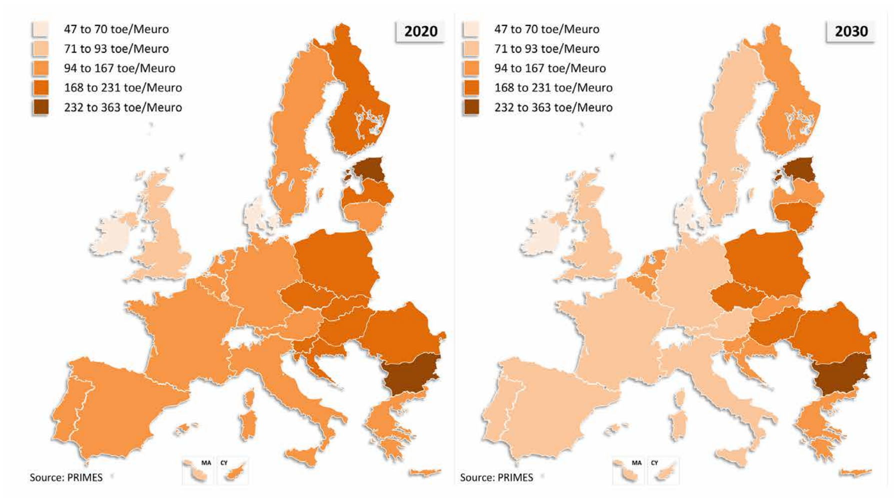

FIG. 1.12 Projected energy intensity, gross inland consumption over GDP, in the EU member states by both 2020 and 2030 (European Commission, 2016. pp. 49).

Data since the 1990s show that the residential emissions of the Netherlands are significantly higher than that of EU countries. The energy gap between the Netherlands and other countries has roughly stayed the same since 1990, when which the per capita emission in the Netherlands was 28% higher than the EU average. The corresponding number in 2016 was 25% higher than the EU average (Figure 1.13).

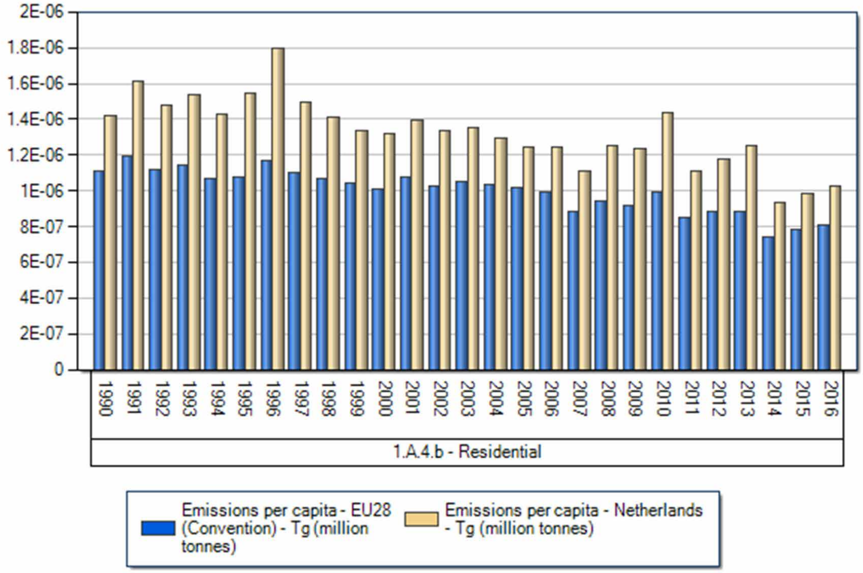

FIG. 1.13 Per capita amount of emission consequent to energy consumption in the residential sector of both the Netherlands and EU-28 countries (Source: European Energy Agency, 2018).

The level of household energy consumption (HEC) in the Netherlands is corrected for climate and GDP, and is therefore relatively low when compared to other EU states. However, the environmental impact of HEC can be quite severe. When calculated per capita and adjusted for climate, HEC in the Netherlands ranks 10th out of the 28 EU states – about 8% higher on average than the EU-28 HEC. When normalizing this amount for GDP per capita, Dutch residential energy use is ranked 22nd, and is 16% lower than an average EU-28 resident (Figure 1.14, Eurostat, 2017 a; Eurostat, 2017 b; Odyssee-mure key indicators, 2017).

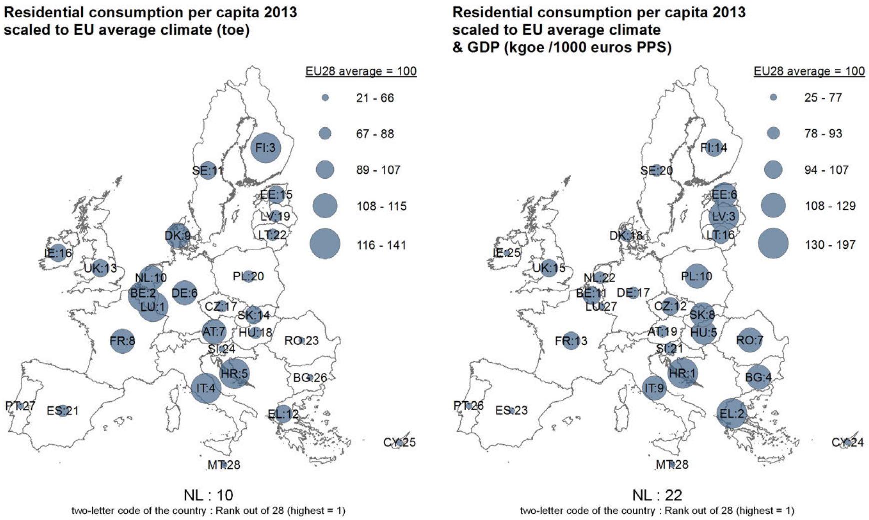

FIG. 1.14 Household energy consumption per capita corrected for climate in 2013 (left), and corrected for climate and GDP (right).

What sets the Netherlands apart from other EU member states is the households' substantial consumption of natural gas. This is largely due in part to the existence of a large amount of natural gas in the northern parts of the Netherlands, in particular the regions around Groningen, the Slochteren gas field. On its discovery in 1959, it seemed that there was an abundant enough source in the field to satisfy Dutch (and other European countries') needs for natural gas. This (erroneous) assumption led to the nationwide implementation of natural gas driven infrastructure, consequently leading to an exponentially increased amount of both gas consumption and GHG emission production by Dutch households. In 2013, sales of gas in the residential and commercial sectors per capita in the Netherlands were the highest of all the EU-28 (202% higher than the average). Consequently, the greenhouse gas emission per capita of Dutch households was 37% higher than the EU-28 average, and was ranked 5th most polluting country in the EU (Figure 1.15, Eurostat, 2017 b; Eurostat, 2016; Eurogas, 2013).

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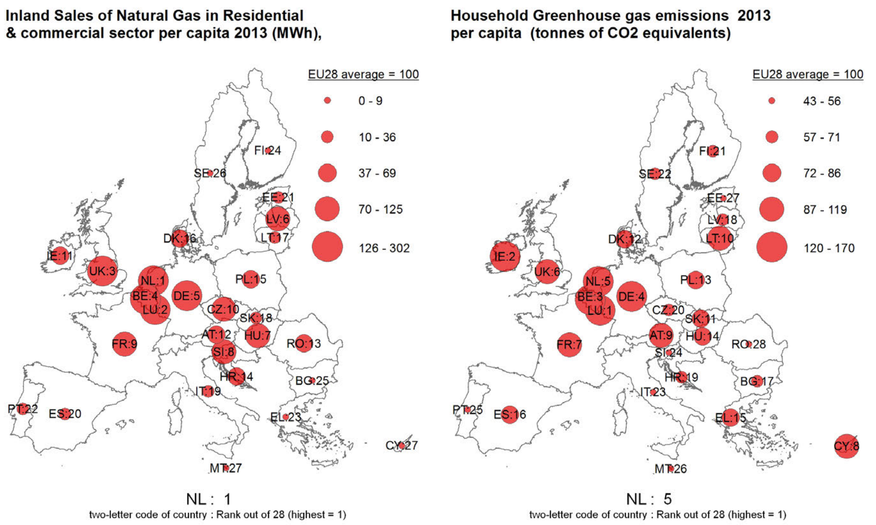

FIG. 1.15 Inland sale of natural gas in residential and commercial sectors per capita in 2013 (left), and households GHG emission per capita (right).

1.3 Previous empirical studies on household energy consumption

1.3.1 Determinants of household energy consumption

A variety of previous studies have established links between household energy consumption (HEC) and a wide range of determinants. In this chapter, the determinants of HEC that have been identified by the previous studies are categorized into seven groups: (i) energy price, (ii) socioeconomic characteristics, (iii) housing tenure, (iv) urban form, (v) climate, (vi) user behaviour, and (vii) energy efficiency of the buildings and appliances. In the following paragraphs, the findings of the previous studies are briefly presented and discussed.

1.3.1.1 Energy price

A variety of previous studies have concluded that the higher the energy price is, the level of energy consumption tends to be lower. The magnitude of this correlation, however, is found to be highly location specific. For example, previous quantifications of Energy Demand Price Elasticity (i.e. the changes in the level of energy demand in response to the change of energy price) in the Netherlands show that an increase of 20% in the gas and electricity prices could lower the level of energy consumption between 7 to 13%. The study, however, also shows that the elasticity of energy consumption could be positive if the price of either gas or electricity increases. For instance, if price of gas increases 20% and price of electricity stabilizes, elasticity of gas demand becomes -0.15. In spite of the decreased demand, electricity consumption will increase +0.03. In other words, levels of gas and electricity consumption are not only elastic to their own price. They are also elastic to the price of other types of energy sources available to households (Boonekamp, 2007). A study on residential electricity demand in China found that price elasticity of electricity demand is around -0.3 (He et al., 2011). The elasticity of electricity demand to price in both the USA and the other G7 countries is supposed to be higher than that of China, with a corresponding value of elasticity that ranges from -1.5 to -0.5 in the USA (Miller. 2001), and -1.5 to -1.4 in the other G7 countries (Narayan et al. 2007).

Price elasticity of energy demand can also vary, depending to the level of income in a household, and the country that household is in. For example, the estimated price elasticity of household electricity consumption in Japan from 1990 to 2007 was found to contrast between high and low income regions: -0.479 in rich regions, -0.425 in middle income regions, and -0.305 in poor regions (Okajima and Okajima, 2013). In addition to this, a study on the energy demand of different income deciles in Portugal show that price elasticity tends to be higher in the upper deciles of electricity use (Silva, 2017). In Germany, it was found that price elasticity of electricity consumption is higher in case of low income households, with an increase in the electricity price resulting in higher compensation and consumption within low-income households (Schulte and Heindl, 2017). In comparison, price elasticity of energy demand of an average household in Norway is estimated at -0.53. However, households with an income level higher than average are estimated at -0.66, while households with an income level lower than average are supposedly -0.33 (Nesbakken, 1999).

1.3.1.2 Socioeconomic characteristics

As it has commonly been concluded by the previous studies, the level of energy consumption seems to be associated with socioeconomic characteristics of the households in question. Inhabitants' level of income, for example, is found to be a significant determinant of HEC. Studies done at the country scale, like the ones conducted by York (2007), mostly concluded that there is a positive association between the HEC and the GDP of a country. Many studies have further elaborated the association between income and HEC by putting forward the following question: does the higher level of income cause a higher level of energy consumption, or does a higher level of energy use cause a higher level of prosperity? It appeared that the answers to this question are not straightforward, particularly when it concerns developing countries. Insight on this issue can be evaluated by the review realized by Lee (2006).

The studies on the causality between income and energy consumption differ in their conclusions. Many studies have found that the causality runs from income to energy consumption, which can be described as when the level of income of the a household increases, it leads to higher level of comfort created by the use of more appliances combined with an overall larger dwelling. Such a causal mechanism, for instance, is observed in South Korea and the Philippines (Yu and Choi, 1985), India (Masih and Masih, 1996), and Malawi (Jumbe, 2004). An opposite causal direction is observed by studies that drew the causality direction from energy consumption and into income, which can be described as when higher levels of energy consumption are associated with higher levels economic growth, resulting in higher levels of national productivity and thus higher levels of income. Observations such as these are made in both Sri Lanka (Morimoto and Hope, 2004) and Indonesia (Fatai et al., 2004). The third group of studies concluded that there is a circular causality between energy use and income, describing that the two phenomena simultaneously regenerate one another. The circularity of energy use and income are best described in the cases developed by. Glasure and Lee (1997) in case of Singapore, and Asafu-Adjaye (2000) in case of Thailand.

The studies conducted based on the HEC of different income deciles within a country, region, or city, have found varying and sometimes contradicting results. The majority of the studies have found a positive elasticity between energy consumption and household income (in researches done by Yun and Steemers, 2011; Druckman and Jackson, 2008; Aydinalp et al., 2004; Lenzen et al., 2004; Tso and Yau, 2003; Gatersleben et al., 2002). Some demonstrate a negative association between the two (in researches done by Santamouris et al., 2007; Yust et al., 2002), while some studies have illustrated a mixed effect of level of income on household energy consumption, which can be best described as when the level of income is higher, the energy consumed for heating is lower and the energy consumed for cooling is higher (Steemers and Yun, 2009).

Many studies have established links between household size and HEC. The majority of studies have concluded that energy consumption per capita declines in larger households. For example, a comparative analysis on household energy requirements in Australia, Brazil, Denmark, India, and Japan, indicates that the requirements per capita decrease in response to an increase in the size and scale of households (Lenzen, 2006). Similar conclusions were drawn by both a study on HEC in the subdivisions of city of Sydney (Lenzen et al., 2004), and on HEC in different climate zones in Japan (Fong et al., 2007). The decrease in the level of HEC in response to the increase in size of a household is explained by the economies of scale and the use of energy (e.g. O'Neill and Chen, 2002). An often neglected impact of household size on HEC concerns the possible increase of energy consumption per capita in larger households that have an increased need for space cooling (Yun and Steemers, 2011; Steemers and Yun, 2009; Tso and Yau, 2003), for cooking (Weber and Perrels, 2000), and even the reduced motivation for energy saving exhibited in households with children (Abrahamse and Steg, 2009).

The age of the inhabitants was also found to be a significant determinant of HEC. Many previous studies have concluded that energy consumption of households with inhabitants older than 65 years old was higher than average (e.g. York, 2007). Senior citizens are expected to consume more energy for space cooling than the other types of inhabitants (Yun and Steemers, 2011; Steemers and Yun, 2009). The number of children that live in a household was also found to be associated with both higher electricity consumption (Aydinalp et al., 2002) and energy consumption for space heating (Yust et al., 2002).

1.3.1.3 Housing tenure

A variety of the previous studies have also concluded that housing tenure (i.e. ownership and the dwellings year of construction) affects household energy consumption, with many previous studies showing that HEC is higher in older buildings (e.g. Van Hoesen and Letendre, 2013; Robinson and Edwards, 2009). While the amount of energy spent for space heating is lower in newer buildings (Steemers and Yun, 2009), the electricity consumption tends to be higher in older dwellings (Lam, 2000). A study conducted on HEC shows that British Household Thermal units (BTU) consumption (electricity, natural gas, liquefied petroleum gas, and fuel oil) tend to decline in dwellings built after 1980 (Yust et al., 2002). Housing tenure can also affect HEC as investment in a buildings' energy efficiency can vary across different types of tenures (Druckman & Jackson, 2008). The amount of investment in buildings, for example, can also significantly differ between both public and private rental dwellings (Tso & Yau, 2003). As the investment in building maintenance can be less frequent in the privately rented dwellings when compared to owner-occupied and publicly rented dwellings, maintenance is therefore considered as one of the main sources for high HEC and energy poverty among households (Robinson et al., 2018; Kholodilin et al., 2017; Bouzarovski and Petrova, 2015; Bickerstaff et al., 2013). Some authors have also concluded that the HEC in owner-occupied houses could be higher than that of renter-occupied dwellings, probably due to the possession of more appliances in the former (Aydinalp et al., 2004; Aydinalp et al., 2002).

1.3.1.4 Urban form

A variety of previous studies have established links between HEC and building/population density. In their seminal publication, The Impact of Urban Form on U.S. Residential Energy Use, Ewing and Rong (2008, p.1) conceptualized three path ways in which to explain the impact: the "electric transmission and distribution losses, energy requirements of different housing stocks, and space heating and cooling requirements associated with urban heat islands." The level of HEC in settlements with a high building density is lower than that of other settlements (ibid), as the residents of the latter "are more likely to live in single-family detached houses than otherwise comparable residents of compact counties and also more likely to live in big houses. Both lead to higher residential energy use." Many studies have found that higher population densities are associated with lower levels of HEC (e.g. Chen et al., 2017, York, 2007). A comparative study on the HEC of households in Brazil, Australia, Japan, Denmark, and India found that the HEC of large metropolitan areas are significantly lower than that of rural areas, and concluded that urbanity (i.e. population density) is a driver of lower energy use (Lenzen et al., 2006). A study on fourteen different statistical zones of Sydney which show that higher levels of urbanity (i.e. population density) are significantly associated with a lower energy intensity (measured in Joule/$) of the zones. Higher urban densities also contribute to lower direct energy requirements, and also lowers domestic energy use in the households. However, the study concludes that the indirect energy requirement of the households, and the energy used for building construction and public transportation, tends to be higher in zones with higher building density (Lenzen et al., 2004).

Several previous studies have drawn opposite conclusions regarding impact of urban density on energy consumption for both space heating and cooling. For example, a study based on a household survey in Canada concluded that higher population density is associated with lower levels of energy consumption in relation to space heating and domestic hot water (Aydinalp et al., 2004). However, Ko and Radek (2014) have concluded, while controlling for other variables, that residential electricity use for space cooling soars in the high-density areas of Sacramento, California.

Surface-to-volume ratio (i.e. the ration of total area of the both the external walls and roofs of a building to its total volume) has been introduced as a significant driver of HEC by a variety of previous studies. This is due to the fact that the thermal exchange between the inside and outside of dwellings decline in buildings that have lower values of surface-to-volume ratio (e.g. Rode, et al., 2014; Steemers and Yun, 2009). For example, a comparison between HEC in detached, semi-detached, and terraced dwellings in the UK shows that the level of consumption with the controlling and the decreasing of other variables (Druckman and Jackson, 2008). Similar conclusions have been drawn by comparing HEC of the different buildings types in different countries, among them being either flat unit or apartment, semi-detached, row or terrace house, and freestanding dwellings (Lenzen et al., 2004). Two studies on HEC in Canada concluded that electricity consumption for appliances, lighting, space heating and cooling, and energy used for domestic water heating, is higher in single detached dwellings than single attached houses (Aydinalp et al., 2004; Aydinalp et al., 2002). In studies that look at the energy consumed for cooling purposes in the US residential sector, Yun and Steemers (2011) concluded that a higher surface-to-volume ratio associates with higher energy consumption. Ratti et al (2005), elaborated this concept by defining a buildings' "passive zone," which can be defied as areas inside the buildings which are not further than twice of ceiling height from an opening (e.g. door, window), as areas that have a high amount of thermal loss (Figure 1.16).

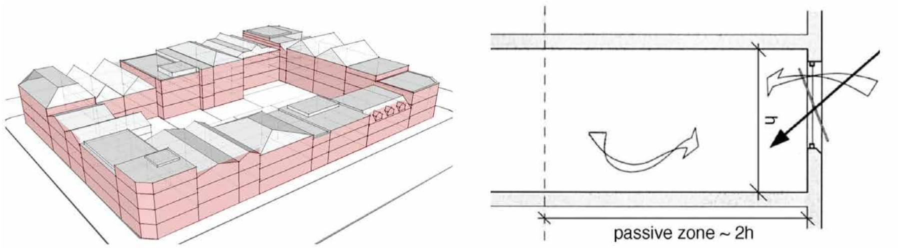

FIG. 1.16 The external surfaces of the buildings consist of the total external walls (in pink) and the roofs (left picture, source Caliskan, 2013, pp.164). A section that displays the passive zone of a building (right picture, Ratti et al., 2005, pp. 767).

Several authors have established links between geometrical properties such as Urban Canyons and Wind Corridors, and household energy consumption. The geometrical properties of urban canyons affect the intensity of wind in the urban areas, therefore altering the amount of air infiltration and exfiltration of the buildings. This change then affects the amount of energy consumed for space heating, cooling, and ventilation (e.g. Sanaiean et al., 2014; Suder and Szymanowski, 2014; Ng et al, 2011; Wong et al, 2010; Gál, and Unger, 2009; van Moeseke et al., 2005; Ratti et al., 2002). Oke (1998) conceptualized the impact of street design on urban canopy layer climate by classifying the winds of urban areas into three types: isolated roughness flow, wake interference flow, and skimming flow. Oke argues that the type of wind is related to the geometrical properties of the canyon, which is comprised from three dimensions: the width of canyon (W in Figure 17), the length of the canyon (L) and the height of the canyon (H). Adolphe (2001) formulates this link between wind and form by introducing the concept of Rugosity (i.e. variation in height of the buildings). Adolphe argues that the intensity of wind in urban areas is a function of irregularities in the height of the buildings that slow down the speed of wind in urban areas (Figure 1.17). The high variation of wind speeds in deep urban canyons can cause a difference in temperature of up to five degrees (Georgakis and Santamouris, 2006), which can increase thermal comfort in the summer, and decrease it in the winter (Johansson, 2006).

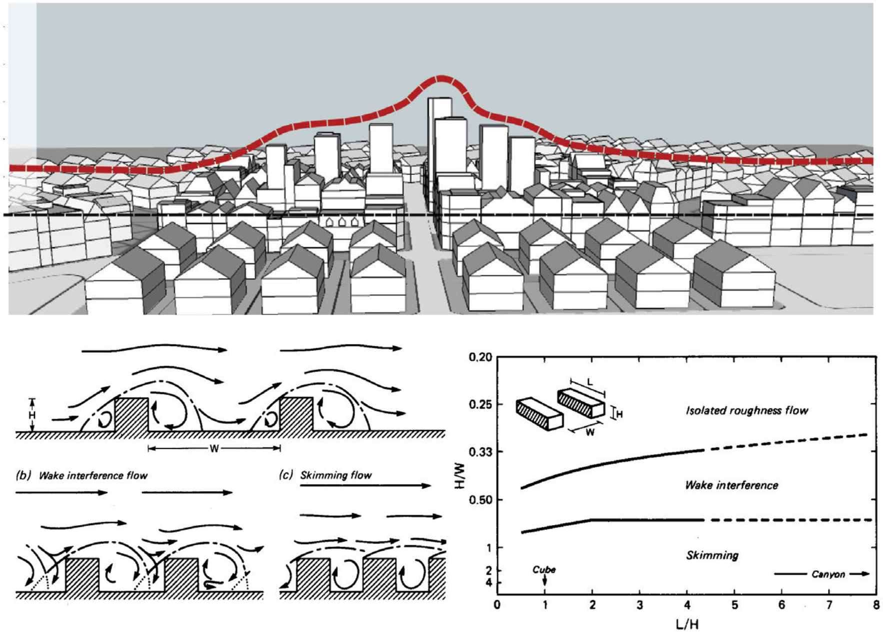

FIG. 1.17 Rugosity is the variation of the buildings height (top picture, illustration by Caliskan, 2013, pp.169), three types of wind in the urban areas (bottom left, Oke, 1988, pp. 105), and their relation to urban morphology (bottom right, Oke, 1988, pp. 105).

The characteristics of urban form affect the properties of the Urban Boundary Layer (i.e. the height over the cities in which the air flow is affected by the urban surface), and consequently affects both the wind intensity and level of household energy consumption (HEC). The so-called “roughness” properties of the city affect the intensity of wind and turbulences, as well as the height at which the wind profile in the city takes place (Landsberg, 1981). Oke (1987) formulates the wind profile in cities based on two aerodynamic properties: zero-plane displacement length (Z_d) and roughness length (Z_0). Z_d is the height over the roughness elements (e.g. buildings) at which the momentum of air flow is associated with the location and shape of the roughness element. Z_0 is the height above the Z_d at which the wind speed at the logarithmic wind profile become zero. In short, the roughness of urban surface determines the height below the wind-profile at which irregular wind flow is expected, i.e. a “ground surface” that is equal to the combined zero-plane displacement length (Z_d) and roughness length (Z_0) (Oke, 2006) (Figure 1.18).

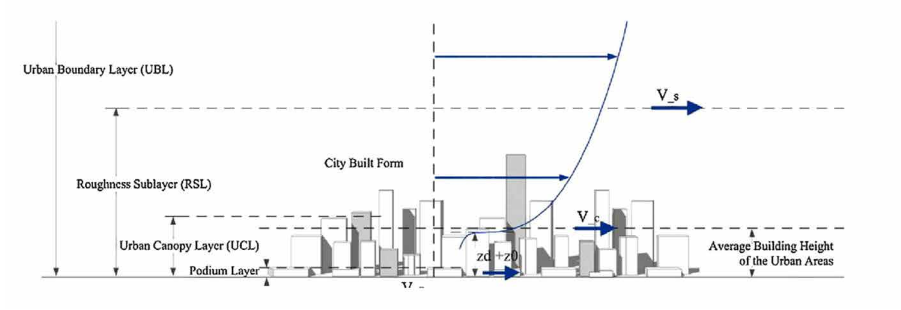

FIG. 1.18 Wind speed profile on top of the urban canyon layer (Ng et al., 2011, pp. 61).

According to a review by Grimmond and Oke (1999), a variety of previous studies have suggested that the aerodynamic roughness length in cities is affected by three morphological properties: (i) building height, (ii) frontal area, and (iii) buildings' footprint. The models are based on the frontal area index of the buildings, which is defined by the ratio of the total external surfaces of the buildings facing air flow in relation to the total area of the neighborhoods. These more commonly applied methods demonstrate how the geometry of buildings affect wind speed (Figure 1.19). The morphometric model introduced by Macdonald et al. (1998), one of the most comprehensive models according to a review by Grimmond and Oke (1999), shows that the combination of frontal index and buildings footprint suffice for calculation of aerodynamic roughness length:

$$\frac{Z_d}{Z_H} = 1 + \alpha^{-BCR}(BCR\text{-}1)$$

EQUATION 1.1

$$\frac{Z_0}{Z_H} = \left(1 - \frac{Z_d}{Z_H}\right)\exp\left(-\left(\frac{0.5\beta C_D \lambda_f}{k^2}\left(1 - \frac{Z_d}{Z_H}\right)\right)^{-0.5}\right)$$

EQUATION 1.2

Where Z_0 is aerodynamic roughness length for momentum, Z_d is the zero-plane displacement height, Z_H is the height of the roughness element (m), BCR is the building coverage ratio, l_f is the frontal area index, α = 4.43, β = 1.0, k = 0.4, and C_D @ 1.

The concept of aerodynamic roughness length has been previously employed to model the impact of urban form on both urban microclimate and HEC. For example, Ratti et al. (2006) used the Macdonald et al. (1998) method for comparing "urban texture" in London, Toulouse, and Berlin. Wong et al. (2010) used the method for designation of ventilation corridors that exist on the Kowloon peninsula of Hong Kong. Doing so verified its application to identify both locations and intensity of the urban heat island effect there. Using the map of aerodynamic roughness length, the authors identified the wind corridors in the peninsula that spatially coincide with the locations in which urban heat islands occur. Ng et al. (2011) has used the method to improve the permeability of the urban tissue in Honk Kong.

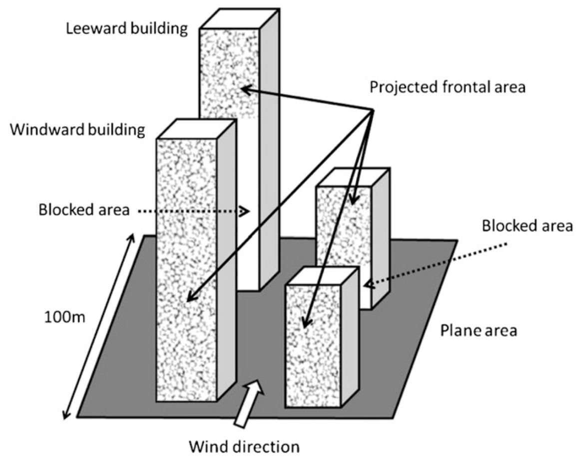

FIG. 1.19 The frontal surfaces of buildings, i.e. surfaces facing the wind (Wong et al., 2010, pp. 1881).

Sky View Factor (SVF), which is shown in Figure 1.20, is a geometrical property of the street canyons that quantify the ratio of visible sky in a hemisphere view from the center of a street looking straight upwards (Oke 1981). This is found to be an influential determinant of urban heat islands and ambient air temperature (Park, 1987). For example, Unger et al. (2004) have studies which look at the impact urban surface temperature has on air temperature in Szeged, Hungary. By studying two different periods in the year (March to February and April to October), the authors demonstrated that SVF and the height of buildings are the most determinant factors which affect urban heat islands, and create variation of air temperature.
In Göteborg, Sweden, Svensson (2004) showed that there is a strong association between SVF and air temperature. In addition to this, Krüger et al. (2011) found that urban geometry in general (and SVF in particular) has had a significant impact on outdoor thermal comfort in Curitiba, Brazil. In short, these studies on the associations between passive and active solar radiation with HEC in urban areas

shows that access to solar radiation reduces the energy use in buildings. However, the magnitude of such an impact is limited (e.g. Niemasz et al., 2013; O'Brien et al., 2010; Mihalakakou, 2002).

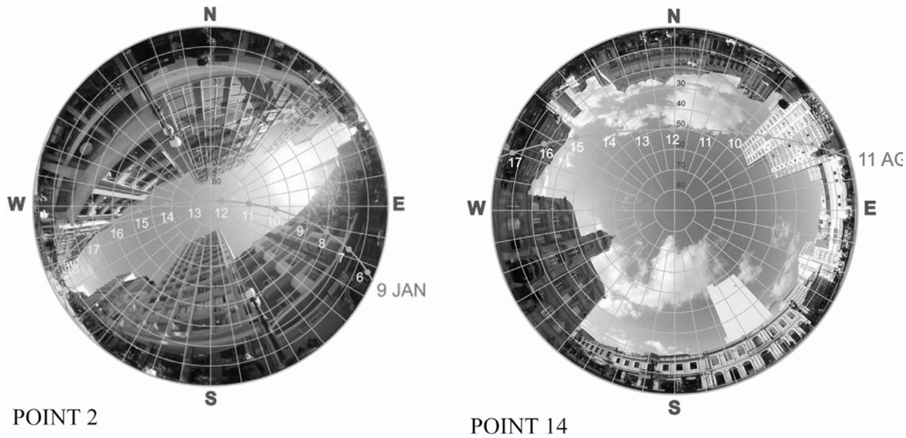

FIG. 1.20 The measurement of sky view factor in Curitiba, Brazil (Krüger et al., 2011, pp. 624).

1.3.1.5 Climate

Previous studies in a variety of cities and countries have shown that an increase in land surface temperature (LST) is linked with higher ambient temperatures around buildings. These effects are significantly associated with higher levels of energy consumption for space cooling (see the review by Santamouris et al., 2015). However, various studies (e.g. Kolokotroni et al., 2007; Santamouris et al., 2001; Hassid et al., 2000) have shown that higher a LST can be associated with lower levels of energy consumed for space heating. Previous empirical studies have tried to generalize the impact of LST on the average HEC by the estimation of a single rate.

Many studies have also established links between the number of degree days and HEC. For example, Christenson et al. (2006) concluded that due to the climate change in the coming decades, the energy demand of the buildings will be increasing in response to it. The authors suggest that current estimation methods are underestimating the effect of climate on space cooling energy demand, while overestimating the demand on space heating. In order to properly respond to this problem, the thermal behaviour of buildings in summers must be carefully studied within the next couple of decades. Pardo et al. (2002) concluded that the effect of weather variables on electricity load in Spain is remarkably strong. By studying HEC in 39 US cities, Sailor and Pavlova (2003) showed that the expected increase in the amount of warm days will eventually make a significant impact on the level of electricity consumption in long term. The authors emphasized that the behavioral response to climate change could end up resulting in an unexpected rise of HEC.

1.3.1.6 User behaviour

A variety of studies in the field of environmental psychology have shown that the behaviour of users is an influential determinant of household energy consumption. Gardner and Sten (2002) categorized these behaviours related to HEC into two classes: efficiency and curtailment. Efficiency behaviours are one-time decisions that largely affect the level of HEC, such as purchasing of energy efficient appliances and additional insulation for dwellings. Curtailment behaviours are repetitive actions that decrease energy consumption of a household, such as switching off the heating or extra lights before leaving the house. Lopes et al. (2012) categorizes user behaviour that affects energy use into four groups: (i) utility-based decisions – i.e. the rational behaviours of the users aim at maximising “utility” of energy use that is increase of comfort, reduction of the expenditure for the appliances, and reduction of energy cost; (ii) technology adaptation – i.e. the acceptance of new energy-efficient technologies; (iii) social and environmental psychology – i.e. the individual consciousness of the environmental consequences of energy consumption, and the sense of responsibility toward reduction of such consequences; (iv) social construction – i.e. the social norms that affect the choice of appliances and behaviour of individuals.

A variety of studies have examined the impact of interventions that aim at adjusting the behaviour of users. One solution for reducing the HEC of high-income residents is to alter their behaviour by providing feedback on their consumption. For example, a previous study on a selected sample of Dutch households showed that changing the level of HEC requires the changing of the households in question’s perceived level of consumption (Abrahamse and Steg, 2009). Feedback devices have been found to be an effective strategy to enforce the cognitive will to promote HEC reduction (Vassileva et al., 2013; Faruqui et al., 2010; Abrahamse et al., 2005). However, the latter was found to be more effective at decreasing HEC among heavy users (Brandon and Lewis, 1999; Van Houwelingen and Van Raaij, 1989), as their effect could differ due to both the format of the feedback (i.e. SMS, TV channels, home display) and the variation across different types of social groups (Vassileva et al., 2013).

1.3.1.7 Energy efficiency of buildings and appliances

The energy efficiency of buildings and appliances have had a significant impact on both the total amount of energy use and the GHG emissions in all sectors (more particularly in the residential sector). An econometric model of associations between energy efficiency and energy intensity in OECD countries (a club of mostly rich countries) displayed in Figure 1.21 show that there is a close relationship between the two factors (Tajudeen et al., 2018). A large opportunity for the reduction of both energy use and carbon emission in the residential buildings of the US lay in use of highly energy efficient electric appliances that are used for cooking, dishes and clothes washing, TVs, and personal computers (Brown et al, 2001). An econometric model of a households use of electricity and natural gas in California show that use of multiple energy-efficient washing and drying machines, combined with energy efficient water and space heating appliances, can have a significant impact on reduction of HEC in short run (Li and Just, 2018). Households in the EU could save up to 48% on their electricity consumption if energy efficient technologies were to be employed, combined with the possibility that behaviour towards energy saving goes viral (De Almeida, 2011). In addition to these potentialities, the energy-efficiency standards set by the US federal government is expected to reduce CO_2 emission by 9% (Meyers et al., 2003).

The energy performance of residential buildings is considered as an effective determinant of HEC. An estimation by the International Energy Agency shows that buildings have the largest unrealized long term energy efficiency potential when compared to facilities related to industry, transport, and power generation. It is estimated that more than 80% of the efficiency potential has not yet been realized (OECD Publishing; International Energy Agency, 2015). A study on 300,000 dwellings in the Netherlands has shown that the potential increase in energy-efficient performance could save up to 50% of the energy currently used for thermal heating (Majcen et al., 2016). A survey on gas consumption in the dwellings of different label classes – a method of assessment that measures the energy performance of dwellings (Government of the Netherlands, 2018) - show that consumption of gas in label-E dwellings is more than double of that of the label-A dwellings (Majcen et al., 2015; Filippidou et al., 2016; Guerra-Santin and Itard., 2010; van den Brom et al., 2018).

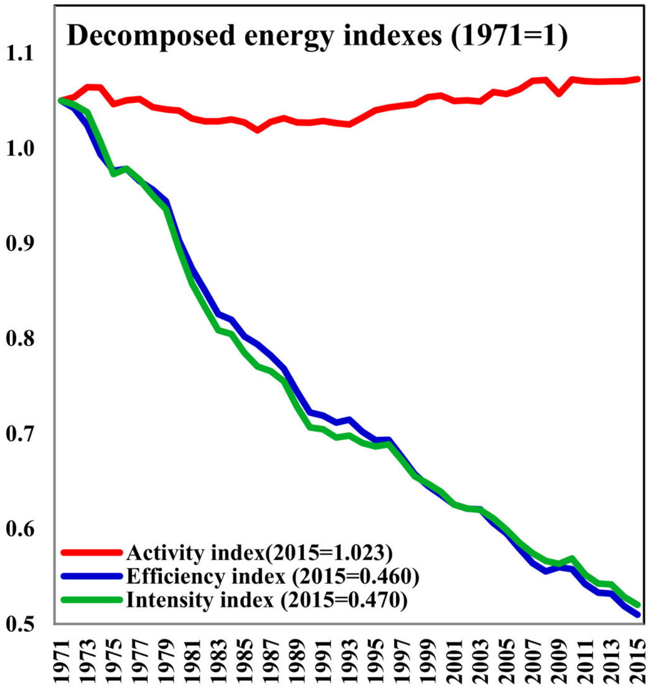

FIG. 1.21 At roughly similar levels of activities, intensity of energy use declines in response to an increase in energy efficiency (Tajudeen et al., 2018, pp.205).

1.4 Measurements of household energy consumption

Previous studies have adopted three types of measures in order to indicate the level of energy consumption of households. The first type of measures are ones which quantify units of energy consumed by a household in question (e.g. Joule, KwH). Such measurements, in effect, are proxies for the environmental consequences of HEC. For example, York (2006) studied units of energy used in residential sectors of fourteen selected member states of EU between 1960 and 2010. This was done in order to examine the impact of demographic trends on both energy consumption and the environment as a whole. The second type of HEC measurement is sourced from the

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energy expenditure of households. In effect, such measurements identify energy as one of the goods and services that are consumed by households, and quantify it in units that are comparable to the expenditures on other goods and services. For example, Durkman et al. conducted a study on the socio-economic dimension of energy consumption in UK, and used a survey to collect data on the expenditures of 7000 households in UK. This was done to study energy-related expenditures and associate them with the socioeconomic characteristics of the households in question (2008).

The third type of measurement is the energy poverty indicator, i.e. the measurements of the burden of expenditure compared to total household budget. Scholars and policy makers in the European Union (EU) have particularly had interest in the energy poverty measurements of HEC. Subsequent to this enthusiasm, the European parliament passed a legislative act called the “Third Energy Package,” which enacted common regulations for domestic gas and electricity markets of its member states (European Parliament, 2009a; 2009b). EU member states has been obliged to identify households who are have trouble meeting their energy expenses, and requires states to take actions to protect them. In order to identify such households, the member states have defined a variety of indicators which can be broken down into two categories: energy vulnerability indicators and energy poverty indicators. Dobbins and Pye (2016, p.121) argue that “the two issues are linked yet distinct,” and that energy vulnerability measures in the European context need to identify consumers who need protection for primary access to electricity and gas. However, energy poverty measurements go beyond the basic needs for energy, and addresses the affordability of energy services.

Former indicators were typically concerned with the basic energy needs of a household (e.g. adequate space heating), whereas the latter indicators are concerned with broader societal aspects, such as income, energy costs, and energy efficiency. A variety of energy poverty measures were proposed by EU member states that allow for only a “yes” or “no” categorization of a household, which is determined by the financial burden created by energy expenditures (Herrero, 2017). In Ireland and Scotland, for example, a household who spends more than 10% of its disposable income on energy bills is considered to be in “energy poverty.” In England, a household with both a high level of energy expenditures (above national median) and low income (less than 60% of national median) is also considered to be in energy poverty. In the Netherlands, the energy poverty policies merely distinguish vulnerable consumers from others. Their definition of a vulnerable consumer is a person whose supply of electricity or gas is halted by the energy supplier, therefore putting her/his health at risk (see the review by Dobbins and Pye, 2016).

1.5 Aggregation unit of data on HEC

The data sources used by the previous studies on household energy consumption could be categorized into three groups which based on their level of aggregation, which are defined by the geographic units that represent information on HEC. The first type of datasets are non-aggregated, which is data based on the energy consumption of individual households. Non-aggregated datasets are provided by surveys which are conducted on households, and have one main advantage: they provide comprehensive data on the final use of energy by the households by producing information about energy use which involve activities such as cooking, water heating, and space heating and cooling. However, the use of such datasets possesses two main disadvantages: the surveys are time consuming and expensive, while the results of a survey could also be subject to sampling bias, i.e. a situation may arise in which a certain type of households is overrepresented in the collected sample when compared to the total population (Eurostat, 2013).

The second type of data on HEC involve datasets that show the average energy use of the residential sector at the country level. This information is provided by governments such as Canada (Office of Energy Efficiency Natural Resources Canada, 2006) and the U.S. (U.S. Energy Information Administration, 2011), or intergovernmental organizations such as Eurostat (Eurostat, 2018b). Datasets such as these are comprised of gross energy data that is reported by the energy providers of a country. The advantage of such datasets is that they provide a basis for comparative studies on both energy consumption and GHG emission at a global scale. For an example of this study, please see the report by the International Panel on Climate Change (IPCC, 2017). However, the disadvantage of this dataset can be the inaccuracy of data and aggregation bias, as the gross energy use of the residential sector of a country does not necessarily reflect that of the different social groups.

The third type of datasets are made up of data aggregated at the neighbourhood level. This type of data is mainly available in the Netherlands and the UK, and are the two richest member states of the EU which, according to a report by Eurostat, are intensely dedicated to the collecting of data on HEC (Eurostat, 2013). In the Netherlands, the data on annual gas and electricity use are measured by the *buurt*, which is defined as a geographic unit with an average population of 1400 inhabitants (Centraal Bureau voor de Statistiek, 2013), and is a dataset which have been available since 2009. In England and Wales, information on HEC is based on the measurement of a Lower Super Output Area (LSOA), which is a geographic unit that on average has a 1700 inhabitant population (Office for National Statistics, 2018), and is data that is readily available to the public. The use of this type of data for HEC studies has two main advantages: it has no sampling bias as the data of a neighbourhood include data of all individuals as registered to the municipalities and energy providers, and access to this data is free of charge. The disadvantages of such datasets for HEC is that there is both a lack of detailed data on final energy use (e.g. portion of energy used for space heating), and there is aggregation bias – which is relatively modest when compared to the aggregation bias of data that is aggregated at the country level.

1.6 Methods of HEC empirical studies

Previously, a variety of methods have been employed by the use of empirical studies on HEC. On the one hand, these studies use data on the energy consumption of individual end users, neighbourhoods, regions, and countries. On the other one hand, the data on the potential determinants of HEC is used to establish links between HEC and latter characteristics. In this part, six of the commonly used methods will briefly be presented, and these approaches use multiple liner regression models, geographically weighted regression models, co-integrated panel data analysis, causality analysis, structural equations models, and neural networks.

Regression analysis is one of the most popular techniques out of all the previous studies (e.g. Tso and Guan, 2014; Poortinga et al., 2004; Brandon and Lewis, 1999). A multiple regression model can be written as follows:

$$y_i = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i$$ EQUATION 1.3

Where y_i is estimated value of HEC at location i, β_0 shows the intercept, and β_k shows the coefficient of kth independent variable. x_{ik} and ε_i are the values of the kth independent variable, and the random error term is in location i. The reason for the frequent use of regression models is due to the "interpretability" of the model, according to the words of Tso and Yu (2007). However, the limitation of regression analysis is that the model cannot determine underlying causal relations.

A small portion of studies using regression analysis have incorporated spatial weights to their analysis (e.g. Robinson et al., 2018; Sultana et al., 2018). In other words, these studies have employed a geographically weighted regression method that was initially proposed by the two seminal papers on modelling spatial associations by Brunsdon et al. (1996) and Fotheringham et al. (1996), and a follow-up book by Fotheringham et al. (2003). This is a method that can be formulated as:

$$y_i = \beta_0(\mu_i, \nu_i) + \sum_k \beta_k(\mu_i, \nu_i) x_{ik} + \varepsilon_i$$ EQUATION 1.4

Where (μ_i, ν_i) denote the x-y coordinates of the location i. $\beta_k(\mu_i, \nu_i)$ and $\beta_0(\mu_i, \nu_i)$ are the estimated local coefficient and local intercept of the independent variable k in the location i. The advantage of geographically weighted methods is the estimation of results specific to each location of each study area. However, the main disadvantages of this model is the lack of explanation on underlying causal mechanisms, and producing a sheer amount of outputs that often hardly can be simplified and summarized (Mennis, 2006).

Cointegrated panel analysis is a technique that tests the relationships between integrated variables in the course of time, and has been employed for HEC and emission studies by the previous studies (e.g. Joyeux and Ripple, 2007; Lee, 2005). At its most general form, as formulated by Pedroni (2004), a panel model could be formulated in form of a regression model:

$$Y_{it} = \propto_i + \delta_i t + \gamma_t + X_{it}\beta_i + e_{it} \quad \text{EQUATION 1.5}$$

Where Y_{it} and X_{it} represent the values of the instances i=1, …, N represents periods of time t=1,…,N. $\propto_i$ and δ_i denotes fixed effects and deterministic trends specific to instance i. γ_t shows the possible effects common to all instances at time t. e_{it} denotes the residual, and β_i is the coefficient. A variety of studies have used causality tests for the analysis of panel data on HEC. In its most common form, causality between these two phenomena refer to the so-called Granger Causality Test, which was named after the seminal work of renown British economist Clive Granger (1969). According to his work, the variable X causes variable Y when the status of X in time t has a unique impact on that of Y in time $t+1$. This method is particularly used to test the causality between HEC and income by previous studies, among them being Yu and Choi (1985) and Lee (2005). The advantage of such a model is to identify the effect of co-integrated determinants of HEC over a course of time. However, the disadvantage of this model is the extremely difficult requirement to provide a data series over a sufficiently long time which contains the data necessary for all the instances of interest.

A variety of studies on HEC have employed Structural Equations Models (SEM) for studying HEC (e.g. Estiri, 2016; Motawa and Oladokun, 2015; Kelly, 2011). SEM models are often used in order to determine both the effects and direct impacts of the so-called latent structure (impacts on HEC that are not direct, but are exercised through other variables). For instance, by analyzing the HEC of the U.S. residential sector, Estiri (2016) argues that demographic characteristics (e.g. marital status and household size) have three types of impact on HEC: (1) the direct impacts due to the different energy requirements of different households; (2) the indirect impact as different demographic groups reside in different housing tenures, which itself has an impact on energy use due to variation of payment methods and frequency of renovations across different housing tenures; (3) the indirect impact as different demographic groups select different dwellings in terms of size and number of rooms, which alter the thermal requirements of the households (Figure 1.22). The advantage with the application of the SEM model for HEC studies is the estimation of the direct and indirect impact of the determinants of HEC. The disadvantage of the SEM model is that application of such methods require a detailed dataset on a large set of individual households. Meanwhile, the employment of SEM models for studying the data aggregated on larger scale (e.g. at neighbourhoods scale) could be troublesome due to aggregation bias.

Several studies on HEC have also employed the Neural Network model in order to model the associations between HEC and its determinants (e.g. Kialashaki et al., 2013; Swan et al., 2011; Aydinalp et al., 2004;). A Neural Network model operates based on a so-called learning process that involves the training of the model through the use of empirical data, which is done first by feeding the model with multiple values of HEC and its determinants for large sample pool, and is then consequently finished by adopting the weights to the HEC determinants (in the so-called hidden layers) of the model in order to predict the expected values of HEC when the values of HEC determinants are available (Figure 1.23). The advantage of the neural network model is its ability to model the impact of the determinants of HEC when there is no clear mathematical formulation that can be obtained. The disadvantage of this model, which is known as one of the so-called "black-box models," is that the technique can only be used for prediction, and can not provide an interpretable description regarding the impact of each of the variables (Tso and Yau, 2007).

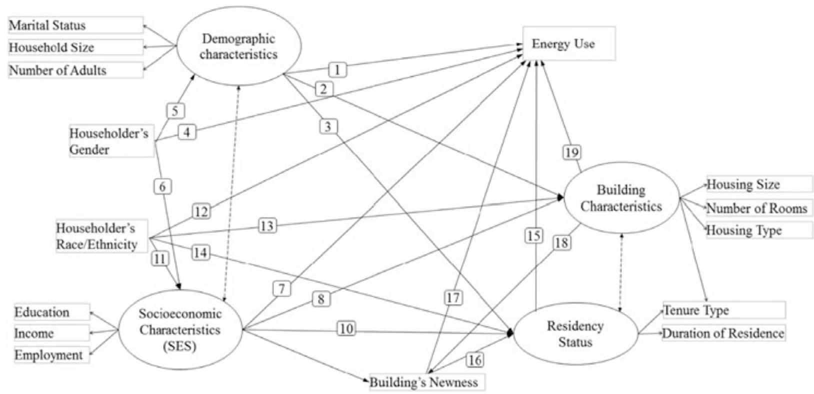

FIG. 1.22 A sample of SEM model applied for studying HEC (Estiri, 2016, pp. 237).

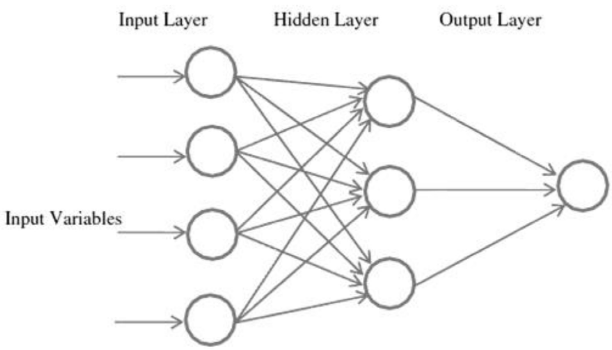

FIG. 1.23 Typical units in a neural network model (Roushangar and Homayounfar, 2015, pp. 66).

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1.7 Knowledge gap in the previous empirical studies of HEC

By using the concepts of global and local determinants, previous empirical studies on both HEC and energy poverty could be categorized into two groups which are in accordance to their underlying presumptions. Subsequent to the publication of two seminal papers on modelling spatial associations by Brunsdon et al. (1996) and Fotheringham et al. (1996), in addition to the follow-up book by Fotheringham et al. (2003), two new concepts went viral among scholars conducting geographic analysis. These approaches were identified as: (i) local determinants, i.e. the insight that the impact of a phenomenon is spatially non-stationary, and thus varies from one location to another; (ii) global determinants, i.e. the stimuli of a phenomena that provoke the same response in all locations of interest. In the next couple of paragraphs, the two categories of the studies are briefly presented, and the knowledge gap in these studies is elaborated.

The first group, accounting for the vast majority of previous studies on HEC, have presumed that the influencing factors of HEC and energy poverty are global. They assume that there are global facts that explain the level of HEC and energy poverty across all areas of a city, country, region, and/or continent. A variety of these studies have adhered to this presumption, and have cited global rules to explain levels of HEC like the following examples:

- The higher the income level is, the higher the HEC will be (Druckman and Jackson, 2008; Joyeux and Ripple, 2007);
- Per capita HEC drops in larger households (Kowsari and Zerriffi, 2011; Isaac and Van Vuuren, 2009);
- The older a building is, the higher the HEC will be (Belaïd, 2016; Steemers and Yun, 2009);
- The higher the surface-to-volume ratio of buildings are, the higher the HEC will be (Steemers and Yun, 2009; Druckman and Jackson, 2008);
- HEC drops in areas with a higher population density (Porse et al., 2016; Pachauri and Jiang, 2008);
- The more cooling and heating degree days there are, the higher the level of consumption will be (Wiedenhofer et al., 2013; Reinders et al., 2003);
- The impact of wind-speed on the heat loss of buildings is substantial enough to change the level of HEC (Sanaieian, 2014; van Moeseke et al., 2005);
- Land surface temperature affects HEC in all urban areas (Azevedo et al., 2016; Lee and Lee, 2014).

Similar presumptions such as these have influenced most of the studies on energy poverty. For instance, Healy and Clinch (2002, p.329) concluded that “in Ireland … over half of elderly households endure an inadequate ambient household temperature in winter.” In Vienna, Brunner et al. (2012, p.7) observed that “energy-inefficient windows, buildings, and housing sites are the cause of a heavy [energy] burden.” Boardman (1991, p. xv), while in the UK, observed that “raising incomes can lift a household out of poverty, but rarely out of fuel poverty.” While Santamouris et al. (2007, p.893) were in Athens, they noted that a low income level is associated with energy poverty because “low income people are more likely to be living in old buildings with poor envelope conditions.”

There is a second approach that has emerged in the recent years. The major underling presumption of this approach is that factors which are influencing both HEC and energy poverty are assumed to be local. Even though a certain determinant of HEC or energy poverty could explain both the level of consumption and the heavy energy burden in a neighbourhood, the same determinant may not be an influential factor in another different neighbourhood. It is therefore that the studies following this second approach try to disclose location-specific determinants of HEC and energy poverty. Bouzarovski and Simcock (2017, p. 640) formulate the basic foundation of this approach as follows: “there are clear geographic patternings associated with [HEC and] energy poverty, as well as the geographically embedded and contingent nature of … underlying causes.” For example, Yu (2012) concludes that in eastern China, the intensity of energy use in a province is strongly associated with that of its neighbouring provinces, and that there is a “convergence [between] provincial energy intensity” (2012, p. 583). Robinson et al. (2018, p. 11) conclude that living in a privately rented dwelling has a significant impact on energy poverty “in urban areas in the Midlands and Northern regions, in particular the north-east [of England].” Robinson et al. (2018, p. 12–13) also were able to find “vulnerabilities [to energy poverty] associated with disability or illness … are stronger … in some southern cities [of England] including London, Luton, and Southampton.” An analysis of the carbon emissions related to HEC in north-west China concluded that the determinants of pollution vary from one region to another. For instance, the analysis found that “income indicates a greater influence…in northern Ningxia and northern Shaanxi” (Li et al., 2016, p.183). A study on HEC in California (Sultana et al., 2018) estimated that the aging population has a significant impact on increasing HEC in north-eastern areas of the state, whereas no significant effect is expected in the north-western areas.

According to the results based on the previous studies, a knowledge gap in the research is apparent. Most studies on energy consumption (or energy poverty) could be based on the presumption that the determinants of energy poverty are either global or local. However, none of these studies have examined the validity of the presumptions of which they have followed. In other words, the question "what are the global and local determinants of household energy consumption and energy poverty?" is not answered by any of the previous studies. The standpoint of this study is that the question stated above should be central to any exploration of HEC and energy poverty. A study on HEC or energy poverty in the neighbourhoods of a city, country, region, or continent needs to firstly identify what the global and local determinants of HEC and energy poverty actually are.

The knowledge gap in the scientific studies on HEC and energy poverty can also be seen in the policies regarding household energy consumption in the Netherlands. The policies of the Third National Energy Efficiency Action Plan for the Netherlands (Ministry of Economic Affairs, 2014) regarding the reduction of household energy consumption (HEC) are developed based on a one-size-fits-all approach: the "geographical area" of all the proposed incentive and regulations is specified as "the Netherlands." This was done without implementing any differentiation in accordance to location-specific circumstances such as socioeconomic patterns, climate, level of urbanization, land cover, and housing stock (see Table 1.1). In this respect, the policy mentioned above was made based on two unwritten presumptions: (i) the stimuli of HEC are similar in every and each location of the Netherlands, therefore it is possible to formulate an identical set of incentive and regulations which is optimally suitable in all the locations of the country; (ii) the keystone of the policies need to be building energy efficiency, as most of the incentives and regulations introduced by the policies are related to a buildings' energy efficiency.

TABLE 1.1 The third National Energy Efficiency Action Plan for the Netherlands (2014), which regards the reduction of residential energy use.

Policy measure	Geographical area
Tightening of energy performance standards of buildings (EPC)	The Netherlands
Lente Agreement on energy-efficient new buildings	The Netherlands
More with Less: Agreement for energy saving in existing residential and other buildings	The Netherlands
Changes to the Home Valuation System: link maximum rent of a dwelling to its energy label.	The Netherlands
Reduced VAT rate for the maintenance and renovation of residential buildings	The Netherlands
Block-by-block approach (large-scale approach to improve existing housing stock)	The Netherlands
Acceleration (Facilitating investments in improving the energy efficiency of residential buildings)	The Netherlands
Revolving fund for energy saving (encouraging investment in energy efficiency of existing buildings)	The Netherlands
Energy-saving agreement for the rental sector (corporations, landlords, tenants)	The Netherlands
Subsidy available for landlords in the social rental sector to improve energy efficiency of the buildings	The Netherlands
Energy tax (Tax levy on energy tariffs)	The Netherlands
EIA: Energy Investment Allowance (tax reduction for the purchase of energy-efficient equipment)	The Netherlands
Green Investment and Finance (tax incentive for investment in environmental friendly projects)	The Netherlands
Green Deal (Support for investment in Investments in energy-saving and renewable energy measures)	The Netherlands

1.8 Objective and research questions

The objective of this study is to examine and compare the determinants of HEC in the Dutch neighbourhoods. To do so, two main research questions are formulated:

1. What are the global determinants that affect intensity of energy consumption and level of energy poverty of Dutch households (i.e. the factors which trigger the same response across all neighbourhoods)?
2. What are the local determinants that affect intensity of energy consumption and level of energy poverty of by Dutch households (i.e. the factors which trigger different responses across the neighbourhoods)?

The structure of this thesis is divided into two separate sections. In the first section, by conducting three studies on the neighbourhoods of the Netherlands, three sets of complementary sub questions are posed, and the answers of these studies are explored in three separated research articles.

Sub questions Article #1:

What are the global determinants of a households' annual energy expenditure in the Netherlands? What are the local determinants of a households' annual energy expenditure in the Netherlands?

Sub questions Article #2:

What are the global and local determinants of household annual consumption of energy units (Joules of energy) in the urbanised neighbourhoods of Netherlands? Does land surface temperature (LST) affect the level of consumption? Is the effect of LST local (i.e. the effect is specific to some areas) or global (i.e. HEC of all the neighbourhoods of country is affected by LST)? And, how important is the impact of LST when compared to that of other determines of HEC (i.e. socioeconomic, housing, and climate factors)?

Sub questions Article #3:

What are the global determinants of household energy poverty (i.e. the share of a households' disposable income spent to cover energy expenses) in the Netherlands? What are the local determinants of household energy poverty in the Netherlands?

Subsequent to the conduction of the three studies of the first section, three major prerequisites were obtained: (1) the global determinants and the spatial distribution of the local determinants in the neighbourhoods of the Netherlands; (2) the local impacts in the most urbanized neighbourhoods of the country (that is the Randstad region) are significantly different when compared to other parts of the country; (3) the determinants of electricity consumption have a larger impact on household energy expenditure and energy poverty, rather than the determinants of gas consumption; (4) determinants of gas consumption have a larger impact on a households use of energy units than those of electricity consumption. The two latter findings lead to two sets of research questions explored in two articles, which were conducted on the neighbourhoods of the Randstad region by including a larger set of determinants:

Sub questions Article #4:

What are the global determinants of a households' annual energy expenditure in the neighbourhoods of the Randstad region? What are the local determinants of a households' annual energy expenditure in the neighbourhoods of the Randstad region?

Sub questions Article #5:

What are the global determinants of a households' gas and electricity consumption in the neighbourhoods of the Randstad region? What are the local determinants of a households' gas and electricity consumption in the neighbourhoods of the Randstad region?

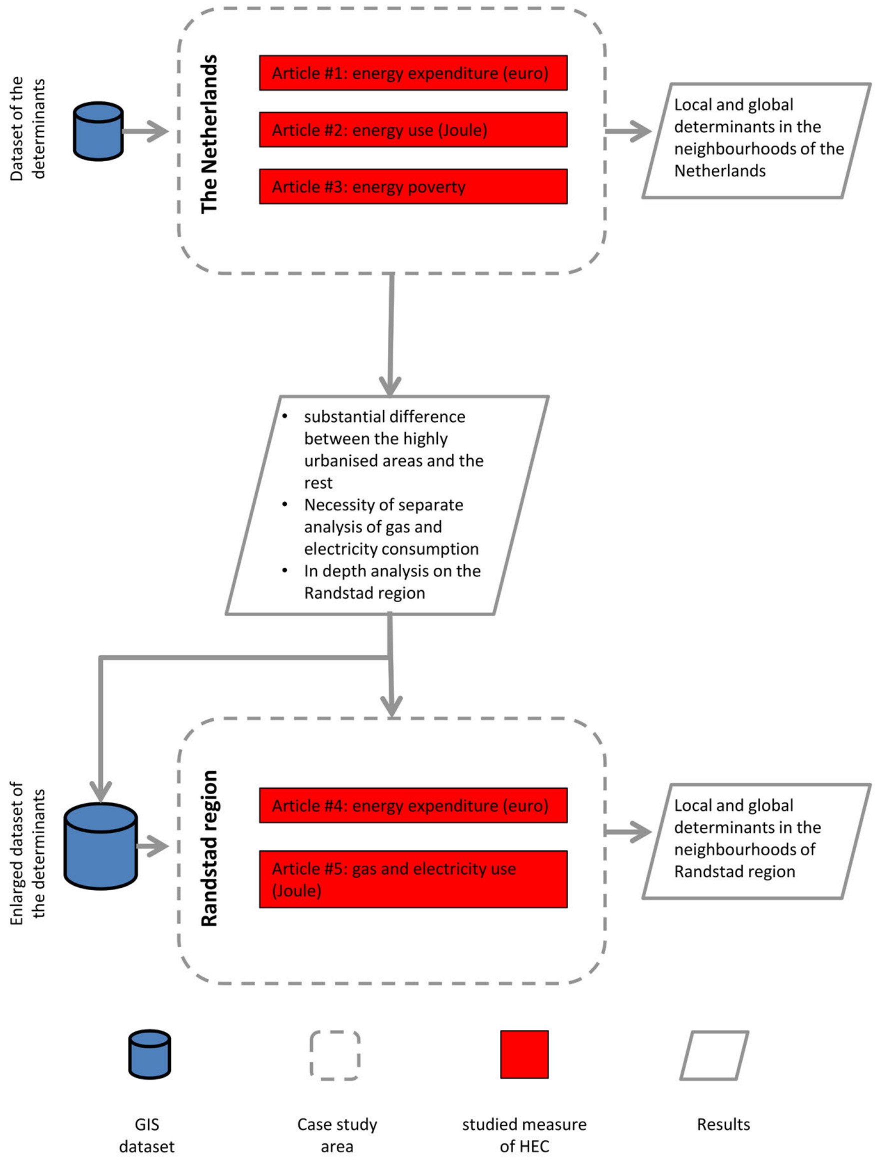

FIG. 1.24 Illustration and summary of the researches conducted in the two sections of this manuscript.

1.9 Data and method

The studies of this manuscript are conducted on the average household energy consumption of neighbourhood units (the so-called *buurt* and *wijk*). The choice of neighbourhood units as the aggregation unit of the studies is due to four main reasons: (i) the country is one of the two most richest member states of the EU in terms of data availability from administrative sources that are aggregated at the neighbourhood units (Figure 1.25); (ii) access to data is free of charge – in contrary to data derived from surveys, which are time consuming and expensive; (iii) available data covers all neighbourhoods of the Netherlands; (iv) the data is not subject to sampling bias.

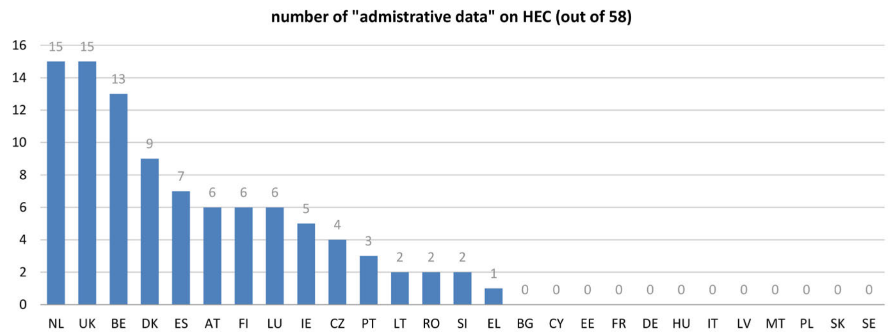

FIG. 1.25 Number of data sources on HEC derived from administrative sources in the member states of the EU (Eurostat, 2013).

Use of neighbourhood units for these studies opens up a unique opportunity in terms of availability in the variety of socioeconomic data at the neighbourhood level that is provided by Centraal Bureau voor de Statistiek (CBS), creating a unique opportunity for studying HEC. In the most prominent case, data on an inhabitants' income is not available to the public at any geographic units smaller than the neighbourhood units, as this is done in order to respect the privacy of the residents. The available neighbourhood data could be completed with data on climate (provided by KNMI), building height and age (3D BAG), land cover data (Bestand bodemgebruik), and satellite photos (Landsat 8). Figure 1.26 (below) uses maps to display some of these datasets that deal with the determinants of HEC.

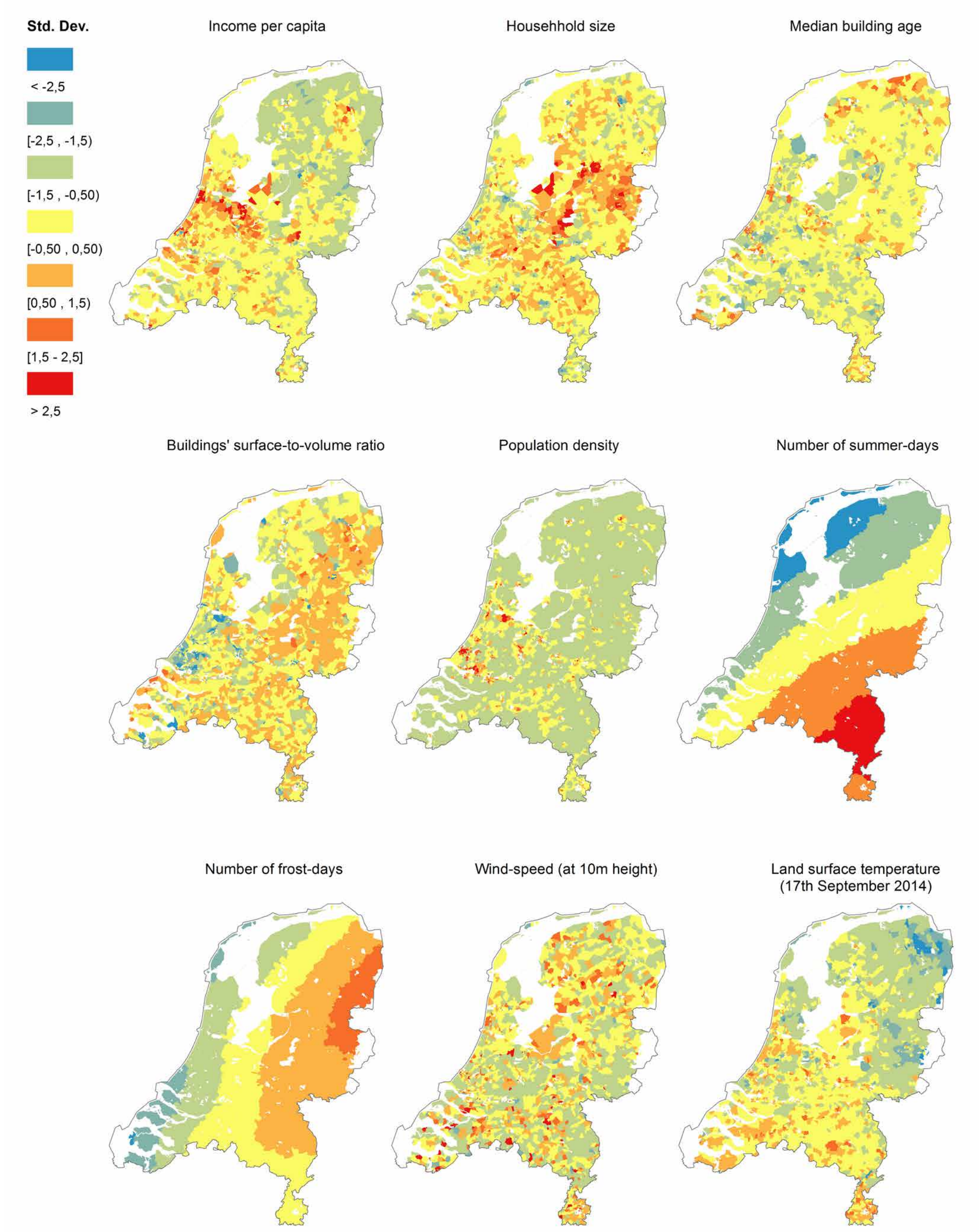

FIG. 1.26 Multiple illustrations of a selected number of datasets available at neighbourhood level in the Netherlands.

Table 1.2 (below) represents the dependent variables of the five studies of this manuscript.

Table 1.3 summarizes the independent variables of the five studies (the potential determinants of HEC and energy poverty) in accordance to the previous studies. These variables characterized the neighbourhoods in multiple terms such as socioeconomic characteristics, urban from, macro climate, micro climate, land cover, and housing. The two studies carried out on the neighbourhoods of the Randstad use an enlarged dataset of independent variables. This is done in order to avoid the potential problem of multi-collinearity between such large amounts of independent variables. Prior to conducting the statistical analyses in these articles, a factor analysis (a technique to compress the effect of inter-correlated variables in limited number of indicators) is carried out.

The methodology of these studies consists of two components: one aspatial and one spatial model. During the first session of the study, an aspatial analysis of the impact of a variety of determinants (i.e. socioeconomic, urban form, housing, macro climate, micro climate). The methodology of the analysis is ordinary least square regression model (OLS). The assumption of the aspatial model is that all the determinants of HEC are global. The results of the OLS models is used in order to test for the multi-collinearity between the independent variables. Subsequently, a geographically weighted regression model (GWR) was employed, with the assumption of the model being that all the determinants are local. In order to define geographic context of each neighbourhood, a spatial weight matrix is applied (Figure 1.27). Subsequent to the application of the GWR model, the variability of the estimated impact of the determinants is tested by either of these two methods: (1) geographical variability test or (2) spatial stationary test. From these there are three possible outcomes: (i) all the determinants are global, thus the results of the OLS model suffice; (ii) all the determinants are local, thus the results of the GWR suffice; (iii) some of the determinants are local and some are global, thus the application of a semi parametric geographically weighted regression (SGWR) model – a model which use combination of local and global determinants – is essential. Ultimately, performance of the applied models is compared by means of three tests: (1) the adjusted R-squared, (2) the Akaike information criterion, and (3) the Moran Index of residuals (see the details in the appendix).

TABLE 1.2 The dependent variables in the five studies.

Article #	Dependent variable	Unit	Geographic area
1	Household energy consumption	euro	Netherlands
2	Share of energy expenditure of households' disposable income	NA	Netherlands
3	Household energy consumption	Joule	Netherlands
4	Household energy consumption	euro	Randstad
5	Household gas consumption	Joule	Randstad
5	Household electricity consumption	Joule	Randstad

TABLE 1.3 Independent variables in the five studies.

	Independent variable	Article #
1	income per capita	1,2,4,5
2	Household-size	1,2,3,4,5
3	Building-age	1,2,3,4,5
4	Surface-to-volume	1,2,4,5
5	Population-density	1,2,4,5
6	Summer-days	1,2,3
7	Frost-days	1,2,3
8	Wind-speed at 10 meter height	1,2
9	Land surface temperature	1,2
10	Private-rent (%)	3
11	Low-income (%)	3
12	Unemployment (%)	3,4,5
13	Pensioner (%)	3
14	Built-up coverage (%)	4,5
15	Building coverage ratio (BCR)	4,5
16	Green-coverage (%)	4,5
17	Frontal area index	4,5
18	Public-rent (%)	4,5
19	Property-value	4,5
20	Disability (%)	4,5
21	Population ages 65+(%)	4,5
22	Population ages 0-14 (%)	4,5
23	Floor area after 1988 (%)	4,5
24	Solar radiation per building volume	4,5
25	Rugosity	4,5
26	Solar radiation on neighbourhood	4,5
27	Aerodynamic roughness length (ARL)	4,5
28	Floor area ratio (FAR)	4,5
29	Humidity (%)	2

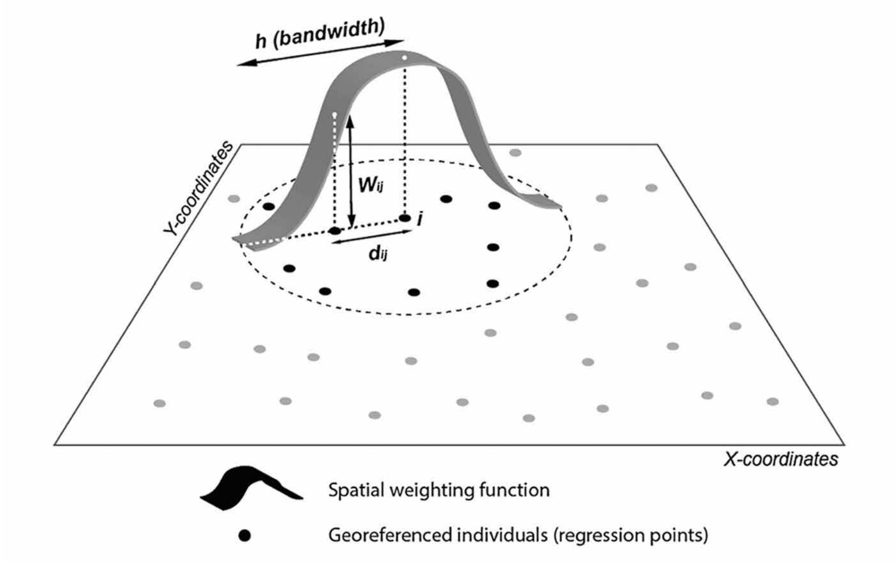

FIG. 1.27 Geographic context of a neighbourhood consists of neighbourhoods adjacent to it – not further than a bandwidth value – *dij*. Within a geographic context, closer neighbourhoods have a greater weight – *Wij* (image source: Feuillet et al., 2015. pp. 6).

1.10 Structure of the thesis and acknowledgment

This thesis is divided into three sections. The first section contains three chapters, and are studies conducted on the all neighbourhoods of the Netherlands. The first chapter, titled "Local and national determinants of household energy consumption in the Netherlands," contains an article published in the journal of *GeoJournal*. The second chapter, titled "Urban heat islands and household energy consumption," reports an article submitted to the journal of *Urban Climate*, and is currently under review. The third chapter, titled "Spatial homogeneity and heterogeneity of energy poverty: a neglected dimension," contains an article published in the journal *Annals of GIS*, and waits for a second round of review. The second section contains two studies on the neighbourhoods of the Randstad regions. The first chapter, titled as "Spatial dynamics of household energy consumption and local drivers in Randstad, Netherlands," reports an article published in the journal of *Applied Geography*.

The next chapter, titled “Local determinants of household gas and electricity consumption in Randstad region, Netherlands: application of geographically weighted regression,” reports an article published in the journal of *Spatial Information Research*. The third section presents the results of all the five studies.

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PART 1

Studies on the neighbourhoods of the Netherlands

2 Local and national determinants of household energy consumption in the Netherlands

ABSTRACT

The policies of Third National Energy Efficiency Action Plan for the Netherlands, regarding the reduction of household energy consumption (HEC), introduces an identical set of policy measures for all neighbourhoods of the Netherlands. This raise a question that is possible to formulate an identical set of incentives and regulations that are optimally suitable in all the locations of the country. The objective of this study is to seek answers to this question by formulating two research questions: what are the national determinants of HEC, i.e. the stimuli that trigger the same response across the whole country? What are the local determinants of HEC, i.e. the stimuli which trigger different responses across the country? To identify local and national determinants of HEC, the impact of nine determinants of HEC in 2 462 neighbourhoods of the Netherlands is assessed by employing the geographical variability test. The results show that two of the determinants are national: (i) the number of frost-days, (ii) wind speed. The results indicate that seven of the determinants are local: (i) income, (ii) household size, (iii) building age, (iv) surface-to-volume ratio, (v) population density, (vi) number of summer days, and (vii) land surface temperature. By employing a semi-parametric geographically weighted regression analysis, the impact of the local and national determinants of HEC is estimated and mapped.

KEYWORDS

Household energy consumption, semi-parametric geographically weighted regression, mixed geographically weighted regression, energy policy, Netherlands

2.1 Introduction

The policies of Third National Energy Efficiency Action Plan for the Netherlands (Ministry of Economic Affairs, 2014) regarding the reduction of household energy consumption (HEC) were developed based on a one-size-fits-all approach: in the policy document, as it is reported to the European commission, the “geographical area” of all the proposed incentives and regulations is specified as “the Netherlands”, without any differentiation according to location-specific circumstances, i.e. socioeconomic patterns, climate, level of urbanisation, land cover, and housing stock (see Table 2.1). In this respect, the policy is made based on an based on an one-size-fits-all approach as that the stimuli of HEC are similar in each and every location of the Netherlands, and that it therefore is possible to formulate an identical set of incentives and regulations that is optimally suitable in all locations of the country. This reflects a gap in the existing body of literature on HEC. Almost all the previous studies are based on the assumption that the determinants of HEC are identical across all areas, and almost all have tried to discover the universally applicable rules that explain the level of HEC. A small portion of previous studies, in contrast, has presumed that all determinants of HEC are location-specific. These studies, however, have failed to prove whether or not that is the case for each and every determinant of HEC.

The objective of this study is bridge the knowledge gap by seeking answers to two research questions: what are the national determinants of HEC, i.e. the stimuli that trigger the same response across the whole country? What are the local determinants, i.e. the stimuli that trigger different responses across the country? This study analyses annual energy consumption per capita within dwellings (HEC) in the neighbourhood units – a rough translation of the Dutch *wijk* – of the Netherlands in 2014. The level of HEC is studied against nine independent variables that have previously been considered effective determinants of HEC: income, household size, building age, surface-to-volume ratio of buildings, population density, degree days (i.e. number of summer days and number of frost days), wind speed, and land surface temperature. The methodology of this study is twofold. First, by employing the geographical variability test (Nakaya et al., 2009), the local and national determinants of HEC are identified. Second, by employing a semi-parametric geographically weighted regression (SGWR) analysis, the impact of national and local determinants of HEC is estimated and mapped. In the next parts, the previous studies are briefly reviewed, and the methodology and data of this study are described. Results and conclusions are presented at the end.

TABLE 2.1 Third National Energy Efficiency Action Plan for the Netherlands (2014) regarding the reduction of residential energy use - all of the listed measures are applicable to the Netherlands as a whole.

Policy measure	
1	Tightening of energy performance standards (EPC) of buildings
2	Lente Agreement on energy-efficient new buildings
3	More with Less: agreement for energy saving in existing residential and other buildings
4	Changes to the Home Valuation System: link maximum rent of a dwelling to its energy label
5	Reduced VAT rate for the maintenance and renovation of residential buildings
6	Block-by-block approach (large-scale approach to improve existing housing stock)
7	Acceleration (facilitating investments in improving the energy efficiency of residential buildings)
8	Revolving fund for energy saving (encouraging investment in the energy efficiency of existing buildings)
9	Energy-saving agreement for the rental sector (corporations, landlords, tenants)
10	Subsidy available for landlords in the social rental sector to improve the energy efficiency of buildings
11	Energy tax (tax levy on energy tariffs)
12	EIA: Energy Investment Allowance (tax reduction for the purchase of energy-efficient equipment)
13	Green Investment and Finance (tax incentive for investment in environmental friendly projects)
14	Green Deal (support for investment in energy-saving and renewable energy measures)

2.2 Previous studies on local and global determinants of household energy consumption

Subsequent to the publication of the two seminal papers on modelling spatial associations (Brunsdon et al. (1996) and Fotheringham et al. (1996)), and the follow-up book by Fotheringham et al. (2003), two new concepts went viral among scholars conducting geographic analysis: (i) local determinants, i.e. the insight that the impact of a phenomenon is spatially non-stationary and thus varies from one location to another; (ii) global determinants, i.e. the stimuli of a phenomena that provoke the same response in all locations of interest. This new perspective sharply contrasted with the presumption that underlies studies prior to that date – which merely searched for global explanations for different spatial phenomena – and left a profound impact on the studies in different fields; scholars in different disciplines have disclosed the local determinants of a variety of geographic phenomena, e.g. violent crime (Stein et al., 2016), regional development (Yu, 2014), poverty (Vaziri et al., 2018), residential burglary (Zhang and Song, 2014), and utilisation of prenatal care (Shoff et al., 2012). It has also raised a new and fundamental question for scholars in different disciplines: what are the local and global determinants of the phenomenon in question? A variety of studies have shown that the best understanding of a range of phenomena – e.g. hedonic house price (Geniaux and Napoléone, 2008), academic performance (Figueroa et al., 2018), soil organic matter (Zeng et al., 2016) – is achieved only when global and local determinants are distinguished.

In the last two decades, while the local and global determinants of the phenomena of interest have been explored in a variety of disciplines, HEC studies have significantly lagged behind in the application of the new methods of geographic analysis. Previous empirical studies on HEC could be categorised into two groups according to their methodology. The first group, accounting for the vast majority of previous studies on HEC, neglects the possibility that determinants of HEC could be local. These studies are based on an underlying presumption that all determinants of HEC are global, i.e. they presume that there are some generic rules applicable to all locations. A variety of the studies following this presumption have cited global rules to explain levels of HEC, such as the following examples: the higher the income level, the higher the HEC (Druckman and Jackson, 2008; Joyeux and Ripple, 2007); per capita HEC drops in larger households (Kowsari and Zerriffi, 2011; Isaac and Van Vuuren, 2009); the older a building, the higher the HEC (Belaïd, 2016; Steemers and Yun, 2009); the higher the surface-to-volume ratio of the buildings, the higher the HEC (Steemers and Yun, 2009; Druckman and Jackson, 2008); HEC drops in areas with a higher population density (Porse et al., 2016; Pachauri and Jiang, 2008); the more cooling and heating degree days there are, the higher the level of consumption (Wiedenhofer et al., 2013; Reinders et al., 2003); the impact of wind-speed on the heat loss of buildings is substantial enough to change the level of HEC (Sanaiean, 2014; van Moeseke et al., 2005); land surface temperature affects HEC in all urban areas (Azevedo et al., 2016; Lee and Lee, 2014).

The second group of the earlier studies is based on the underlying assumption that all determinants of HEC are local. Bouzarovski and Simcock (2016, p. 640) state that “there are clear geographic patternings associated with [household] energy [consumption and] poverty, as well as a geographically embedded and contingent nature of … underlying causes.” Yu (2012) concludes that in eastern China, the intensity of energy use of a province is strongly associated with that of its neighbouring provinces, and that there is a “convergence [between] provincial energy intensity.” (2012, p. 583). Robinson et al. have observed that “vulnerabilities [to energy poverty] associated with disability or illness … is stronger … in some southern cities [of England] including London, Luton and Southampton.” (2018,

p. 12–13). An analysis of the carbon emissions related to HEC in north-west China conclude that the determinants of pollution vary from one region to another: “income indicates a greater influence,” for instance, “in northern Ningxia and northern Shaanxi” (Li et al., 2016, p.183). A study on HEC in California (Sultana et al., 2018) estimated that the aging of the population has a significant impact on increasing HEC in north-eastern areas, whereas no significant effect is expected in the north-western areas. Two studies on HEC in the Randstad region in the Netherlands show that building age, as a proxy for buildings’ energy efficiency, has a greater impact in rural areas than in urban areas (Mashhoodi, 2018), and the main determinant of households’ gas consumption –i.e. building age, household size, income, and population density – vary across neighbourhoods of the region (Mashhoodi and van Timmeren, 2018).

There is a knowledge gap in the previous studies on HEC. Most of the earlier studies presumed that the determinants of HEC are global, while some studies presumed that all determinants of HEC are local. A central and fundamental question, however, has never been posed: what are the local and global determinants of HEC?

2.3 Methodology

This study aims at estimating the local and national determinants of HEC. In the first step of the analysis, a convectional linear regression model, OLS, which holds all the determinants as national determinants of HEC, is employed:

$$y_i = \beta_0 + \sum_k \beta_k \, x_{ik} + \varepsilon_i \qquad \text{EQUATION 2.1}$$

Where y_i denotes the estimated value of HEC in the location i, β_0 denotes the intercept, and β_k shows the coefficient slope of the kth independent variable. x_{ik} and ε_i show the values of independent variables and random error term in location i. In the second step of the analysis, the GWR model, all the independent variables are held as local determinants of HEC:

$$y_i = \beta_0(\mu_i, \nu_i) + \sum_k \beta_k(\mu_i\,, \nu_i) x_{ik} + \varepsilon_i \qquad \text{EQUATION 2.2}$$

Where (μ_i, ν_i) shows the x-y coordinate of location $\boldsymbol{i}$. $\beta_k(\mu_i, \nu_i)$ and $\beta_0(\mu_i, \nu_i)$ are the local coefficient and intercept of kth independent variable in location $\boldsymbol{i}$. A fixed Gaussian function is used to weight the instances around location $\boldsymbol{i}$:

$$W_{ij} = \begin{cases} exp\left(-d^2{}_{ij}/\theta^2{}_{i(k)}\right), if\ d_{ij} < \theta \\ 0, otherwise \end{cases} \qquad \text{EQUATION 2.3}$$

Where W_{ij} is the weight assigned to the instance observed at location $\boldsymbol{j}$ for the estimation of local coefficients at location $\boldsymbol{i}$, $\boldsymbol{d_{ij}}$ is the geodesic distance between $\boldsymbol{i}$ and $\boldsymbol{j}$ in metres, and $\boldsymbol{\theta_{i(k)}}$ is the fixed bandwidth. Using the golden selection function of the GWR 4.0 tool (Nakaya et al., 2009), the optimal $\boldsymbol{\theta_{i(k)}}$, which minimises the AICc (Akaike information criterion) value of the GWR model, is determined.
To identify local and national determinants of HEC, for each of the k independent variables in equation 2, a geographical variability test is applied. The third session, a semi-parametric geographically weighted regression, SGWR, estimates the effect of national and local determinants of HEC:

$$y_i = \beta_0(\mu_i, \nu_i) + \sum_m \beta_m(\mu_i, \nu_i)x_{im} + \sum_n \gamma_n z_{ni} + \varepsilon_i \qquad \text{EQUATION 2.4}$$

Where $\beta_m(\mu_i, \nu_i)$ denotes the coefficient of the mth local determinant at location $\boldsymbol{i}$, and γ_n shows the coefficient of the nth national determinant. A fixed Gaussian function is used. The optimal bandwidth for the SGWR model is estimated by the golden selection function of GWR 4.0.

The performance of the OLS, GWR, and SGWR models is compared by means of four tests: adjusted R2, AICc (corrected Akaike information criterion), cross-validation (CV), and randomness of the spatial distribution of the residuals (assessed by Moran's I).

2.4 Data and Case study

2.4.1 Case study

The case study of this research is comprised of the neighbourhood units, *wijken* in Dutch, of the Netherlands. The neighbourhoods are spatial divisions defined by the Dutch central bureau of statistics (CBS). The CBS divides all areas of the Netherlands into 2 836 neighbourhood units. The reason for the use of the neighbourhood units is the availability of data: the CBS annually publishes data on a variety of socioeconomic characteristics of the neighbourhoods. This study is carried out on 2 462 out of the 2 836 neighbourhoods of Netherlands. The neighbourhoods excluded from the study, accounting for 15% of the total, are of six types: (i) water bodies; (ii) the neighbourhoods that are not covered by the satellite image of 17 September 2014 (which is used to calculate land surface temperature); (iii) the neighbourhoods covered by cloud in the satellite image; (iv) the neighbourhoods of the three isolated islands of Texel, Terschelling and Nes; (v) non-residential neighbourhoods; (vi) neighbourhoods identified as an outlier based on an abnormally low level of HEC per capita. The reason for excluding the latter is that the CBS database on households' gas and electricity consumption merely reports the consumption supplied from the distribution grid of gas and electricity in the neighbourhoods. The supply from district-heating systems or solar panels, however, is not reported by the CBS database. It is likely that a neighbourhood with an abnormally low level of consumption in the CBS database is provided with district-heating or a large number of solar panels. In this case, the neighbourhoods with an abnormally low values (z-score <2.5) are excluded from this study (Figure 2.1).

2.4.2 Dependent variable

The dependent variable of this study is annual expenditure per capita, on gas and electricity, within dwellings in 2014 (Figure 1). The data on gas and electricity is provided by the CBS (Centraal Bureau voor de Statistiek, 2014). The average gas and electricity price for domestic use in the Netherlands, in 2014, is provided by Eurostat (Eurostat, 2015).

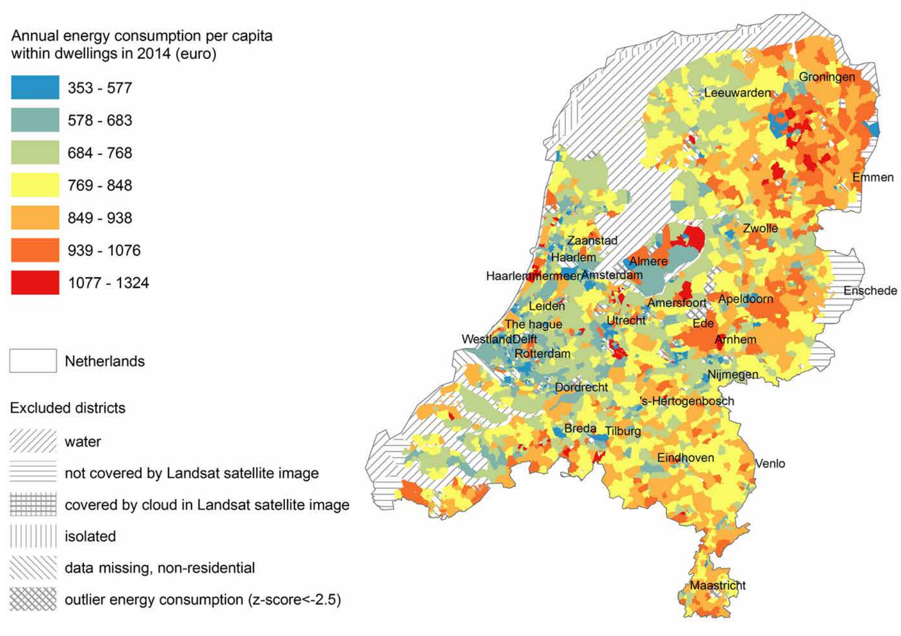

FIG. 2.1 Case study and dependent variables of the study

2.4.3 Independent variables

This study is conducted on nine independent variables (see Table 2.2). *Income* shows annual disposable income per capita. *Household size* shows the average household size in the neighbourhoods in question. *Building age* shows the median age of the buildings. *Surface-to-volume* shows the ratio of buildings' external surfaces to their volume. *Population density* denotes the number of inhabitants per square kilometre. Following the definitions of degree days provided by the Royal Netherlands Meteorological Institute (KNMI), the air temperature in neighbourhoods is measured by two variables: *Summer days*, the number of days with a maximum temperature higher than 25 degrees Celsius, and *Frost days*, the number of days with a minimum temperature lower than 0 degrees Celsius. To obtained the variables, based on KNMI guidelines (Sluiter, 2012), the number of summer days and frost days in the KNMI's 28 meteorological stations is interpolated – universal kriging with external drift of log distance to shore.

Wind-speed shows the speed of the wind blowing at a height of ten metres above ground. The variable is obtained based on a two-layer model of the planetary boundary layer (for a detailed description see Stepek and Wijnant, 2011). To conduct the calculations three datasets are used: wind speed at KNMI meteorological stations in 2014 (KNMI, 2018); the CORINE land-cover database (European Environment Agency, 2016) and the roughness length classifications of the CORINE land-cover classes (Silvia et at., 2007); and finally the land surface temperature (LST) on 17 September 2014. The variable is used as a proxy for the average LST in different seasons. The choice of the date was due to two facts. First, there are few days in which the Landsat-8 satellite image of the Netherlands is available and a large part of the country the areas is not covered by cloud. Secondly, most of the vegetation and trees are green in September, therefore miscalculation of the NDVI (Normalized Difference Vegetation Index), which is used as the basis for calculating LST, could be avoided. To obtain LST, the atmosphere spectral radiance is first calculated:

$$L_\lambda = M_L Q_{cal} + A_L$$ EQUATION 2.5

where L_λ is the top of the atmosphere spectral radiance, M_L is the band 10 multiplicative rescaling factor from metadata (3.3420E-04), Q_{cal} is the band 10 value in the Landsat-8 image, and A_L is the band 10 additive rescaling factor from metadata (0.1). Subsequently the satellite brightness temperature is calculated:

$$T = K_2/(\ln(K_1/L_\lambda + 1))$$ EQUATION 2.6

where T is the satellite brightness temperature and K_2 (1321.08) and K_1(774.89) are thermal conversion constants for band 10. To correct T for land-cover emissivity, the emissivity-corrected surface temperature, LST, is corrected as follows:

$$LST = T/(1 + \left(\frac{\lambda T}{\rho}\right).\ln(\varepsilon))$$ EQUATION 2.7

$$\varepsilon = 0.004P_V + 0.986$$ EQUATION 2.8

$$P_V = \left(\frac{NDVI\text{-}NDVI_{min}}{NDVI_{max}\text{-}NDVI_{min}}\right)^2$$ EQUATION 2.9

$$NDVI = \frac{NIR\text{-}Red}{NIR+Red}$$ EQUATION 2.10

where LST is the emissivity-corrected surface temperature, λ is the wavelength of emitted radiance (11.5), ε is emissivity, P_V is vegetation proportion, NIR is near infrared (band 5), and Red is band 4 in the Landsat-8 image (USGS, 2018a; Stathopoulou and Cartalis, 2009; Kim, 2013).

The data on Income, Household size and Population density are provided by the Wijk-en-buurt-kaart 2014 (Centraal Bureau voor de Statistiek, 2014). The data used to calculate Building age and Surface-to-volume are obtained by use of the building height database – 3D BAG (Esri Netherlands, 2016). Data of meteorological stations – used to calculate Summer days, Frost days and Wind speed – are provided by Royal Netherlands Meteorological Institute (KNMI, 2018). Data on land-cover – used to calculate surface roughness length to obtain Wind speed – is provided by the CORINE database (European Environment Agency, 2016). The Landsat-8 satellite images – used to calculate LST – is taken from the USGS website (USGS, 2018b).

TABLE 2.2 Descriptive statistics of the independent variables.

Variable	Mean	Minimum	Maximum	SD
Income	23,11	12,00	52,70	3,80
Household size	2,35	1,24	4,00	0,30
Building age	39,33	0	164	15,01
Surface-to-volume	0,2691	0,1128	0,3972	0,0347
Population density	1777,66	3	21656	2591,81
Summer days	23,1080	6,0600	37,6800	8,0470
Frost days	68,8040	52,6200	80,7400	6,3187
LST	21,75	15,23	26,22	1,03
Wind speed	39,58	28,39	64,63	5,28

2.5 Results

2.5.1 The identification of local and national determinants of HEC

The geographical variability test, formulated by Nakaya et al. (2009), is used for the identification of local and national determinants. The test is based on a comparison between performance of multiple GWR models. To assess geographical variability of the *k*th independent variable a model comparison between two models is carried out: first, a GWR model which holds all variables as local and the *k*th variable as national; second, a GWR model which holds all the variables as a local variable. A comparison between AICc of the two models determines whether the *k*th variables are local or national determinants of HEC: if the AIC of the second model is lower than that of the first model, the “DIFF of Criterion” measure is smaller than zero, then the *k*th variable is a local determinant of HEC; if not, the *k*th is a national determinant. The application of the geographical variability test shows that two of the variables are national: *Frost days*, and *Wind speed*. The results indicate that seven of determinants are local: *Income*, *Household size*, *Building age*, *Surface-to-volume*, *Population density*, *Summer days*, and *LST* (Table 2.3).

In order to check for multicollinearity between the nine determinants, an OLS model is applied. The results show that the Variance Inflation Factor (VIF) of all the independent variables is well below the maximum threshold of 2.5. This implies that the effect of the variables is fairly unique and therefore there is no multicollinearity bias (Table 2.3).

TABLE 2.3 Geographical variability test and estimates of OLS and GWR models.

Variable	OLS results		GWR results				Geographical variability test	
	β	VIF	β mean	β min	β max	β SD	DIFF of Criterion	determinant type
Intercept	0,000**		0,032	-17,568	15,424	2,315	-1078,42	
Income	0,271**	1,1	0,406	-0,958	0,839	0,129	-16,96	local
Household size	-0,098**	1,63	-0,042	-0,795	0,555	0,205	-60	local
Building age	0,340**	1,36	0,336	0,019	0,761	0,125	-18,79	local
Surface-to-volume	0,061**	1,34	-0,015	-0,277	0,256	0,101	-8,62	local
Population density	-0,532**	1,76	-0,528	-1,271	-0,027	0,216	-48,36	local
Summer days	0,043*	1,81	0,53	-11,497	11,805	1,668	-97,16	local
Frost days	0,173**	1,78	-0,184	-5,603	4,36	1,001	3,84	national
Wind speed	0,003	1,14	-0,016	-0,515	0,184	0,059	42,79	national
LST	-0,097**	2,06	-0,058	-0,435	0,547	0,152	-11,89	local

β: standardized regression coefficient.
** p-value < 0,05.*
*** p-value <0,01.*

TABLE 2.4 Estimates of the SGWR model.

Variable	national coefficients		local coefficients			
	β	SE	β mean	β min	β max	β SD
Intercept			-0,451	-13,240	3,247	0,995
Income			0,410	-0,803	0,946	0,155
Household size			-0,047	-0,969	0,729	0,217
Building age			0,336	-0,038	0,906	0,138
Surface-to-volume			-0,011	-0,389	0,293	0,113
Population density			-0,547	-1,605	-0,016	0,255
Summer days			-0,316	-7,809	2,236	0,688
Frost days	0,623**	0,170				
Wind speed	-0,017	0,014				
LST			-0,048	-0,567	0,618	0,175

β: standardized regression coefficient.
*** p-value <0,01.*

TABLE 2.5 Diagnostics of the OLS, GWR and SGWR models.

	OLS	GWR	SGWR
AIC	5394,08	4711,53	4645,60
AICc	5394,19	4788,57	4733,63
CV	0,5251	0,4349	0,4311
R-square	0,481	0,686	0,699
Adjusted R-square	0,479	0,626	0,638
Residuals Moran's I	0,1718	0,0211	0,0163
Bandwidth (metres)	NA	12867,58	11070,30

2.5.2 Comparison between the performance of the SGWR model and that of the GWR and OLS models

Subsequent to the identification of the local and national determinants of HEC, a SGWR model is employed. The model estimates the impact of the determinants of HEC by simultaneously holding two of the variables as national determinants and seven of the variables as local determinates (Table 2.4).

The comparison between the performance of the SGWR model and that of the OLS model (which holds all variables as national determinants) and the GWR model (which holds all variables as local determinants), shows that the former model provides the best understanding of HEC in the neighbourhoods of the Netherlands: the SGWR model has the lowest level of AIC, AICc and CV, the highest value of the adjusted R-square, and the most random spatial distribution of residuals – assessed by Moran's Index (Table 2.5).

2.5.3 Estimates of the local and national determinants of HEC

The results of the SGWR model show that the estimated coefficient of one of the two national determinants, *Frost days*, is significant at the *p-value*<0.01 level. The coefficient is larger than the estimated effect of the local determinants of HEC in almost all neighbourhoods of the Netherlands. This result implies that the number of frost days is the most influential determinant of HEC, and this statement could be generalised for all neighbourhoods. The estimated coefficient of the other national determinant, *Wind speed*, is not significant at the *p-value<0.05* level. Wind speed, therefore, is not an effective factor of HEC in the neighbourhoods of the country.
In the case of the estimated local coefficients, it is found that, *Income* and *Building age* have a substantial impact on increasing HEC levels. *Population density* has a considerable impact on decreasing the HEC levels of most neighbourhoods. In the case of *Summer days*, *LST* and *Household size*, the local impact of the determinate could vary in nature across the neighbourhoods, i.e. in some neighbourhoods they contribute to mitigate levels of HEC, whereas in others they boost the levels of HEC (Figure 2.2).

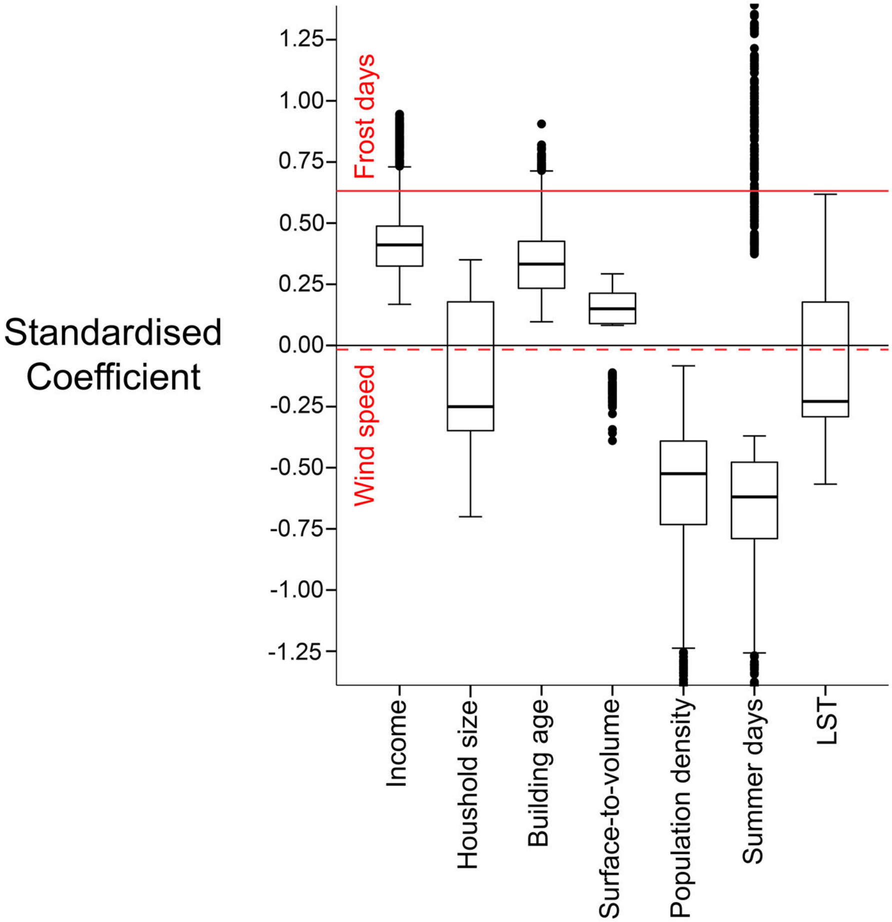

FIG. 2.2 The box plot illustrates the variability of the coefficients of local determinants of HEC. The solid red line shows the coefficient of the significant national variables (Frost days). The dashed red line shows that of the not-significant national variable (Wind speed).

The distribution of local coefficients across the neighbourhoods of the Netherlands shows that more than 93% of the local coefficients of Income are significant at the p-value <0.05 level, which are all positively associated with HEC. A pocket of high values is observed in the north-east of the country between the cities of Groningen, Emmen, Zwolle and Leeuwarden (Fig. 2.3a).

Some 37% of the local coefficients of Household size are significant at the p-value<0.05 level. The sign of almost 71% of the significant coefficients is negative, where that of 29% is positive. Most of the negative coefficients are observed in the areas of The Hague, Rotterdam and the area north and west of Amsterdam, i.e. Haarlem and Zaanstad. The largest positive coefficients are observed in vicinity of Tilburg and Breda. Also, in some neighbourhoods Amsterdam and Utrecht a modest positive coefficient is observed (Fig. 2.3b).

In the majority (89%) of neighbourhoods, the local coefficient of Building age is significant at the p-value<0.05 level, which is positively associated with HEC. The magnitude of the association is remarkably lower in the case of the most urbanised part of Netherlands, the so-called Randstad, comprised of the four main Dutch cities of Amsterdam, Utrecht, Rotterdam and The Hague (Fig. 2.3c).

In merely 13% of the neighbourhoods the local coefficient of Surface-to-volume is significant at the p-value <0.05 level. The majority of the significant coefficients, nearly 78%, are positive. The largest pockets of positive values are observed in the areas enclaved between the Markermeer lake and the North Sea, as well as on the banks of the river Nieuwe Maas. The areas with negative local coefficients are dispersed (Fig. 3d). In a majority of the neighbourhoods, nearly 91%, coefficients of Population density are significant at the p-value <0.05 level, which is associated with lower levels of HEC. The magnitude of the effect is lower in the more urbanised area – eminently the Randstad (Fig. 2.3e).

In the case of Summer days, almost in 39% of the neighbourhoods local coefficients are significant (p-value<0.05). Distribution of the coefficient value shows a clear geographical pattern: there is a gradual change from largest negative coefficients in the north-west to large positive coefficients in the south-east. Almost 84% of the significant coefficients are negative (Fig. 2.3f). Some 26% of the local coefficients of LST are significant at the p-value<0.05 level. Most of the negative coefficient values are concentrated in the vicinity of Westland, The Hague, Rotterdam and south of Utrecht. About one fourth of the positive local coefficients are located in the vicinity of Tilburg and Breda (Fig. 2.3g).

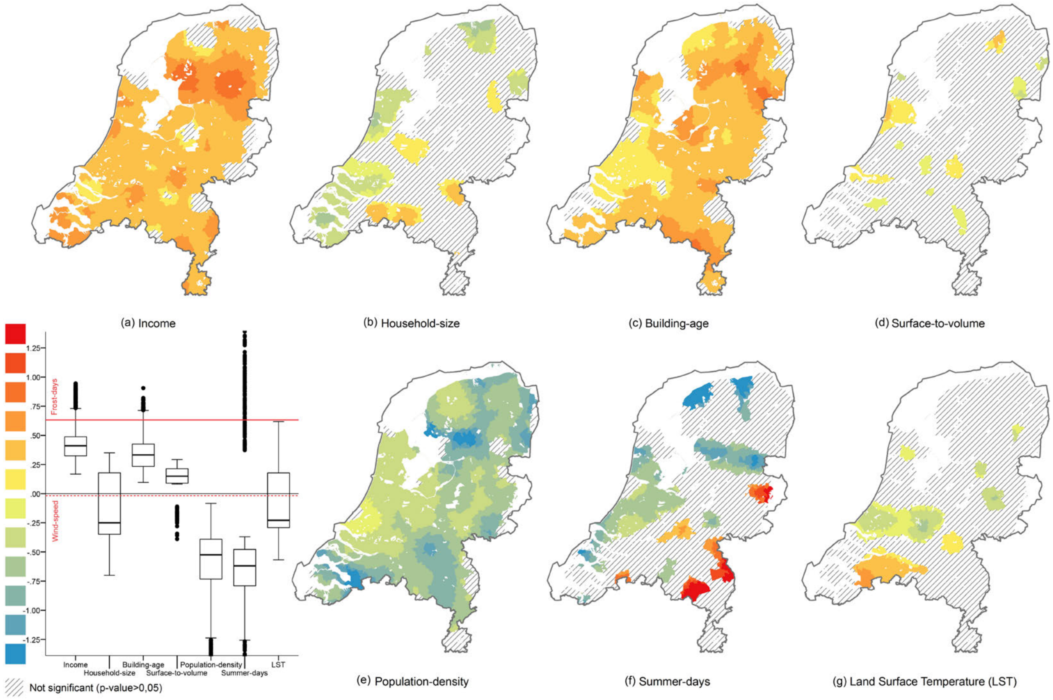

FIG. 2.3 Spatial variation of the estimated standardised coefficients of the local determinants of HEC.

2.6 Discussion

The results show that most of the determinants of HEC are local, i.e. their impact varies across the neighbourhoods of the country. Merely two of the nine determinants of HEC are identified as national determinants: *Frost days* and *Wind speed*. The results show that the impact of merely one of the national determinants, *Frost days*, is statistically significant. The impact is remarkably large; in most of the neighbourhoods, *Frost days* is the most decisive determinant of HEC. This national impact could be explained by the substantial share of heating-related consumption of total HEC in the Netherlands. The data on end-use of energy in the Netherlands published by Eurostat shows that 63% of total energy consumed by the households is related to space heating and nearly 17% is related to water heating

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(Eurostat, 2018). In short, there is just one national explanation for HEC in all neighbourhoods of Netherlands: the higher the number of frost days, the higher the level of HEC. The impact of the rest of the determinants of HEC, however, is highly variable across the neighbourhoods of the Netherlands. In the next paragraphs the local determinants of HEC and their spatial variability across the country are discussed.

The results reveal a strong association between levels of *Income* and HEC. The strongest association is observed in the north-east of the country. Given that the neighbourhoods in the north-east of the country are among the most energy intensive neighbourhoods of the Netherlands, presumably the associations between *Income* and HEC increases at the upper end of the consumption spectrum. This could be explained from a behavioural point of view: the life-style of a heavy user is constructed such that (s)he increases the level of consumption if and when it is affordable to do so (similar to conclusions drawn by Kaza, 2010).

The results show that Household size could have an opposite impact on the HEC of different neighbourhoods. In most of the neighbourhoods, a larger Household size is associated with lower levels of HEC. This is in line with the conclusions drawn by a variety of previous studies (e.g. O'Neill and Chen, 2002) which explain a similar observation by referring to economies of scale in large households. Unexpected results are observed in some neighbourhoods of Amsterdam and Utrecht where larger Household size is found to be associated with higher levels of HEC. This is presumably due to higher HEC per capita in households with young children compares to young single-person-households. Amsterdam and Utrecht are cities with a relatively large young population and known for their lively urban life. A large portion of small households accounts for young people who are less bounded to indoor activities, do not parent children, and possess a smaller number of appliances. The HEC in such a household could be significantly lower than in a larger household with young children in which energy consumption for cooking and water heating is higher (Weber and Perrels, 2000); the motivation for energy saving is lower (Abrahamse and Steg, 2009; Barr et al., 2005); and the possession of a variety of appliances is more common.

The results show that a higher *Building age*, as a proxy for buildings' energy inefficiency, is associated with higher levels of HEC. This is no unexpected discovery. However, what is special to the results of this study is that this association is weaker in the more urbanised areas, specifically in the Randstad region. In other words, the more urbanised the areas, the less important the energy efficiency of the buildings. This result opens a new dimension for studies focused on the relation between urbanisation and energy consumption. A variety of previous studies have examined the effect of urbanisation on the total amount of energy consumption (e.g. Wang, 2014); however possible changes to the determinants of HEC in response to the level of urbanisation has barely been studied.

In most of the neighbourhoods no significant association between HEC and *Surface-to-volume* is found. In the areas with a scattered pattern of urbanisation and exposure to the sea breeze from the North Sea, *Surface-to-volume* is found to be associated with a higher level of HEC. As suggested by various previous studies, presumably this is due to higher heat loss of the dwellings. Higher *Surface-to-volume* has an opposite impact on HEC of some neighbourhoods in the east and south of the Netherlands. In the latter a higher *surface-to-volume* is associated with lower levels of energy consumption. Considering the warmer weather in these areas, presumably a larger building surface decreases the energy used for ventilation.

The results show that, in almost all areas of the Netherlands, a higher *Population density* is associated with lower levels of HEC. The association is remarkably higher in less urbanised areas, e.g. the neighbourhoods located in the south of Friesland and Zeeland provinces. Presumably, this is due to a marked difference between the life-styles of residents of more urbanised neighbourhoods and to those in adjacent rural neighbourhoods: urbanites tend to be more engaged in outdoor activities and spend less time at home; this can result in a substantial decrease in levels of HEC (similar to the conclusions drawn by Heinonen et al., 2013; Yu et al., 2013).

The number of *Summer days* could have a different impact in different neighbourhoods. In the neighbourhoods toward the north-west, where *Summer days* are less frequent, an increase in the number of *Summer days* is associated with lower HEC. This is presumably due to less energy consumed for water heating and more outdoor activities. In contrast, in the south-east, with more frequent heat waves in summer, the factor is associated with higher HEC. Presumably, the increase in the number of *Summer days* boosts electricity consumption for space cooling in these neighbourhoods.

In areas in the vicinity of Rotterdam, The Hague and Utrecht, higher values of *LST* are associated with lower levels of HEC. Higher levels of *LST* could result in an increase in air temperature. Presumably, this contributes to a decreased amount of energy consumed for space heating in these areas. An opposite association is observed in some southern neighbourhoods – with a warmer climate – where higher levels of *LST* is associated with higher HEC. Presumably, the higher air temperature consequent to higher levels of LST results in higher energy consumption for space-cooling in these neighbourhoods (similar to what is suggested by Lee and Lee, 2014; Ewing & Rong, 2008).

2.7 Conclusion and policy implications

The core objective of this study was to examine whether the stimuli of HEC are similar in each and every location of the Netherlands, and that it is therefore possible to formulate an identical set of incentives and regulations that is optimally suitable in all locations of the country. As result, it is established that the determinants of HEC in the Netherlands could be categorised in two types: national determinants and local determinants. The effect of national determinants (*Frost days* and *Wind speed*) on HEC could be generalised across all the neighbourhoods of the country, whereas the effect of local determinants (*Income*, *Household size*, *Building age*, *Surface-to-volume*, *Population density*, *Summer days*, and *LST*) vary from one neighbourhood to another. In this case the most effective way to reduce HEC could be related to a variety of factors that could vary from one neighbourhood to another. These findings have two major policy implications: first, one-size-fits-all policies need to be completed with location-specific strategies; secondly, in order to properly address the local determinants of HEC, the policies need to be enriched by the addition of socioeconomic, morphological and climate-related angles to their approach. The two policy implications are elaborated in the next paragraphs.

It is established that the nature and magnitude of local determinants' impact vary across the neighbourhoods of the Netherlands. In the most eminent cases, an increase in Household size and Summer days can have an opposite impact on the HEC of different neighbourhoods. In the case of other local determinants, though the nature of the effect is similar in all the neighbourhoods, their magnitude differs vastly from one neighbourhood to another. For instance, though it is established that a higher Building age, as a proxy for buildings' energy efficiency, is associated with higher levels of HEC, such an effect is substantially smaller in highly-urbanised neighbourhoods. In this respect, a rigid set of policies would not optimally suit the different local circumstances in various parts of the country. As the energy efficiency of buildings is more crucial in less urbanised areas, for instance, building regulations could be tightened up in suburban and rural neighbourhoods, and additional incentives for building renovation could be introduced.

Most of the incentives and regulations introduced by the policies are related to buildings' energy efficiency. The results of this study, however, show that energy consumption within dwellings is affected by a variety of factors such as income, household type, urban morphology, population density and urbanisation, land surface temperature and urban heat islands. It is established that in some neighbourhoods the effect of such factors outnumbers that of buildings' energy efficiency. Presumably, this is the reason that the actual energy consumption of the labelled dwellings in the Netherlands does not necessarily match to their theoretical energy consumption (Majcen et al., 2013). This calls for for a shift in the approach of the current policies regarding the reduction of HEC in the Netherlands – in which energy efficiency of buildings is the keystone of introduced incentives and regulations (see Table 1). Policies need to break through the narrow perspective of building energy efficiency and take a more multidimensional approach. This is eminently necessary in order to properly adapt to ongoing trends in the Netherlands: the projected changes in household type towards smaller and more aged households – see population projections by the CBS (CBS, 2011); the planned construction of half a million new dwellings in the Randstad region which will transform morphology of the cities – see the Randstad structural vision for 2040 (Rijksoverheid, 2008); the expected change of climate in terms of temperature, wind speed, precipitation, solar radiation and cloudiness – see the climate scenarios by the KNMI (KNMI, 2015); the growing concerns about the urban heat island effect in Dutch urban environments and its effects on the urban microclimate –see, e.g., the study on urban heat islands in Amsterdam and Rotterdam (van der Hoeven and Wandl, 2015a, van der Hoeven and Wandl, 2015b). Energy polices should not pass all these trends unnoticed. Household energy consumption within dwellings is not just about dwellings; policies shouldn't be either.

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3 Urban heat islands and household energy consumption

ABSTRACT

It is widely accepted that urban heat islands affect household energy consumption (HEC). To verify the validity of this proposition, a variety of studies have examined the impact of land surface temperature (LST) on HEC. however, often the variation of LST's impact in different locations is not examined. A number of questions arise: for how many percentage points of HEC does LST account? Furthermore, does LST's impact differ with regard to demography, housing, urban form, and urban microclimate of the neighbourhood in question? To study the impact of LST on the HEC of the urbanised neighbourhoods of the Netherlands in 2014, this study develops two semi-parametric geographically weighted regression models: first, estimating the impact of LST and nine control variables; second, estimating the impact of the control variables only. We conclude that: (i) the impact of LST varies from one neighbourhood to another; (ii) the impact of LST is significant in 31% of the neighbourhoods, where it accounts for 6% of HEC on average; (iii) the impact varies from one neighbourhood to another, and is vastly affected by geographic context of the neighbourhood in question.

Highlights

- The impacts of land surface temperature on energy use vary from one area to another.
- The impact of land surface temperature on the energy use is smaller than other determinants.
- The impact of land surface temperature is affected by geographic context of the neighbourhood.

KEYWORDS urban heat island, remote sensing, land surface temperature, household energy consumption, geographically weighted regression , Netherlands

3.1 Introduction

3.1.1 Urban heat islands and household energy consumption: a knowledge gap

Urban heat islands, that in effect are the disproportionate concentration of high land surface temperature (LST) in urban areas compared to adjacent neighbourhoods, are a growing 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 and Wandl, 2015a; van der Hoeven and Wandl, 2015b). Although the circumstances that contribute to the formation of urban heat islands are rigorously studied, the impact of urban heat islands 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 urban heat islands, which we interchangeably refer to as LST, and household energy consumption (HEC) are introduced, and the objective and structure of this study is elaborated.

It is widely accepted that urban heat islands 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 et al., 2015). Various studies (e.g. Kolokotroni et al., 2007; Santamouris et al., 2001; Hassid et al., 2000) show that a higher LST decreases the amount of energy consumed for space heating.

The number of previous studies which account for spatial variation of LST's impact, however, is few. In the Netherlands, for example, a series carried out in the Climate Proof Cities programme have studies various aspects of climate change, among them urban heat islands, and have measured the influence of such factors across different

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cities and neighbourhoods (e.g. Echevarría Icaza et al., 2016; Icazaet et al., 2016; Lenzholze et al., 2018).

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, the majority of 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 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 neighbourhoods of Netherlands in 2014. The article is divided in four 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 part the results of the study are presented and discussed.

3.1.2 Objective and approach of this study

This study aims to study the impact of LST on HEC in the neighbourhoods of Netherlands. To do so four research questions are put forward. First, is the effect of LST spatially variant (i.e., is the effect specific to some areas) or spatially invariant (i.e., is the HEC of all the neighbourhoods 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 locations? Third, does the impact of LST differ in response to the geographic circumstances of an area, 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 et al., 2009), in order to identify spatially variant and spatially invariant determinants of HEC, among them LST. Subsequently, in the second step, two semi parametric geographically weighted regression models (SGWR) are developed, which allow for the simultaneous estimation of spatially variant and invariant impacts. In the first SGWR 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.

Eight types of control variable are used to control for the socioeconomic, housing, and climate characteristics of neighbourhoods. 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. Yun and Steemers, 2011; Druckman and Jackson, 2008; Joyeux and Ripple, 2007);
2. household size, as per capita consumption could decrease in larger households due to economies of scale (e.g. Fong et al., 2007; Lenzen et al., 2006; Tso and Yau, 2003);
3. building age, as a proxy for energy efficiency of dwellings (e.g. Druckman and Jackson, 2008; Aydinalp et al., 2004; Tso and 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 and Yun, 2009; Lenzen et al., 2006);
5. population density as an indicator of urbanisation (for instance York, 2007; Mashhoodi, 2018; Mashhoodi and van Timmeren, 2018);
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 et al., 2011; Chow et al., 2010);
8. wind speed, as it affects the air infiltration and exfiltration of buildings, ambient temperature of dwellings, and felt temperature (Sanaiean et al., 2014; van Moeseke et al., 2005).

3.2 Methods and data

3.2.1 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 the determinants are that affect the HEC of all neighbourhoods at a similar rate, i.e., the spatially invariant determinants, and in which determinants does their effect vary across neighbourhoods, 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. 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:

$$y_i = \beta_0(\mu_i, \nu_i) + \sum_k \beta_k(\mu_i, \nu_i)x_{ik} + \varepsilon_i \qquad \text{EQUATION 3.1}$$

Where y_i denotes the estimation of HEC at the neighbourhood 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:

$$\hat{\beta}(\mu,\vartheta) = (X^T W(\mu,\vartheta)X)^{-1} X^T W(\mu,\vartheta)y$$ EQUATION 3.2

Where $\hat{\beta}(\mu,\vartheta)$ is the unbiased estimate of β, and $W(\mu,\vartheta)$ the spatial weight matrix specific to location $\boldsymbol{i}$. The spatial weight matrices are adopted based on the fixed bisquare formulation:

$$W_{ij} = \begin{cases} (1 - \left(\frac{d_{ij}}{\theta}\right)^2)^2, if\ d_{ij} < \theta \\ 0, otherwise \end{cases}$$ EQUATION 3.3

W_{ij} is the weight of neighbourhood j in the GWR model adopted for the location $\boldsymbol{i}$. d_{ij} denotes the geodesic distance between the two neighbourhoods. 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 semi-parametric geographically weighted models (SGWR) are developed. The first model estimates the impact of LST, as well as the control variables, on HEC:

$$y_i = \beta_0(\mu_i,\nu_i) + \lambda\beta_{LST}(\mu_i,\nu_i)LST_i + (1-\lambda)\gamma_{LST}LST_i + \sum_m \beta_m(\mu_i,\nu_i)x_{im} + \sum_n \gamma_n z_{ni} + \varepsilon_i$$ EQUATION 3.4

$$\lambda = \begin{cases} 1, LST\ is\ identified\ as\ a\ spatially\ variant\ variable \\ 0, LST\ is\ identified\ as\ a\ spatially\ invariant\ variable \end{cases}$$ EQUATION 3.5

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 the nth spatially invariant control variable. The second SGWR model estimates only the impact of the control variables on HEC:

$$y_i = \beta_0(\mu_i,\nu_i) + \sum_m \beta_m(\mu_i,\nu_i)x_{im} + \sum_n \gamma_n z_{ni} + \varepsilon_i$$ EQUATION 3.6

The comparison between the performance of the two models is used to measure the impact of LST on the overall HEC of the neighbourhoods. To do so, the difference between goodness-of-fit (expressed as adjusted R2) 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 et al., 2002) – i.e. the average value of a certain variable in a neighbourhood and its adjacent neighbourhoods, with regard to a spatial weight matrix – is adopted:

$$Mean\ contextual\ value\ of\ variable\ K\ at\ location\ i = \frac{\sum_j W_{ij}\, x_{jk}}{\sum_j W_{ij}} \qquad \text{EQUATION 3.7}$$

3.2.2 Dependent variable

This study is conducted on neighbourhood units in the Netherlands (Figure 3.1) – the so-called ‘wijken’ in Dutch, the institutional boundaries of which are defined by the Dutch central bureau for statistics (CBS). The study is conducted on urbanised neighbourhoods of the Netherlands, excluding agricultural, natural and industrial areas. The criteria for selection of the neighbourhoods is the CBS’s urbanity index, as only the top four levels of urbanity, with a minimum population density of 500 inhabitants per square kilometre, are included in the analysis. Ultimately, the study area comprises 1 406 neighbourhoods. The dependent variable of this study is annual energy consumption, in Joules, for gas and electricity combined, per capita aggregated at the neighbourhood units in 2014. The data on the gas and electricity consumption of the neighbourhoods is provided by the CBS (Centraal Bureau voor de Statistiek, 2014).

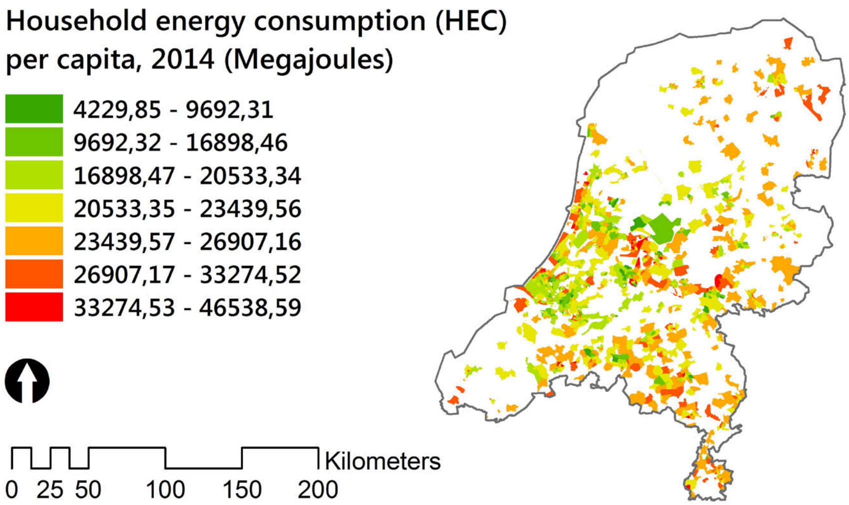

FIG. 3.1 Case study areas and dependent variable.

3.2.3 Independent variables

The independent variable of this study is land surface temperature (LST). To retrieve LST values from Landsat 8 images, some factors first need to be considered. The thermal measurements of remote sensors are sensitive to the surface emissivity of the areas in question. Ignoring the surface emissivity could therefore result in inaccuracy in the retrieval of LST (Voogt and Oke, 2003). To account for the impact of surface emissivity, a variety of methods have previously been proposed, among them the emissivity methods based on the Normalized Difference Vegetation Index (NDVI) – initially proposed by Valor and Caselles (1996). Because of their simplicity, the NDVI-based methods are some of the most used emissivity measurement methods (Ferreira and Duarte, 2019), and have been employed by a variety of studies in different contexts (e.g. Shi and Zhang, 2018; Ziaul and Pal, 2018; Bokaie et al., 2016).

There are, however, some drawbacks to the use of the NDVI-based methods. As a remotely sensed measurement, NDVI is merely a proxy for the abundance of vegetation in a pixel of a satellite image, and not an indication of the real status of the area in question. NDVI measurements, in this respect, are sensitive to the real land cover of the areas in question and may be biased under particular conditions, among them bare soil (Sobrino and Raissouni, 2000), water, ice, snow, and rocks (Sobrino et al, 2008). The NDVI-based emissivity methods, like any other remote sensing technique, are additionally sensitive to the presence of highly reflective materials such as glass roofs and white marble (Mitraka et al., 2012).

In order to account for surface emissivity, this study uses the NDVI and vegetation proportion methods of estimating surface emissivity and LST (Artis and Carnahan, 1982). To compensate for the shortcomings associated with NDVI-based methods, two steps are taken. First, agricultural, natural and bare soil lands are excluded from the study areas, as this study solely focuses on the urbanised areas of the Netherlands. Second, glass houses, as buildings with highly reflective roofs, are identified and excluded from the LST pixels.

To obtain the values of LST at the neighbourhoods, Landsat 8 images of three different dates in 2014 are used: 9 March, 17 September, and 3 October. The images are taken at around 10:30 am local time. The choice of the dates is driven by the availability of Landsat 8 images: the three images are the only available images that cover most of the neighbourhoods of this study, i.e. a relatively small portion of the images is covered by cloud. As a proxy for the annual level of LST in the neighbourhoods, the average value of the three LST measurements is used in the statistical analysis. To calculate LST, the atmosphere spectral radiance is first obtained:

$$L_\lambda = M_L Q_{cal} + A_L \qquad \text{EQUATION 3.8}$$

where L_λ denotes the top of the atmosphere spectral radiance, $\mathrm{M_L}$ denotes the band 10 multiplicative rescaling factor from metadata (3.3420E-04), $\mathrm{Q_{cal}}$ shows the band 10 value in the Landsat 8 image, and $\mathrm{A_L}$ denotes the band 10 additive rescaling factor from metadata (0.1). In the next step, the satellite brightness temperature is obtained:

$$T = K_2/(\ln(K_1/L_\lambda + 1)) \qquad \text{EQUATION 3.9}$$

$\boldsymbol{T}$ denotes the satellite brightness temperature. K_2 (1321.08) and K_1 (774.89) show the thermal band 10 conversion constants. To calculate the LST, corrected for land-cover emissivity, the formulation of Artis and Carnahan (1982) is used:

$$LST = T/(1 + \left(\frac{\lambda T}{\rho}\right).\ln(\varepsilon))$$ EQUATION 3.10

$$\varepsilon = 0.004P_V + 0.986$$ EQUATION 3.11

$$P_V = (\frac{NDVI\text{-}NDVI_{min}}{NDVI_{max}\text{-}NDVI_{min}})^2$$ EQUATION 3.12

$$NDVI = \frac{NIR\text{-}Red}{NIR+Red}$$ EQUATION 3.13

LST denotes the emissivity-corrected surface temperature, λ shows the wavelength of emitted radiance (11.5), ε denotes emissivity, P_V shows vegetation proportion, NIR is near infrared (band 5), and Red is band 4 in the Landsat 8 image (USGS, 2018b; Kim, 2013; Stathopoulou and Cartalis, 2009).

Subsequent to the retrieval of the LST maps of the three dates, 9 March (Figure 3.2a), 17 September (Figure 3.2b) and 3 October 2014 (Figure 3.2c), two types of pixel are excluded from the LST datasets. First, pixels covered with cloud and cirrus, which are obtained from the QA bands of Landsat images (Figure 3.2d, 3.2e, 3.2f); second, pixels overlapping with the locations of glass houses, as the high reflection of the glass roof could create a bias for the retrieved values of LST (Figure 2g). The exact locations of the glass houses are provided by the Dutch land cover database (Centraal Bureau voor de Statistiek, 2019).

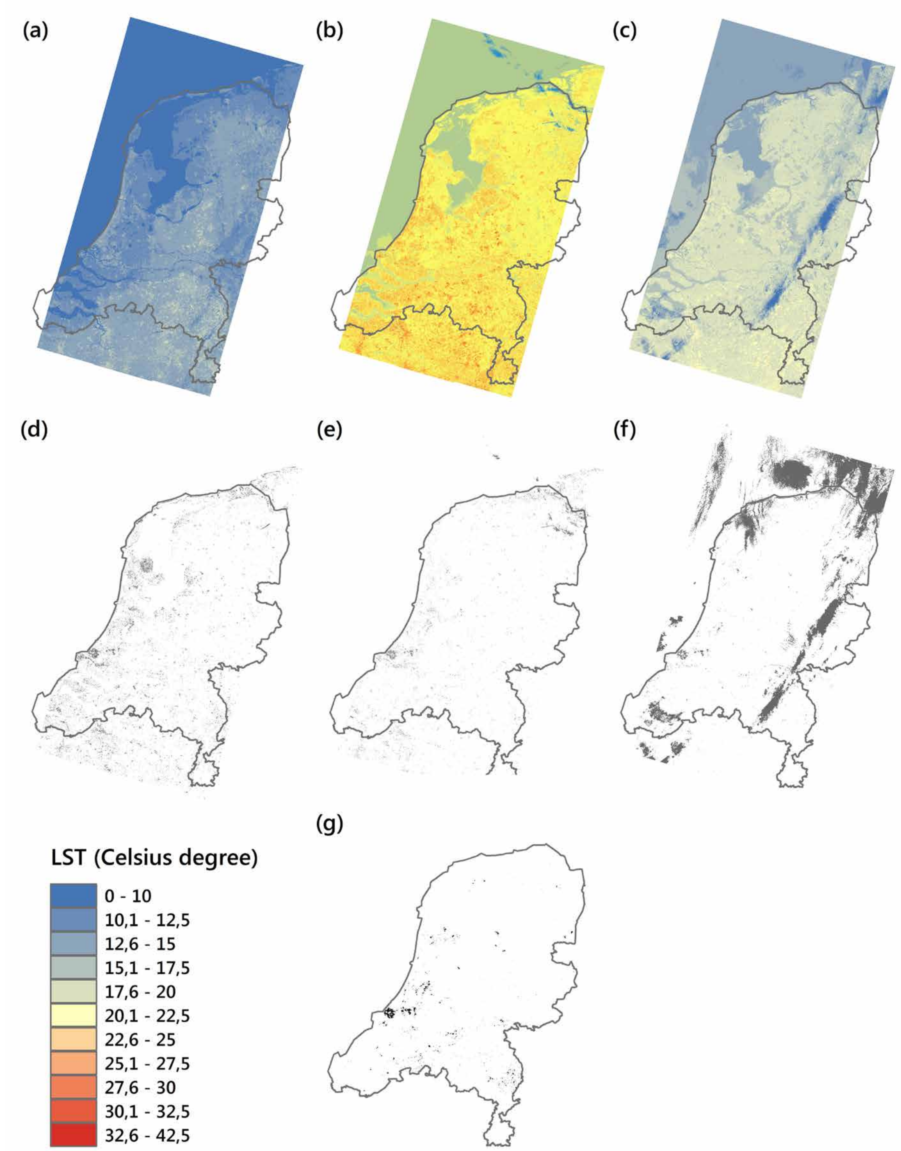

FIG. 3.2 Land surface temperature (LST) on 9 March (a), 17 September (b), and 3 October (c); pixels covered by cloud and cirrus on 9 March (d), 17 September (e), and 3 October (f); glass houses (g) – according to the Dutch land cover database.

3.2.4 Control variables

This study uses nine control variables (see Table 3.1). Income represents the average annual disposable income per capita in the neighbourhoods. 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 neighbourhood 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 neighbourhoods, climate 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). The climate conditions of the neighbourhoods 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 degrees Celsius. 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. Wind-speed, the speed of the wind blowing at a height of ten metres above ground level, is retrieved based on the two-layer model of the planetary boundary layer interpolation (for a detailed description see Stepek and 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 Silvia et at. (2007).Data on the observations of meteorological stations are extracted from KNMI database (KNMI, 2018).

TABLE 3.1 Descriptive statistics of control variables.

Variable	Mean	Minimum	Maximum	SD
Income	23,69	12,00	66,30	4,50
Household size	2,22	1,20	3,50	0,31
Population density	3162,64	23	21656	2900,32
Building age	40,0023	0,0000	164,0000	18,5599
Surface to volume ratio	0,25	0	0	0,04
Number of summer days	22,8518	7,4954	37,6955	7,7189
Number of frost days	67,52	52	81	6,08
Humidity (%)	80,71	79	83	0,70
Wind speed	40,1086	28,5885	68,1731	6,6043

3.3 Results

3.3.1 Identification of spatially variant and invariants impact

The first step is to apply the geographical variability test, in order to identify spatially variant and invariant impacts. The results of the test show that the DIFF of criterion is positive in the case of seven of the independent variables, indicating that the impact on HEC of these variables are spatially invariant (Table 3.2):

1. Income
2. Household size
3. Surface to volume ratio
4. Number of summer days
5. Number of frost days
6. Humidity
7. Wind speed.

The results of the test show that the impact on HEC of three of the independent variables are spatially variant (indicated by negative values of the DIFF of criterion):

1. Population density
2. Building age LST.

The findings indicate that the association between LST and HEC cannot be generalised across all the neighbourhoods, as the association differs from one neighbourhood to another. The results of the geographical variability test are used to develop two SGWR models.

TABLE 3.2 The results of the geographical variability test and identification of the spatially variant and invariant impact.

Variable	DIFF of Criterion*	Type of spatial impact
Income	5,84	spatial invariant
Household size	8,76	spatial invariant
Population density	-43,44	spatial variant
Building age	-22,42	spatial variant
Surface to volume ratio	6,69	spatial invariant
Number of summer days	3,59	spatial invariant
Number of frost days	5,32	spatial invariant
Humidity (%)	5,49	spatial invariant
Wind speed	10,66	spatial invariant
Land surface temperature	-14,97	spatial variant

** result of the geographical variability test*

3.3.2 Results of the two SGWR models

In the second step of the analysis, subsequent to the identification of the spatially variant and invariant independent variables, two SGWR models are developed. The first model estimates the impact of the LST and the nine control variables on HEC. The second model tests the impact of the nine control variables only (Table 3.3). 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 SWGR by a 1,5 percentage point – which quantifies the overall impact of LST on HEC of all the urbanised neighbourhoods of the Netherlands. 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. The estimates of seven of the control variables is significant in both models; the estimates of the Number of summer days is not significant in either of the models; the estimates of Humidity is only significant in Model 1, indicating that the impact of humidity on HEC is meaningful only when that of the LST is taken into consideration.

TABLE 3.3 Estimates of the SGWR models.

	Model 1			Model 2		
	spatial homo-geneous coefficients	spatial heterogeneous coefficients		spatial homo-geneous coefficients	spatial heterogeneous coefficients	
Variable	β	β mean	β SD	β	β mean	β SD
Intercept		2,7E-02	6,7E-05		2,7E-02	6,0E-05
Income	8,0E-05**			7,6E-05**		
Household size	-3,6E-05**			-3,3E-05**		
Population density		-1,0E-04	4,9E-05		-8,9E-05	3,6E-05
Building age		8,9E-05	3,2E-05		8,9E-05	3,0E-05
Surface to volume ratio	2,4E-05**			1,7E-05**		
Number of summer days	-2,00E-05			-1,0E-05		
Number of frost days	4,3E-05**			3,8E-05**		
Humidity (%)	2,0E-05**			1,70E-05		
Wind speed	4,0E-05**			3,4E-05**		
Land surface temperature		2,3E-05	3,6E-05			
R-squared	0,5765			0,551		
adjusted R-squared	0,5351			0,5172		
AICc	-19687,6			-19655,76		
residual Moran's I	0,046708			0,054262		
bandwidth (meter)	39023,78			39317,42		

β: standardized regression coefficient.
*** p-value <0,05.*

3.3.3 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 only 31% of neighbourhoods. In this case, the effect of LST is of less significant than most of the control variables. In the case of the control variables with a spatially invariant effect, six variables significantly affect the HEC of all neighbourhoods: Income, Household size, Surface to volume ratio, Number of Frost days, Humidity, and Wind speed. In this respect, only the Number of summer days, the only spatially invariant control variable with no significance (p-value> 0,05), has a less significant impact than LST. Compared to the impact of the two spatially variant control variables, the impact of LST is significant, by a wide margin, in fewer neighbourhoods, while the impact of Population density and Building age are significant in 85% and 88% of the neighbourhoods (p-value> 0,05).

Should the impact of LST be significant in a neighbourhood, its impact outweighs those of Surface to volume ratio and Humidity in more than 75% of cases, and those of Wind speed and Number of frost days in more than 50% of the neighbourhoods. The impact of LST, however, is outnumbered by that of Income, Building age, Household size and Population density in the vast majority of areas. An exclusive property of LST impact, compared to the impact of other control variables, is that an increase in LST could have the opposite effect on the HEC of different neighbourhoods. In 29% of the neighbourhoods, higher levels of LST are associated with higher levels of HEC. In 1,5% of neighbourhoods, however, this impact is reversed, i.e. a higher LST significantly contributes to lower HEC (Figure 3.3).

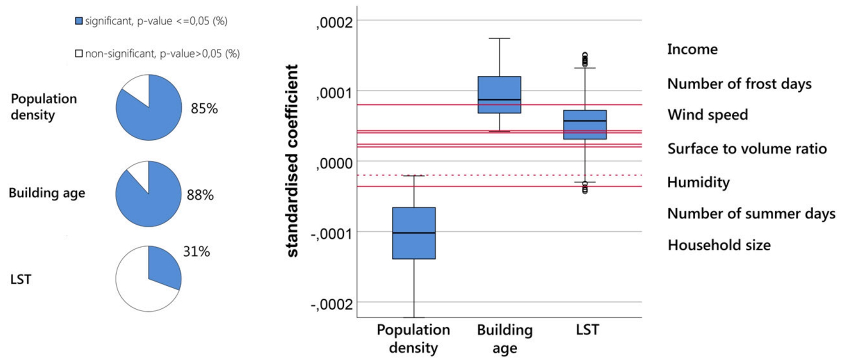

FIG. 3.3 The standardised coefficient of the significant spatially invariant effects (solid red line), not significant spatially invariant effects (dashed red line), and variation of the significant (p-value < 0,05) spatially variant impacts (box plots). Pie charts show the frequency of significant impacts of the spatially variant variables.

3.3.4 The spatial variation of LST's impact on HEC

The impact of LST is significant (p-value <= 0,05) in 31% of the neighbourhoods. The estimated magnitude of this impact varies spatially across the neighbourhoods. As estimated in section 3.2, the overall impact of LST (i.e. impact of LST on the overall HEC of Dutch urbanised neighbourhoods) is estimated at around 1,5%. Focusing on the areas where the LST has a significant impact, the results show that this magnitude is around 6% on average – with a standard deviation of 5%. In extreme cases the magnitude is as small as 1%, and as large as 28%. The results show that the magnitude is larger in the case of inland areas (Figure 3.4a). Should the estimated standardised coefficient of LST be significant, in 95% of the neighbourhoods the sign of the coefficients is positive, i.e. higher levels of LST are associated with higher levels of HEC. An exception is observed in the case of two small towns, Oudewater and Bodegraven-Reeuwijk, in the middle of the so-called Green Heart, a relatively green area in the center of the most urbanised region of the Netherlands, the Randstad (Figure 3.4b).

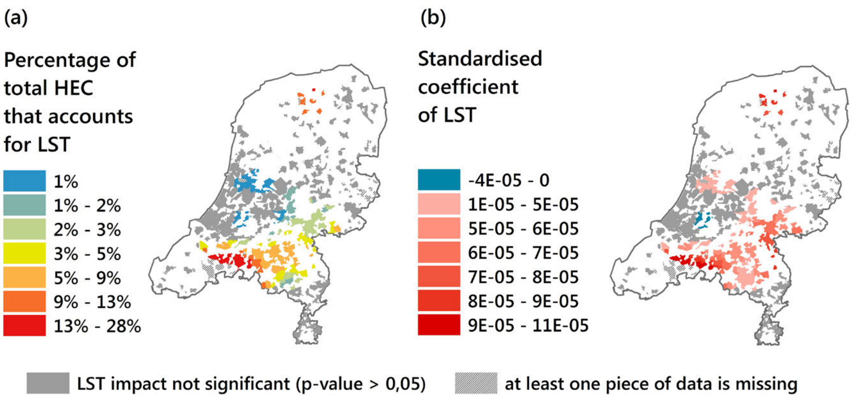

FIG. 3.4 The estimated impact of LST, i.e. the percentage of total HEC of a neighbourhood that accounts for LST (a), standardised coefficient of LST (b).

Given the spatial pattern of LST's impact on HEC (Figure 3.4a), 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 neighbourhoods where the impact of LST is significant are compared with those of the neighbourhoods where the impact is not significant. In order to quantify the geographic context of a neighbourhood, the status of HEC, LST, and the other control variables in the neighbourhood in question, as well as the status of those in the adjacent neighbourhoods within a 39km radius, the bandwidth of the SGWR models, are summarised (see the formulation of Mean contextual value of variable K at location $\boldsymbol{i}$ in section 2.1).

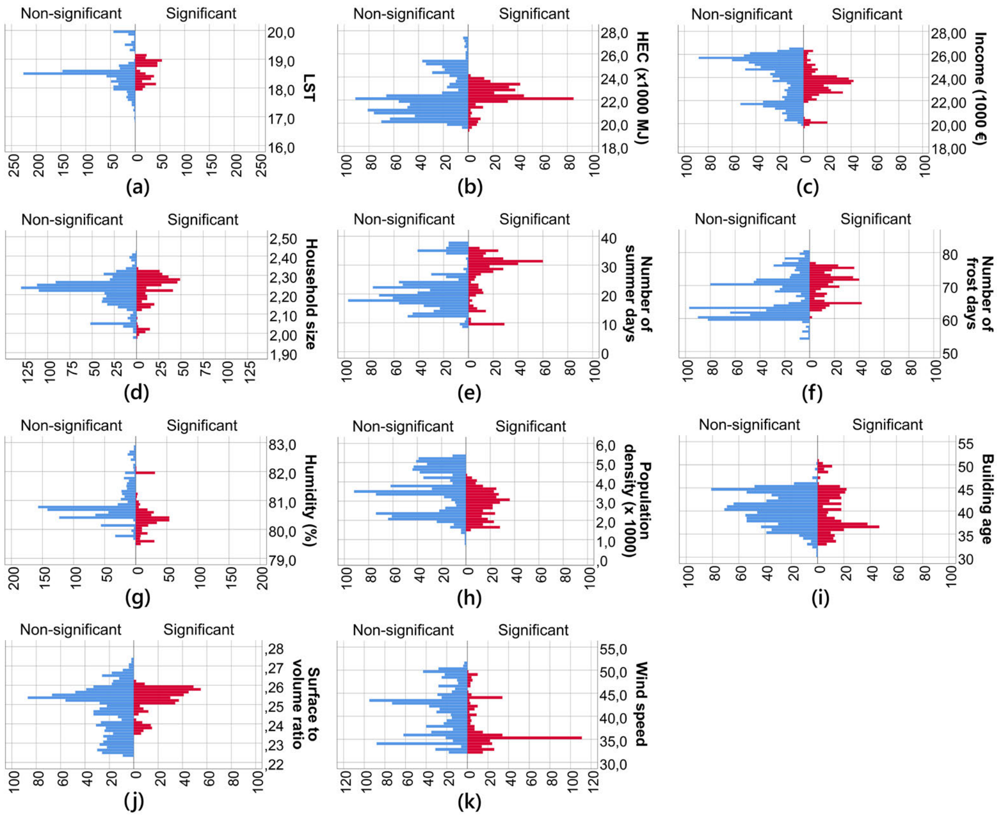

FIG. 3.5 Characterising the impact of LST in relation to the geographic context of neighbourhoods in terms of (vertical axis): Intensity of LST (a), Level of HEC (b), Income (c), Household size (d), Number of summer days (e), Number of frost days (f), Humidity (g), Population density (h), Building age (i), Surface to volume (j), Wind speed (k). Horizontal axis of the histograms show frequency of the observations.

The result of the comparison shows that, on average, there is an association between the level of LST, and its significant impact on HEC – i.e. the higher the value of LST, the more likely that it affects HEC. This association, however, does not necessarily hold in all circumstances; in the contexts with the highest level of HEC, no significant effect is found (Figure 3.5a). The result shows that households with a median level of consumption are more likely to be affected by LST in their neighbourhood than households with high or low levels of consumption (Figure 3.5b). It is found that households that are significantly affected by LST have a lower income level than households that are not affected by LST (Figure 3.5c). The impact of LST is significantly greater in neighbourhoods with larger households than in those with smaller sized households (Figure 3.5d). The impact of LST is likely to be

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more significant in neighbourhoods where summer days (Figure 3.5e) and frost days (Figure 3.5f) are more frequent, even though humidity is lower in such neighbourhoods (Figure 3.5g). The impact of LST is likely to be significant in areas with a median level of population density, as a proxy for the level of urbanisation, whereas such an impact could not be generalised in the case of high and low levels of population density (Figure 3.5h). In the case of the neighbourhoods home to the oldest buildings of the country, the impact of LST is more likely to be significant by a wide margin. In the case of other ranges of building age, however, the impact could be either significant or insignificant (Figure 3.5i). The results show that the impact of LST is likely to be more significant where the surface to volume ratio of the buildings rises (Figure 5j) and wind speed drops (Figure 3.5k).

3.4 Discussion and conclusion

The results of this study show that the effect of LST on HEC is a spatially variant. Such an impact, in other words, could not be generalised for all urbanised neighbourhoods of the Netherlands. On the contrary, the impact varies from one neighbourhood to another. The impact of the LST on HEC is significant in roughly one third of neighbourhoods – where it accounts for 6% 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 results show that, on average, the impact of LST on HEC is more likely to be significant when LST is high. This result, however, could not be generalised for all circumstances, as a medium level of LST could significantly affect the level of HEC in one neighbourhood, while a higher level of LST may have no significant impact on the HEC of another. This 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 neighbourhoods 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 median level of energy consumption are more likely to be affected by LST than households with high or low levels of consumption. Presumably, the overall LST impact, which is negligible compared to other determinants of HEC, can be offset by extensive levels of consumption, e.g. the extensive use of air conditioning of heavy-consumption households, and by behavioural adaptation, i.e. the circumstances under which an individual deals with climate conditions by adapting their behaviour other than consuming extra energy units, of low-consumption households. LST has a greater impact on the HEC of households with relatively lower income levels. Presumably, as low-income households are more likely to use less energy efficient appliances, in order to offset the impact of LST on the so-called felt temperature, low-income households tend to consume more energy than other households. 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 individual within a dwelling, and a greater demand for ventilation in large households. It is found that in the neighbourhoods where outdoor temperatures are 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 more likely to be significant. Whereas in the neighbourhoods with relatively mild temperatures –even with higher levels of humidity, which intensifies the so-called felt temperature – the impact is more likely to be insignificant. In this respect the following conclusion can be drawn: outdoor temperature has a great impact on exacerbating, or alleviating, the impact of LST on HEC, and such an impact could outweigh the effect of humidity on felt temperature.

Considering the level of urbanisation, measured by population density, the results show that the impact of the LST on HEC is overshadowed by other determinants, i.e. is not significant, under two circumstances: first, in highly urbanised and heterogeneous geographic contexts – e.g. the most urbanised region of the country, the Randstad – where a variety of socioeconomic and housing related matters are intermingled and outnumber the effect of heat islands; second, in homogeneously low urbanised circumstances, where LST is not of a significant magnitude. The impact of LST on HEC, however, is likely to be significant in moderately urbanised settlements, where socioeconomic and housing types are more homogeneous and the magnitudes of LST are relatively significant. In turn, one can draw significant conclusions considering other urban circumstances that intensify the impact of LST on HEC: (i) the impact is likely to be significant in those neighbourhoods where the oldest dwellings of the country are located, and therefore the association between indoor and outdoor temperature is strong due to the lower energy efficiency levels of the buildings; (ii) the impact is more significant when greater portions of the dwelling is exposed to the outdoor environment, i.e. is adjacent to windows and external walls; and (iii), when urban form creates an obstacle to the ventilation of dwellings by lowering wind speed.

Policies aimed at reducing HEC need to find an appropriate approach to accommodate a reduction of the urban heat island effect, a factor that is currently not reflected in energy policies at all. On the other hand, the impact of urban heat islands on HEC is less important than that of other determinants, among them building energy efficiency, and it must not be exaggerated. However, in particular situations, where urban heat islands do greatly affect HEC, as well the health of inhabitants, particularly during heat waves, some of the resources assigned to the reduction of HEC could be used to alleviate urban heat islands. The resources assigned by Third National Energy Efficiency Action Plan for the Netherlands (2014) are considerable, among them a €400 million fund for the improvement of the subsidized rental private sector, and €185 million of central government low-interest loans for home owners. As the urban heat island effect could effectively combatted at a relatively low cost, for instance by increasing the green and permeable surfaces in cities (Mushore et al., 2017; Hang and Rahman, 2018; Garuma et al., 2018), a small portion of these funds could be assigned for such projects in the most extreme cases.

By use of appropriate satellite images and the data on daily, or monthly, energy consumption, further studies need to elaborate on the associations between LST and HEC under extreme cases, e.g. during heat waves. (The results of this study, due to limitations of data on LST and HEC, merely hold for aggregated associations between LST and HEC during a year.) The results of this study urge for further studies on the impact of urban heat islands, as it is clear that LST has a greater impact on the energy consumption of low-income households than on households with high or mid-level incomes. When considering the share of disposable income that households spend on energy, a logical conclusion of this result is that urban heat islands probably would increase the financial burden that energy expenditure puts on the household budget, and this extra burden would disproportionally affect those households with lower income levels. This finding opens a new perspective on the impact of urban heat islands: in addition to the environmental impact, i.e., the increase in energy consumption and the emissions associated with it, urban heat islands have a grave social impact, pushing low-income households further into poverty. A variety of previous studies have identified households that have difficulty in meeting their energy expenditures – a phenomenon dubbed energy poverty. These studies examined the effects of various factors on such households, and have determined the spatial variation of such factors across different countries (e.g. Robinson et al., 2018; Mashhoodi et al., 2018). As yet, there is no study of the links between urban heat islands and energy poverty. Further studies therefore need to elaborate on this association, and to inform policy, with both environmental and social improvements in mind.

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4 Spatial Homogeneity and Heterogeneity of Energy Poverty: A Neglected Dimension

ABSTRACT

Since the 1970s, a variety of studies has searched for the sociodemographic, housing, and economic determinants of energy poverty. A central question, however, has not been answered by any of the previous studies: what are the national-level determinants, i.e. the determinants that homogeneously provoke a high level of energy poverty in all areas of a country? What are the neighbourhood-specific determinants, i.e. the characteristics that have a heterogeneous impact across the neighbourhoods of a country? This study seeks to answer these questions by analysing the level of energy poverty, the percentage of households' disposable income spent on energy expenditure, in 2 473 neighbourhoods of the Netherlands in 2014. By employing a semi-parametric geographically weighted regression analysis, the effect of two of the determinants of energy poverty are found to be spatially homogeneous: (i) percentage of low income households; (ii) percentage of pensioners. The results indicate that the impact of four of the determinants are spatially heterogeneous: (i) household size; (ii) percentage of unemployment; (iii) building age; (iv) percentage of privately rented dwellings; (v) number of summer days; (vi) number of frost days. Subsequently, the effects of spatially homogeneous and heterogeneous determinants are estimated and mapped; the results are discusses and some policy implications are proposed.

KEYWORDS

household energy expenditure, energy poverty, household energy consumption, semi-parametric geographically weighted regression, Netherlands

4.1 Introduction

4.1.1 The neglected geographic dimension of energy poverty

Combating energy poverty has been matter of the policy makers' interest in the European Union in the last decade. A European parliament legislation, the Third Energy Package on common regulations for domestic gas and electricity markets of the member states (European Parliament, 2009a; 2009b), has required the member states to identify households that have difficulty meeting their energy expenses and to take actions to protect them. The member states, subsequently, have adopted a variety of measures to identify such households and granted a variety of supports in order to protect them. The policies proposed by the EU member states, however, have no geographic dimension. By offering financial aids to the household that are troubled with meeting their energy expenses, the policies merely aim to mitigate the "effects" of energy poverty rather than addressing the geographic stimuli that "causes" the high level of energy poverty. The policies, Moreover, are spatially homogenous: the EU member states have merely introduced one-size-fits-all policies that are applicable for all locations of their respective countries; supplementary policy instruments specific to different regions, municipalities, and neighbourhoods, however, are lacking (see the review by Dobbins and Pye, 2016).

The geographic dimension of energy poverty is neglected by the previous scientific studies, too. By searching for the generalizable facts that explain the high level of energy poverty across all areas of a city, country, region, or continent, most of the previous studies have implicitly presumed that the stimuli of energy poverty are homogenous across each and every energy-poor neighbourhood. A small portion of the previous studies that have accounted for heterogeneity of energy-poor neighbourhoods, oppositely, have ignored the possibility that some of the characteristic of these neighbourhoods may in fact be generalizable, and thus must be addressed by the national-level policies.

The standpoint of this study is that the questions of "what are the geographic patterns associated with energy poverty, and are these patterns homogenous or heterogeneous?" need to be central to any exploration on energy poverty. This study aims to find the answers to this question by studying energy poverty in the neighbourhoods of the Netherlands in 2014. The article is divided into four main parts. In the next part, the previous studies on energy poverty, and the objective and the approach of this study are explained. In the second part, the method of analysis and the data used in the study are presented. In the third part, the results of the analysis are shown. In the fourth and final part of paper the results are discussed and concluded.

4.1.2 Previous studies on homogeneity and heterogeneity of energy poverty

Subsequent to the publication of the two seminal studies on modelling geographic associations (Brunsdon et al. (1996) and Fotheringham et al. (1996)), and the follow-up book by Fotheringham et al. (2003), two types of geographic impact are distinguishes by a variety of studies in different disciplines: (i) spatially homogeneous impacts, i.e. the insight that the stimuli of a phenomena provoke the same response in each and every geographical context; (ii) spatially heterogeneous impacts, i.e. the stimuli of a phenomenon vary across the locations of interest.

The concepts of spatial homogeneity of heterogeneity of geographic impacts, could be adopted in order to categorise the previous studies on energy poverty. To examine impact of the determinants of energy poverty, two distinct approaches are adopted by the previous studies. First, many studies have presumed that there are some spatially homogeneous factors that explain the level of energy poverty across all areas of a city, country, region, or continent. The conclusions drawn by these studies are location-free statements applicable to every location within a given study area. For instance, "in Ireland … over half of elderly households endure [an] inadequate ambient household temperature in winter," Healy and Clinch concluded (2002, p.329). In Vienna, "energy-inefficient windows, buildings and housing sites are the cause of a heavy [energy] burden," Brunner et al. observed (2012, p.7). "Raising income can lift a household out of poverty, but rarely out of fuel poverty," Boardman observed in the UK (1991, p. xv). A low income level is associated with energy poverty because "low income people are more likely to be living in old buildings with poor envelope conditions," Santamouris et al. observed in Athens (2007, p.893).

A second approach has emerged in the recent years. The underling presumption of this approach is that factors influencing energy poverty are spatially heterogeneous. The studies following this approach, therefore, try to disclose location-specific determinants of energy poverty. Living in a privately rented dwelling, for instance, has a significant impact on energy poverty "in urban areas in the Midlands and Northern regions, in particular the north-east [of England]," Robinson et al. conclude

(2018a, p. 11). “Vulnerabilities [to energy poverty] associated with disability or illness … are stronger … in some southern cities [of England] including London, Luton and Southampton” Robinson et al. found (2018a, pp. 12–13). Bouzarovski and Simcock (2016, p. 640) formulate the basic foundation of this approach as follows: “there are clear geographic patternings associated with energy poverty, as well as the geographically embedded and contingent nature of … underlying causes.”

A knowledge gap in the previous studies is apparent. An earlier study on energy poverty could be based on the presumption that the determinants of energy poverty are spatially homogeneous, as many studies are, or on the presumption that the determinants are spatially heterogeneous, as some studies are. None of the studies, however, has examined the validity of the presumption which it followed.

4.1.3 Objective and approach of this study

This study aims to identify the spatially homogeneous and heterogeneous determinants of energy poverty in neighbourhoods of the Netherlands in 2014, and to estimate the impact of such factor across the neighbourhoods. To do so, two research questions are put forward: first, what are the spatially homogeneous determinants of energy poverty, i.e. the factors that can increase, or decrease, levels of energy poverty in all neighbourhoods of the Netherlands? Secondly, what are the spatially heterogeneous determinants of energy poverty, i.e. the factors whose impact is specific to some neighbourhoods of the Netherlands?

The methodology of this study is twofold. First, by means of a geographical variability test (Nakaya et al., 2009) the spatially homogeneous and heterogeneous determinants of energy poverty are identified. Secondly, in order to estimate the impact of the homogeneous and heterogeneous determinants a semi-parametric geographically weighted regression model (SGWR) is developed. The model estimates the global impact of the homogeneous determinants on energy poverty of all neighbourhoods, as well as the neighbourhood-specific impact of the heterogeneous determinants.

As a proxy for the level of energy poverty, the percentage of disposable income spent on household energy expenditure (HEE) is used. The reason for using HEE instead of the common measures of energy poverty proposed by EU member states is that the proposed measures are all binary indicators allowing only for a “yes/no” categorisation (Herrero, 2017). In the Netherlands, for instance, the policies merely distinguish vulnerable consumers from others: a vulnerable consumer is a person whose supply of electricity or gas is halted by the energy supplier, thus posing a risk to her/his health. In Ireland and Scotland, for example, a household that spends more than 10% of its disposable income on energy bills is considered to be in energy poverty. This study uses HEE instead of the binary measurements of energy poverty for two reasons: first, the criteria proposed by Dutch policies merely accommodate the most severe circumstances and do not provide a wide angle on the issue of energy poverty; secondly, binary definitions of energy poverty are highly threshold-sensitive, as a minor change in the criteria could result in a complete different picture of energy poverty (for instance see the test carried out by Robinson et al., 2018b).

Seven types of independent variables are used to illustrate the socioeconomic and housing characteristics of the neighbourhoods. The variables were previously considered as effective determinants of energy poverty:

1. Household size, as both the number of children and economies of scale in the use of the energy increases in larger households (Middlemiss and Gillard, 2015; Anderson et al., 2012);

2. Percentage of privately rented dwellings, as the investment in the maintenance of privately rented dwellings could be less than in owner-occupied and publicly rented dwellings (Robinson et al., 2018a; Kholodilin et al., 2017; Bouzarovski and Petrova, 2015);

3. Unemployment, as it reflects a modest income level and low motivation for investment in buildings" energy efficiency (Phimister et al., 2015; Buzar, 2007);

4. Building age, as a proxy for buildings' energy efficiency (Brunner et al., 2012; Fahmy et al., 2011);

5. Percentage of low-income inhabitants, as energy bills could account for a relatively larger portion of the disposable income of such inhabitants (Chakravarty and Tavoni, 2013; Bouzarovski, 2009);

6. Percentage of pensioners, as it is associated with a higher sensitivity to climate conditions and longer hours spent inside the dwellings (Legendre and Ricci, 2015; Harrison and Popke, 2011);

7. Number of cooling and heating degree days as they affect level of energy consumption (Wiedenhofer et al., 2013; Reinders et al., 2003).

4.2 Method and data

4.2.1 Method

The methodology of this study is twofold. The first step of the analysis aims at identifying spatially homogeneous and heterogeneous determinants of energy poverty, and to test whether the multicollinearity between the independent variables is at an acceptable level. To do so, an ordinary least square model (OLS) and a geographically weighted model (GWR) are developed. The OLS model is used for examining the level of multicollinearity between the independent variables. The GWR model is employed for the identification of the spatially homogeneous and heterogeneous determinants of energy poverty. The OLS model is formulated as follows:

$$y_i = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i \qquad \text{EQUATION 4.1}$$

Where y_i is the estimated value of HEE at location i, β_0 shows the intercept, and β_k shows the coefficient of the *k*th independent variable. x_{ik} and ε_i are the *k*th independent variable and random error term in location i. Subsequently, a GWR model of HEE is developed:

$$y_i = \beta_0(\mu_i, \nu_i) + \sum_k \beta_k(\mu_i, \nu_i) x_{ik} + \varepsilon_i \qquad \text{EQUATION 4.2}$$

Where (μ_i, ν_i) denotes the x-y coordinate of location i. $\beta_k(\mu_i, \nu_i)$ and $\beta_0(\mu_i, \nu_i)$ are the estimated local coefficient and local intercept of independent variable *k* in location i. The local coefficients are calculated as follows:

$$\hat{\beta}(\mu, \vartheta) = (X^T W(\mu, \vartheta) X)^{-1} X^T W(\mu, \vartheta) y \qquad \text{EQUATION 4.3}$$

Where $\hat{\beta}(\mu, \vartheta)$ is the unbiased estimate of β, and $W(\mu, \vartheta)$ is a fixed bisquare spatial weight matrix adopted for location i:

$$W_{ij} = \begin{cases} (1 - \left(\frac{d_{ij}}{\theta}\right)^2)^2, if\ d_{ij} < \theta \\ 0, otherwise \end{cases}$$ EQUATION 4.4

W_{ij} quantifies the weight of neighbourhood j in the GWR model developed for neighbourhood i . d_{ij} is the metric distance between neighbourhood i and neighbourhood j . θ denotes the bandwidth size. The optimal value of θ, the bandwidth size at the corrected Akaike Information Criterion of GWR model is minimised. To identify the spatially homogeneous and heterogeneous determinants of HEE, the geographical variability test of GWR 4.0 tool is employed (developed by Nakaya et al., 2009). The test is based on the conduction of multiple GWR models and comparing their performance. In order to assess whether the impact of the *k*th independent variable is homogeneous or heterogeneous, two models are developed: first, a model that holds all the variables as heterogeneous determinants and the *k*th variables as homogeneous determinants; secondly, a model that holds all the independent variables, among them the *k*th variables, as heterogeneous determinants of HEE. Should the AICc of the second model be lower than that of the second model, reflected by the negative value of "DIFF of Criterion" in the geographical variability test, the *k*th independent variable is a homogeneous determinant of HEE. Otherwise, the variable is a heterogeneous determinant. Subsequent to the identification of local and global variables, in the second step, a semi-parametric geographically weighted model (SGWR) is employed. The model estimates the global impact of the independent variables identified as homogeneous variables, as well as the neighbourhood-specific impact of the variables identified as heterogeneous determinants. The SGWR model is formulated as follows:

$$y_i = \beta_0(\mu_i, v_i) + \sum_m \beta_m(\mu_i, v_i)x_{im} + \sum_n \gamma_n z_{ni} + \varepsilon_i$$ EQUATION 4.5

Where $\beta_m(\mu_i, v_i)$ is the estimated coefficient of the *m*th local determinant of HEE at location i, and γ_n denotes the estimated coefficient of the *n*th global determinant. The spatial weight matrix is a fixed bisquare function, and the bandwidth size is specified in order to minimise AICc. Ultimately, in order to select the best model for estimating HEE, the performance of OLS, GWR and SGWR models are compared by means of four tests: adjusted R2, AICc; cross-validation (CV); randomness of spatial distribution of the intercept values (assessed by Moran's Index).

4.2.2 Dependent variable

This study analyses HEE in the neighbourhood units of the Netherlands, *wijken* in Dutch (Figure 1). The premises of the neighbourhood is designated by the Central Bureau of Statistics in Netherlands (CBS). Data on the annual consumption of gas and electricity within dwellings is extracted from CBS data (Centraal Bureau voor de Statistiek, 2014). The average price of gas and electricity for households in 2014 is taken from Eurostat data (Eurostat, 2015). This study includes 2473 residential neighbourhoods of the Netherlands.

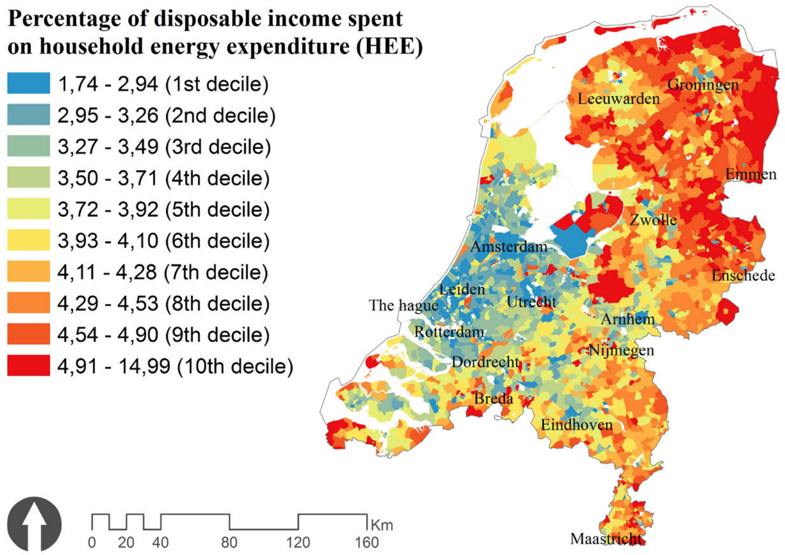

FIG. 4.1 Case study area and dependent variables

4.2.3 Independent variables

This study uses six independent variables (Table 4.1). *Household size* describes the average number of residents in a household. *Private rent* denotes the percentage of dwellings that are neither owner-occupied nor owned by a municipality or a housing corporation. *Low income* is percentage of low-income inhabitants. According to the CBS definition, a low-income inhabitant is a resident whose disposable income is ranked among the four lowest deciles of income in the Netherlands. *Unemployment* denotes the percentage of the population aged between 15 and 65 receiving unemployment benefits as their main source of income. *Pensioner* is the percentage of the population that receives a pension. *Building age* shows the median age of residential, or partially residential, buildings in the neighbourhoods.

Annual air temperature in the neighbourhoods is reflected by use of two variables, defined by Royal Netherlands Meteorological Institute (KNMI): *Number of summer days*, the number of days in which maximum temperature outnumber 25 degrees Celsius, and *Number of frost days*, the number of days in which minimum temperature fall below 0 degree Celsius. To obtained these variables, based on the KNMI guideline (Sluiter, 2012), the measurements of the summer and frost days of the 28 meteorological stations of KNMI are interpolated across the country.

TABLE 4.1 Descriptive statistics of independent variables

Variable	Mean	Minimum	Maximum	SD
Household size	2,35	1,20	4,00	0,31
Private rent (%)	12,06	1,00	78,00	7,25
Low income (%)	40,05	18	72	5,47
Unemployment (%)	2,13	0,00	7,14	0,81
Pensioner (%)	17,81	1	62	5,34
Building age	38,58	1	163	15,01
Number of summer days	23,27	5,98	37,70	7,96
Number of frost days	68,79	50,40	81,06	6,62

TABLE 4.2 Geographical variability test and estimates of OLS and GWR models

Variable	OLS results		GWR results				Geographical variability test	
	β	VIF	β mean	β min	β max	β SD	DIFF of Criterion †	Type of determinant impact
Intercept	0,000**		-0,205	-26,673	18,538	3,037	-3897,98	heterogonous
Household size	0,382**	1,91	0,302	-0,384	1,308	0,176	-54,14	heterogonous
Private rent (%)	0,192**	1,21	0,188	-0,119	1,146	0,163	-297,64	heterogonous
Low income (%)	0,537**	1,16	0,401	-0,311	1,032	0,083	2,84	homogenous
Unemployment (%)	0,072**	1,40	0,023	-0,249	0,435	0,094	-22,89	heterogonous
Pensioner (%)	0,201**	1,29	0,137	-0,243	0,646	0,092	4,61	homogenous
Building age	0,127**	1,33	0,148	-0,164	0,526	0,095	-22,58	heterogonous
Number of summer days	-0,121**	1,33	0,540	-17,380	13,487	2,016	-13,68	heterogonous
Number of frost days	0,230**	1,64	-0,153	-6,849	5,229	1,377	-23,30	heterogonous
R-square	0,514		0,74					
Adjusted R-square	0,512		0,71					

β: standardized regression coefficient.
** p-value < 0,05.*
*** p-value <0,01.*

4.3 Results

4.3.1 Identification of spatially homogeneous and heterogeneous determinants

In the first step, an OLS model is employed. The results of the model show that coefficients of all six independent variables are significant (p-value < 0,01). All the estimated coefficients are positively signed – indicating that higher values of all the variables is associated with higher levels of HEE. The Variance Inflation Factor (VIF) of all six independent variables is well below the threshold value of 2,5. This shows that the multicollinearity between the variables is low and the effect they represent is fairly unique. Subsequently a GWR model is employed. The bandwidth size of the model is 30km – the optimal bandwidth size to minimise AICc. The geographical variability test shows that the DIFF of criterion is positive in the case of two of the independent variables. This identifies these variables as spatially homogeneous determinants of HEE (Table 4.2):

1. *Low income*;
2. *Pensioner.*

The results of the test identify four of the independent variables as spatially heterogeneous determinants of HEC (indicated by negative values of DIFF of criterion):

1. *Household size*;
2. *Private rent*;
3. *Unemployment*;
4. *Building age;*
5. *Number of summer days;*
6. *Number of frost days.*

The findings of the first step of the analysis are used to develop the SGWR model.

4.3.2 Results of the SGWR model and its performance compared to the GWR and OLS models

In the second step of the analysis a SGWR model is developed. The identification of the spatially homogeneous and heterogeneous variables is used as the basis for the SGWR model, as the model estimates the spatial stationary impact of the former variables as well as the spatial non-stationary impact of the latter (Table 4.3).

TABLE 4.3 Estimates of SGWR model

Variable	Spatially homogeneous determinants		Spatially heterogeneous determinants			
	β	SE	β mean	β min	β max	β SD
Intercept			-0,083	-66,402	24,721	4,040
Household size			0,308	-0,393	3,108	0,183
Private rent (%)			0,188	-0,275	3,072	0,216
Low income (%)	0,403**	0,014				
Unemployment (%)			0,014	-0,443	0,671	0,122
Pensioner (%)	0,128**	0,014				
Building age			0,155	-0,182	2,425	0,130
Number of summer days			0,636	-29,257	17,760	2,556
Number of frost days			-0,24617	-16,0184	10,76843	1,769067
R-square	0,759					
Adjusted R-square	0,725					

β: standardized regression coefficient.
*** p-value <0,01.*

The map of the local R-square values of the SGWR model (Fig. 4.2) show that the values of R-square range from 18% to 99%, with an average of 57% and a standard deviation of 12%. The highest values are observed in Eindhoven and Leeuwarden where the observed values of R-square outnumber 90%. The two areas with relatively low level of R-square are rural areas in vicinity of Groningen, as well as the city of Amsterdam, where the values are significantly lower than other large cities of the country.

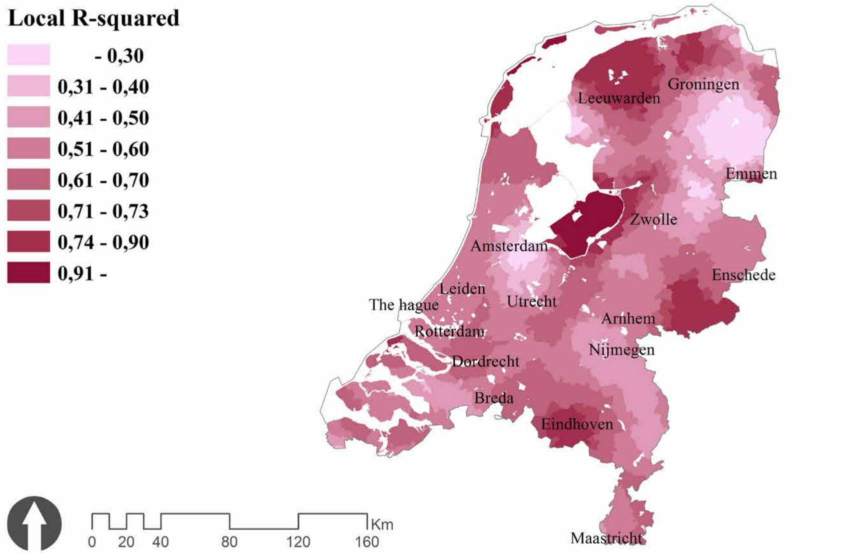

FIG. 4.2 Local R-square produced by the SGWR model.

A comparison between performance of the three models shows that SGWR provides a better estimate of HEE. The lowest level of AIC, AICc and CV as well as the highest adjusted R-square are obtained in the SGWR model. Random spatial distribution of residual is merely observed in case of the SGWR model. This indicates that distinguishing between spatially homogeneous and heterogeneous determinants of the HEE provides a better understanding of the phenomenon compared to the holding all variables as homogeneous determinants, in the case of the OLS model, or as heterogeneous determinants, in the case of the GWR model (Table 4.4).

TABLE 4.4 Diagnostics of the OLS, GWR and SGWR models

Method	OLS	GWR	SGWR
AIC	5251,55	4091,24	3502,29
AICc	5251,64	4123,15	3975,18
CV	0,4951	0,3795	0,3723
R-square	0,514	0,737	0,759
Adjusted R-square	0,512	0,709	0,725
Residuals Moran's I	0,1668	0,0241	0,0100
Bandwidth (meter)	NA	40047,96	29847,42

4.3.3 Estimates of the impact of spatially homogeneous determinants

Estimates of both of the spatially homogeneous determinants of HEE are significant at the p-value < 0,01 level. The results show that the impact of the first homogeneous determinant, *Low income*, is more than three times larger than that of the second homogeneous determinant of HEE, *Pensioners*. The estimates of the standardised coefficient of *Low income* show that the factor outnumbers the neighbourhood-specific impacts of the heterogeneous determinants in almost all of the neighbourhoods. The impact of *Low income* outnumbers the neighbourhood-specific impacts of *Household size* in more than 72% of the neighbourhoods. The corresponding number compared to the neighbourhood impacts of *Private rent*, *Unemployment*, *Building age*, *Number of summer days*, and *Number of frost days* are 93%, 99%, 98%, 88% and 87%. *Low income*, in short, is found to be the strongest, or one of the strongest determinants of HEE across all neighbourhoods of the Netherlands.

The comparison between the estimated effect of the second homogeneous determinant, *Pensioners*, and the neighbourhood-specific impacts of heterogeneous determinants, illustrates a diverse picture. The impact of *Pensioners* is smaller than that of *Household size* in more than 74% of the neighbourhoods. The impact, however, outnumbers that of *Unemployment* in 91% of the neighbourhoods. In almost two-thirds of the neighbourhoods the impact of *Pensioners* is outnumbered by that of *Private rent* and *Building age* (59% and 68%). Whereas in almost 88% of the the neighbourhood the presence of pensioners has a larger contribution to HEE than *Number of summer days* or *Number of frost days* (Figure 4.3).

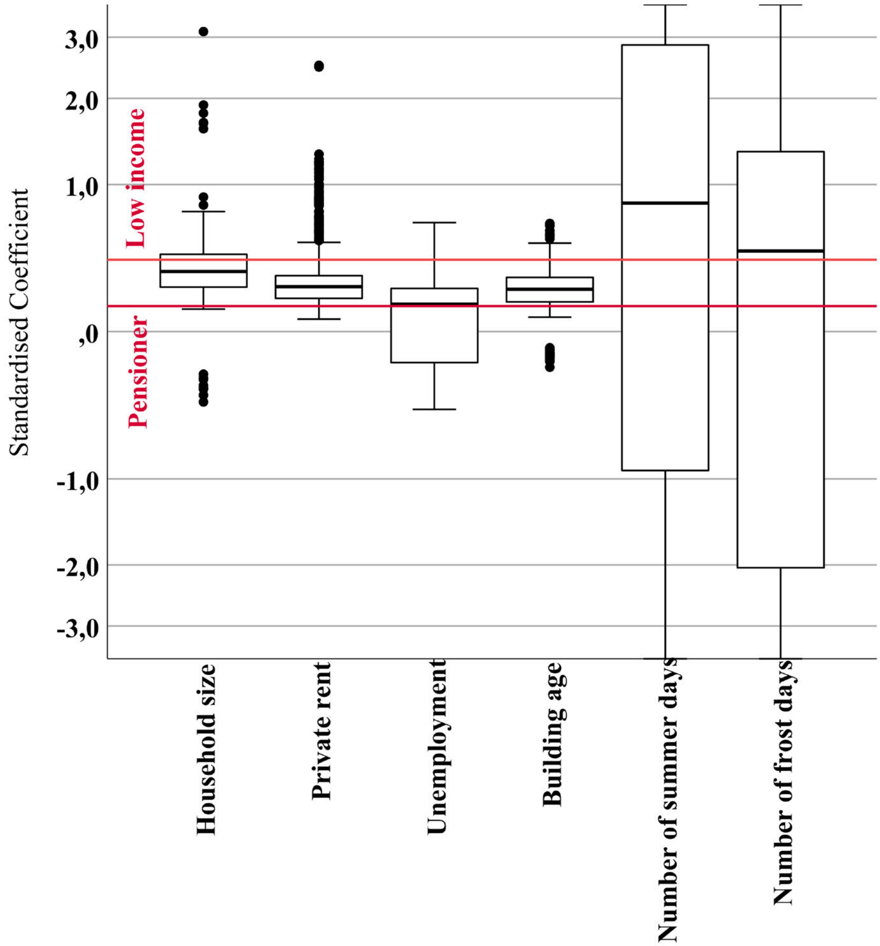

FIG. 4.3 The box plot represents the standardised coefficient of the spatially homogeneous determinants of HEE (in red) compared to significant (p-value < 0,01) localized coefficients of the heterogeneous determinants.

4.3.4 Estimates of the impact of spatially heterogeneous determinants

The results show that the impact of heterogeneous determinants of HEE is not necessarily significant in all neighbourhoods. The localized coefficients of *Household size* are significant (p-value < 0,01) in 74% of neighbourhoods (Fig. 4.4a). The corresponding numbers for that of *Private rent* (Fig. 4.4b) and *Building age* (Fig. 4.4d) are 42% and 35%. In the case of *Number of summer days* (Fig. 4.4e) and *Number of frost days* (Fig. 4.4f), the localized coefficients are significant in 20% of the neighbourhoods. The smallest percentage of significant neighbourhood-specific coefficients is observed in the case of *Unemployment* where the HEE of a mere 13% of neighbourhoods is significantly affected by the factor (Fig. 4.4c). In the case of *Household size*, *Private rent* and *Building age,* the sign of almost all the neighbourhood-specific coefficients is positive. In the case of *Unemployment*, *Number of summer days*, and *Number of frost days*, however, the sign of the neighbourhood-specific coefficients varies across the neighbourhoods: the sign of three fifth of the coefficients is positive and that of one third of the coefficients is negative. The latter indicates that the nature of the association between HEE and these variables varies from one neighbourhood to another.

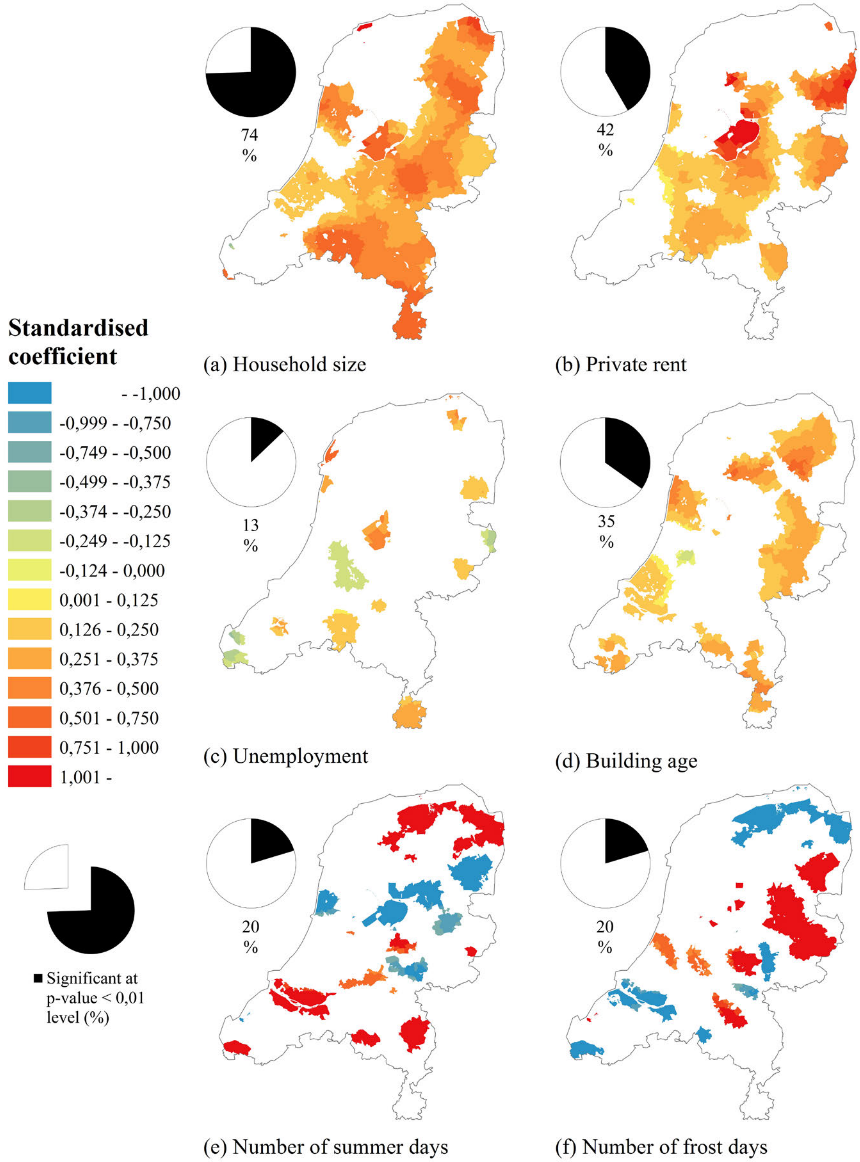

FIG. 4.4 Maps show the localized coefficients of the heterogeneous determinants of HEE.

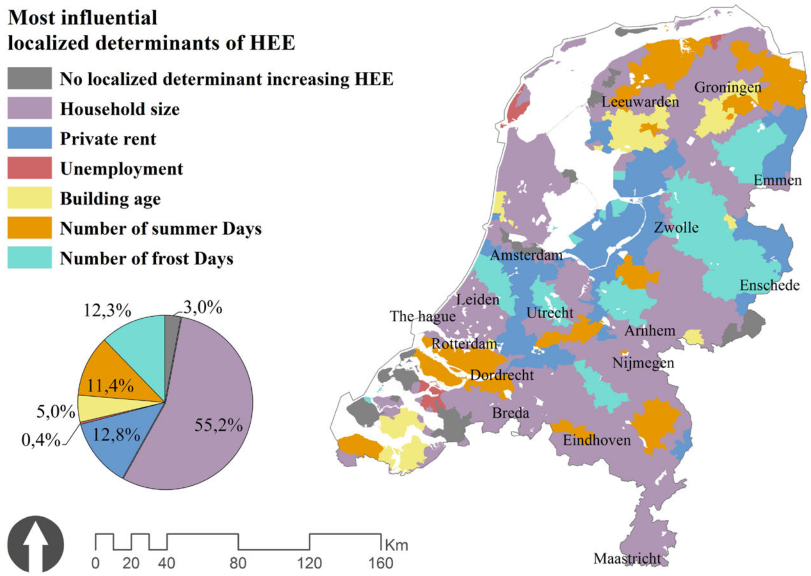

FIG. 4.5 The most influential localized determinants of HEE. The pie-chart represents the frequency of the most influential localized determinants.

Figure 4.5 illustrates the most influential localized determinant of HEE, the heterogeneous determinant with the largest estimated standardised coefficient in the neighbourhood in question, in the neighbourhoods of Netherlands. The results indicate that in almost 55% of the neighbourhoods, *Household size* is the most influential localized determinant of HEE. Such neighbourhoods comprise the major cities of the province of Zuid-Holland, Rotterdam, and The Hague, as well as the city of Maastricht. In more than 12% of the neighbourhoods, *Private rent* is the most influential localized determinant of HEE. The neighbourhoods of Enschede, Amsterdam, Almere, as well as those of the so-called green heart, central areas of the Randstad region, fall in this group. In almost 5% of the neighbourhoods, *Building-age*, as a proxy of building energy efficiency, is the most influential localized determinant of HEE. The neighbourhoods of Groningen and Dordrecht fall in this group.

In more than 11% of the neighbourhoods, *Number of summer days* is the most influential localized determinant. Such neighbourhoods are mostly locate by the coast in the North of the country, the northern neighbourhoods of the provinces of Groningen and Friesland, as well as in the vicinity of the largest rivers in the province

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of Zeeland. In more than 12% of the neighbourhoods, *Number of frost days* is the most influential localized determinant of HEE. Most of these neighbourhoods are located in the east side of the country, with large agglomerations observed in the provinces of Overijssel between the cities of Zwolle and Enschede. In more than 3% of the neighbourhoods, the level of HEE is explained by global determinants only. Such neighbourhoods are partially located in the province of Zeeland. *Unemployment* is the most influential local determinant in a mere 0,4% of the neighbourhoods.

4.4 Discussion

4.4.1 Homogeneous determinants

The results show that the impact of two of the determinants of HEE are spatially homogeneous. It is found that low-income inhabitants, i.e. those within the lowest four deciles of income, are in danger of energy poverty in all neighbourhoods of the Netherlands. As the financial resources available to this social group are relatively limited, such an observation is not unexpected. The finding, however, should serve as a warning of the social consequences of the implementation of the policies aimed at phasing out gas used for cooking and heating in the Dutch residential sector before 2050 (Energieagenda, 2016). Replacing natural gas, a relatively cheap source of energy, with electricity, a more expensive energy source, could push this social group further into energy poverty. Further studies need to analyse the impact of the energy transition on the budget of low-income households and offer respective support measures. Low-income households could, for instance, be equipped with energy-efficient heating and cooking appliances. Insulating the dwellings of low-income households could be supported by the national government. A new tax scheme could allow low-income households a refund of the Regulatory Energy Tax – a levy on gas and electricity consumption imposed by the government, accounting for 28% of the total tariff in 2013 (Deloitte Conseil, 2015) – included in energy prices.

Another social group that is homogeneously in danger of energy poverty is the pensioners. Given the demographic trends in the Netherlands – rising single person elderly households – such a danger will most probably continue to rise in the coming decades. According to CBS projections (Centraal Bureau voor de Statistiek, 2011), in

2060 the average household size will be 2,08 persons (compared to 2,25 in 2011) and single-person households will account for 44% of all households (compared to 36% in 2011). Furthermore, nearly half of one-person households are expected to be older than 65 in 2050 (compared to just 31% in 2011). Policies need to accommodate these demographic trends. A variety of policy instrument, ranged from improving energy-efficiency of the dwellings of senior citizens to promotion of communal places to curb the number of lonely-at-home-hours of the elderlies, could be adopted.

4.4.2 Heterogeneous determinants

In 55% of the neighbourhoods, Household size is the main localized determinant of energy poverty. Energy expenditure rises in larger households, say the households with children, due to higher consumption for cooking, space warming and cooling, water heating, appliances, etc. (see Weber and Perrels, 2000). Additionally, given the trend in Netherlands and the increased use of laptop, desktops, smartphones, and tablets (Centraal Bureau voor de Statistiek, 2017), the gap between electricity consumption of households with school-age children and other households could further widen in years to come. Further studies need to survey the detailed energy use of the households in energy-poor neighbourhoods and determine whether or not energy expenses affect the health, education and personal development of children. Neighbourhood-specific support measures to satisfy such demands need to be introduced.

In more than one eighth of the neighbourhoods of the Netherlands, privately rented dwellings are the main localized determinant of energy poverty. The low motivation of the renter for investing in the building's energy efficiency is, presumably, the main reason for this observation. The housing subsidy (*huurtoeslag*) offered by the government, meanwhile, could be a reason for low motivation of the landlords. The subsidy is granted if the amount of rent and the income of the renter fall below certain thresholds (*Voorwaarden voor huurtoeslag in 2016*, 2016). The cap on rent price may encourage landlords to not renovate older buildings in order to keep the rent lower than the threshold and thus attract low-income renters. Renters who apply for a housing subsidy therefore receive a subsidy on their rent in exchange for a higher energy expenditure – a hidden rent in effect. Since July 2014, a sharp-eyed "energy saving" scheme in the Dutch government's energy policy has proposed 400 million euros of funding to renovate rental houses receiving subsidies, on the condition that the rent doesn't exceed 700 euros (Government of the Netherlands, 2014). As a complementary policy instrument, in neighbourhoods with high levels of energy poverty, applying for this fund could be mandatory.

In 5% of the neighbourhoods, the energy efficiency of buildings is the main local determinants of energy poverty. Currently, improving the energy efficiency of buildings is the keystone of the Third National Energy Efficiency Action Plan (Ministry of Economic Affairs, 2014) as most of the actions, incentives and resources proposed by the policy target buildings' energy efficiency, among them the so-called block-by-block approach, large-scale projects to improve the energy efficiency of the existing housing stock. The notion of energy poverty could be utilised in order to prioritise the blocks in which the low quality of the buildings causes higher levels of energy poverty.

Number of summer days and *Number of frost days* are the most influential determinants of energy poverty in one fifth of the neighbourhoods. This observation could be explained from two different perspectives: thermal comfort and user behaviour. The former refers to circumstances in which thermal comfort in a warm, or a cold, neighbourhood is reduced by an additional number of summer, or frost, day. The latter refers to a circumstance when number of warm days have a great influence on HEE of a cold area, and vice versa. In such circumstances, as inhabitants are exposed to a climate condition that they do not used to, energy consumption may drastically increase. This result show that climate change could have a very complex impact on energy poverty. Further explorations need to study the impacts of climate change, see the scenarios by KNMI (2015), and urban heat islands, see the study by van der Hoeven and Wandl (2015), on energy poverty, and bring forward location-specific policy measures that accommodate these trends.

In a relatively small portion of the neighbourhoods, unemployment is the main neighbourhood-specific determinant of energy poverty. In order to offset the high burden of energy expenditure, the government could utilise smart technologies, i.e. smart meters providing detailed information about the energy use of consumers, to cover expenses directly related to the health of energy-poor unemployed people, e.g. expenses related to space heating on days with sub-zero temperatures.

4.5 Concluding remarks

Energy poverty is a geographic phenomenon spatially coinciding with a complex and reciprocal landscape of people, physical infrastructures, institutions, and natural climate. How energy poverty interacts with its embedding geography, remained unanswered, and unnoticed, by the policy makers and scholars. The policies on energy poverty need to shift their perspective, and to acknowledge the embedding geography of the energy-poor neighbourhoods. Policies, to do so, need to target the geographic patterns which “cause” energy poverty rather than offering financial aid to mitigate the “effects” of energy poverty.

The results of this study show that the impact of the determinants of energy poverty could be spatially homogeneous or heterogeneous. Policies need to accommodate this fact by diversifying in their spatial extent. To do so, two types of policies could be adopted. First, national-level policies offering a safety net to social groups who are intrinsically in danger of energy poverty, low-income households and pensioners in the case of the Netherlands, of all the neighbourhoods of a country. Secondly, neighbourhood-level funds come into effect when a particular social group of a neighbourhood is in danger of energy poverty due to its sociodemographic characteristics, employment or the conditions of housing tenure, or climate conditions. In order to offer support at the neighbourhood level, it is essential to carefully study the geographic context of each and every energy-poor neighbourhood, and, by introducing location-specific policies, to address the local factors that foster the high level of energy poverty - for example see the studies by Guo (2008) and Mu et al. (2015) . To do so, a close collaboration between energy network companies, the ministry of economic affairs and municipalities is essential. Combating energy poverty is, and must be, a shared responsibility of all decision makers on the national, regional and local level.

The result of this study urge for a shift in the methodologies of the studies on energy poverty. By application of aspatial methods, most of the previous studies have effectively ignored spatial heterogeneity of the determinants of energy poverty. A variety of previous studies, meanwhile, have shown that the best understanding of a wide range of phenomena – among them academic achievement (Figueroa et al., 2016), effects of ozone pollution (Lin and Lu, 2009), vulnerability to terrorism (Eisman et al., 2017), household energy consumption (Mashhoodi, 2018; Mashhoodi and van Timmeren, 2018), social vulnerability in slums (Jankowska et al., 2011)- is achieved only when spatial heterogeneity of the effects is taken into consideration. The result of this study is beneficial for future studies on energy poverty; there is a central question to start with: what are the spatially homogeneous and heterogeneous determinants of energy poverty?

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PART 2

Studies on the neighbourhoods of the Randstad region

5 Spatial Dynamics of Household Energy Consumption and Local Drivers in Randstad, Netherlands

ABSTRACT

This study is an attempt to bridge an eminent knowledge gap in the empirical studies on Household Energy Consumption (HEC): the previous studies implicitly presumed that the relationships between HEC and the geographic drivers is uniform in different locations of a given study-area, and thus have tried to disclose such everywhere-true relationships. However, the possible spatially varying relationships between the two remain unexplored. By studying the performance of a conventional OLS model and a GWR model -adjusted R2, randomness of distribution of residual (tested by Moran's I), AIC and spatial stationary index of the geographic drivers, ANOVA test of residuals- this study demonstrates that the GWR model substantially provides a better understanding of HEC in the Randstad. In this respect, the core conclusion of this study is: the relationships between HEC and geographic drivers are spatially varying and therefore needed to be studied by means of geographically weighted models. Additionally, this study shows that considering spatially varying relationships between HEC and geographic drivers, by application of hierarchical clustering, the areas of the Randstad can be classified in four clusters: building age and income impact areas, building density impact areas, population density and built-up impact areas, household size and income impact areas.

Highlights

- The geographic drivers of household energy consumption are spatially varying
- Household energy consumption has to be studied by geographically weighted models
- Policies regarding household energy consumption need to be location-specific

KEYWORDS Household Energy Consumption, Geographically weighted regression, Randstad, Netherlands

5.1 Introduction

Curbing level of energy consumption has been matter of policy makers' interest since 1970s subsequent to geopolitical turmoil in 1973 and 1979. The interest has been widened into the environmental impact of energy consumption, particularly greenhouses gases (GHG) emission and global warming, following United Nations Framework Convention on Climate Change (UNFCC) in 1992, and preparation of Kyoto treaty in 1997, and United Nations Climate Change Conference held in Paris, 2015. However, despite the effort spend on international treaties, between 1990 and 2012, final energy consumption in EEA countries (the European Economic Area) increased by 6.5% (European Environment Agency, 2015a). In EU-15 countries between 1990 and 2011, the GHG emission decreased for 14.9% (European Environment Agency, 2013), which is still short of the target set by 2020 climate & energy package: 20% cut from 1990 level (Climate Action 2020 European commission, 2009). The share of Households energy consumption (HEC) in total energy use is substantial. In EU-27 countries in 2010, HEC accounts for some 27% of the total final energy consumption (European Environment Agency, 2015b) and creates 25% of GHG emissions (European Environment Agency, 2012). In the Netherlands, in order to reduce HEC, Third National Energy Efficiency Action Plan for the Netherlands (Ministry of Economic Affairs, 2014) introduces set of incentives and regulations, applicable for all the locations of the country, which mainly aim for improving quality of buildings e.g. low interest loans for building insulation, low-interest loans for building renovation, stricter energy standards for new construction, and compulsory measures to ensure efficiency of buildings' heating and ventilation appliances.

Many previous studies explored the impact of variety of geographic drivers on the HEC. Plenty of the previous studies have established links between level of the income of the inhabitants and the level of HEC (for instance Yun & Steemers, 2011; Druckman & Jackson, 2008; Joyeux & Ripple, 2007). Several previous studies found associations between family type and HEC, mainly concluding that consumption per head drops as the size of family grow (for instance Fong et al., 2007; Lenzen et al., 2006; Tso & Yau, 2003). The age of the inhabitants is also introduced as one of the significant drivers of HEC, particularly the portion of children and senior citizens from total population (Yun & Steemers, 2011; York, 2007; Yust et al., 2002). Moreover, the higher percentage of economically inactive inhabitants –for instance inhabitants with disability or retired- has been seen as sources of higher HEC (for instance Fong et al., 2007). The HEC of the inhabitants of different housing tenure also found to be meaningfully different due to varying level of investment in insulation and different methods of payment for energy cost (for instance Druckman & Jackson, 2008; Tso & Yau, 2003; Aydinalp et al., 2004). Several studies highlighted significant variation of HEC between different types of dwellings, for instance between single-family and multi-family houses, and also between dwellings of different age (for instance Yun & Steemers, 2011; Druckman & Jackson, 2008; Aydinalp et al., 2004). Moreover, land-cover has been found to be effective on HEC due to its links with formation of urban heat islands (for instance Madlener & Sunak, 2011; Georgakis & Santamouris, 2006; Hui, 2001). Wind intensity is found to impact HEC by affecting the thermal exchange between buildings and outside space by affecting infiltration and exfiltration of the buildings (for instance Sanaiean et al., 2014; van Moeseke et al., 2005). Ewing and Rong (2008) suggest that higher building density could decrease the energy used for heating, and increase that for cooling. Several studies suggest that the surface-to-volume ratio of the building affects the heat loss of buildings and HEC (for instance Steemers and Yun, 2009; Druckman and Jackson, 2008; Lenzen et al., 2006). Population density is also considered as an effective determinant of HEC (for instance York, 2007; Lenzen et al., 2006).

A knowledge gap is eminent in the current body of literature on HEC: all of previous studies implicitly presumed that geographic drivers have an unvarying impact on HEC across a given area, and therefore attempted to disclose such everywhere-true impacts. Consequently, the policies-recommendation brought forward by previous study are uniform and generic for all areas in question instead of location-specific and spatially varying. The core objective of this research is to tackle such knowledge gap chasing answers to the following questions: (a) Are the relationships between HEC and the geographic drivers spatially varying across the areas of the Randstad region, the Netherlands? (b) If yes, how such relationships differ across the areas of the Randstad region?

To do so, this study aim to conduct geographically weighted regression (GWR) for studying HEC. The method has been successfully deployed in several geographic studies of different disciplines such as afforestation (Clement et al., 2009), regional wealth and land cover (Ogneva-Himmelberger et al., 2009), urban landscape fragmentation (Gao & Li, 2011), agriculture and urbanization (Su et al., 2012), land use and water quality (Tu, 2011), residential land price (Hu et al., 2016), late-stage prostate cancer diagnosis (Goovaerts et al., 2015), urban heat island (Ivajnšič et al., 2014), and fire density (Oliveira et al., 2014). However, surprisingly, HEC studies are lagging behind in application of GWR. To bridge this gap, this study investigates the location-specific effect of variety of socioeconomic, housing, urban morphology, solar radiation and wind-intensity related indicators on HEC in the neighbourhoods of the Randstad region, the Netherlands.

5.2 Material and Methods

5.2.1 Case study

The study-area is consisted of 'buurten', a spatial division defined by the Dutch central bureau of statistics (CBS), roughly could be translated as neighbourhoods, in the Randstad region in 2013 (account for 2413 neighbourhoods). The Randstad is a conglomeration of highly urbanized areas located in the south west of the Netherlands comprising the four major Dutch cities of Amsterdam, Rotterdam, The Hague and Utrecht, as well as the relatively less urbanized areas between them – the so-called "green heart". In order to avoid the boundary-effect problem in GWR models, we also defined "analysis areas" which is consist of the study-area plus a 20 km buffer around it (3514 neighbourhoods in total). All the calculations are conducted on the analysis area, however at the end only the results obtained for areas within the study-areas are reported (Figure 5.1).

TOC

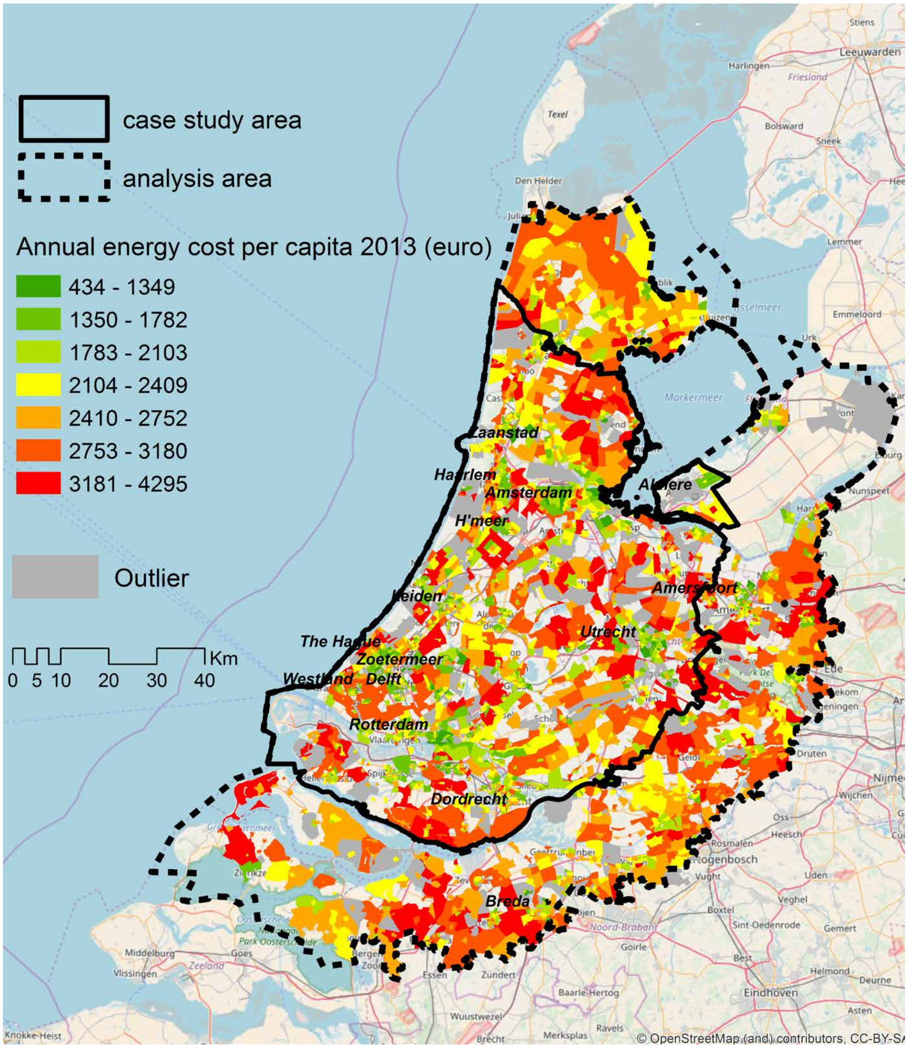


FIG. 5.1 Annual energy expenditure per capita (dependent variable of this study), the study-area and the analysis area.

5.2.2 Data collection and processing

5.2.2.1 5.5.2.1 Dependent variable

The dependent variable of this study is average annual energy expenditure per head within the dwellings on gas and electricity, in 2013 (Figure 5.1). The data on consumption of gas and electricity are extracted from wijk-en-buurtkaart 2013 (Centraal Bureau voor de Statistiek, 2013). As the available data does not indicate the neighbourhoods with solar energy supply or district heating, the abnormal values of gas and electricity use needed to be filtered out thus univariate outliers of gas and electricity use (incidents with z-value <= -2.5 or z-value >= +2.5) are identified as outlier and excluded. The average cost of gas and electricity for domestic consumption in 2013 in Netherlands, is taken from Eurostat (Eurostat, 2015).

5.2.2.2 5.5.2.2 Independent variables

This study is conducted on 21 independent variables (Table 1). The first two variables indicate the portion of the population aged 14 or younger and aged 65 or older. One variable show population density per square kilometer. One variables specify the household structure by demonstrating average household size. Three variables show economic status of the residents: average annual disposable income per head (in euros), Percentage of population aged 15–64 receiving disability benefits, and Percentage of population aged 15–64 receiving unemployment benefits. Four variables are deployed in order to describe the status of housing tenure in the areas: Property-value (WOZ in Dutch), shows the average value of residential real estate in the areas; percentage of housing tenure owned by public associations (not necessarily social housing); median age of residential buildings; and percentage of residential floor area constructed after the introduction of building energy-efficiency standards in 1988. Land-cover of the areas is further explained by means of two variables including the portion of built-up areas, semi built-up areas and portion of green land covers (consisted of recreational, agricultural and natural areas).

The status of urban morphology (properties related to geometrical distribution of the building masses within space) is described using five variables: floor area ratio (FAR); building coverage ratio (BCR); buildings' surface to volume ratio; frontal area index (λf) - the ratio of total building walls facing wind flow to neighbourhoods' total area;

and rugosity, the variation of building height which, adopted from Adolph (2001), is calculated as the standard deviation of height values of Digitally Elevated Model (DEM) of the neighbourhoods. As a proxy for wind speed, aerodynamic roughness length (ARL), the height in which the effective wind speed is theoretically zero, is used. Higher values of ARL correspond with lower wind intensity (Landsberg, 1981). The morphometric model introduced by Macdonald et al. (1998), one of the most comprehensive models according to a review by Grimmond and Oke (1999), is used:

$$\frac{z_d}{z_H} = 1 + \alpha^{-BCR}(BCR\text{-}1)$$ EQUATION 5.1

$$\frac{z_0}{z_H} = \left(1 - \frac{z_d}{z_H}\right) \exp\left(-\left(\frac{0.5\beta C_D \lambda_f}{k^2}\left(1 - \frac{z_d}{z_H}\right)\right)^{-0.5}\right)$$ EQUATION 5.2

Where Z0 is aerodynamic roughness length for momentum, Zd is zero-plane displacement height, ZH is height of roughness element (m), BCR is building coverage ratio, λf frontal area index, $\alpha = 4.43$, $\beta = 1.0$, $k = 0.4$, and $CD \cong 1$.

Deploying the Arcgis 10.2 solar radiation toolbox, status of solar radiation is described by two variables: solar radiation per square meters of neighbourhoods' surface (solar radiation on neighbourhood (WH/m2)) and per cubic meters of the buildings (solar radiation per building volume (WH/m3)). Each of the values show the average solar radiation on the longest (21 June) and shortest (21 December) day of 2013.

The data on the first socioeconomic are provided by wijk-en-buurtkaart 2013 (Centraal Bureau voor de Statistiek, 2013). The data on land-cover are extracted from Bodemgebruik database. 2012(Bodemgebruik, 2012). The DEM used to prepare the urban morphology and wind and solar variables, is prepared based on the building height database in the Netherlands, the so-called as 3D BAG (Esri Netherlands, 2016).

5.2.2.3 5.5.2.3 Factor analysis of the independent variables

To avoid the potential misleading results caused by multicollinearity between the 21 independent variables, factor analysis, with extraction method of principal component analysis and rotation method of Oblimin with Kaiser Normalization, is deployed. As result, the effect of the variables is compressed in five factors (Table 5.1).

TABLE 5.1 The five Independent variables of the study compress the effect of 21 indicators. The pattern matrix show the loading of independent variables on the indicators. Coefficients with absolute value greater than 0,400 are marked bold.

Factors	FAC 1	FAC2	FAC3	FAC4	FAC5
Variables	Population density & built-up areas	Income & private tenure	Household size & population younger than 14 y/o	Building age	Building density
built-up coverage (%)	**,977**	-,089	-,091	-,177	-,067
building coverage ratio (%)	**,905**	,075	,005	,177	-,005
green-coverage (%)	**-,891**	,086	,075	,216	-,065
frontal area index	**,750**	,021	,064	,201	,291
population-density (persons per sq km)	**,621**	-,165	,231	,125	,270
income per capita (euro)	,126	**,892**	-,304	-,113	,121
public-rent (%)	,050	**-,780**	-,070	-,047	,183
property-value (euro)	-,276	**,739**	-,058	,020	-,085
disability (%)	-,147	**-,631**	-,266	-,024	,088
unemployment (%)	,221	**-,481**	-,056	-,040	-,014
population ages 65+(%)	,019	,037	**-,891**	-,067	-,064
population ages 0-14 (%)	-,020	,002	**,748**	-,343	-,125
household-size	-,167	,218	**,478**	-,338	-,380
building median age	-,061	,110	,046	**,855**	,119
floor area after introduction of 1988 building standards (%)	-,013	,205	,283	**-,674**	,267
solar radiation per building volume (WH/m³)	,028	,089	-,055	,002	**-,919**
Rugosity	,288	-,021	,026	,139	**,751**
solar radiation on neighbourhood (WH/m²)	-,260	-,031	-,066	-,273	**-,741**
aerodynamic roughness length	,175	-,168	-,001	-,143	**,721**
floor area ratio (%)	**,484**	,099	,067	,306	**,532**
Buildings' surface to volume ratio (m⁻¹)	,067	-,005	,191	,138	-,379

The five factors account for almost 75% of the total variance of the variables. The first factor, FAC1 Population density & built-up areas, is positively loaded onto built up coverage (%), BCR, λf, population density and FAR, and negatively on green-coverage (%). The second component, FAC2 Income & private tenure, is positively loaded onto income per capita and property value, and negatively loaded onto disability (%), unemployment (%) and public rental (%). FAC3 Household size & population younger than 14, is positively loaded onto population ages 0–14 (%) and household-size, and negatively loaded onto population ages 65+ (%). FAC4 Building age, is positively loaded onto building median age, and negatively onto floor area after 1988 (%). FAC5 Building density, is and positively onto FAR, rugosity and ARL and negatively onto solar radiation per building volume (WH/m3) and solar radiation on neighbourhood (WH/m2).

5.2.3 Geographically weighted regression

The first session of the method is consisted of a conventional linear regression model, (see equation 5.3), which assess the generalizable influence of geographic drivers on HEC:

$$y_i = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i$$

EQUATION 5.3

Where y_i represent the estimated value of HEC in the location i, β_0 show the intercept of the estimation, β_k denote the coefficient slope of the factor k, x_{ik} represents its value of factor in location i. ε_i accounts for the random error term in location i. The second session, GWR model, (see equation 5.4), is deployed on the same dataset:

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

EQUATION 5.4

Where (μ_i, ϑ_i) express the geographic coordination of location i. $\beta_k(\mu_i, \vartheta_i)$ and $\beta_0(\mu_i, \vartheta_i)$ are the local coefficient and intercept of factor *k* estimated specific to location i. The local estimates are obtained by weighting the instances around location i (equation 5.5):

$$\hat{\beta}(\mu, \vartheta) = (X^T W(\mu, \nu) X)^{-1} X^T W(\mu, \nu) y$$

EQUATION 5.5

Where $\hat{\beta}(\mu, \vartheta)$ denote the unbiased estimate of β, $W(\mu, \nu)$ is weighting matrix obtained by means of adaptive Gaussian function (equation 5.6):

$$W_{ij} = \begin{cases} e^{(-d_{ij}^2/\theta_{i(k)}^2)}, if\ d_{ij} < \theta_{i(k)} \\ 0, otherwise \end{cases}$$

EQUATION 5.6

Where W_{ij} denote the weight of instance observed at location *j* for estimating the coefficient at location i, d_{ij} is the bird-fly metric distance between *i* and *j* , $\theta_{i(k)}$ and is an adaptive bandwidth defined as the distance from the *k*th nearest neighbour distance. In this study, using ArcGIS (version 10.2), the bandwidth is specified as 108 neighbours, in order to minimize the Akaike Information Criterion (AIC) of the GWR model. The performance of the OLS and GWR model are compared by means of five test: improvement of adjusted R^2; reduction of AICc (for at least three points as previously established by other authors e.g. Hu et al., 2016; Gao & Li, 2011); the randomness of the spatial distribution of the residual of the two models (assessed by Moran's I); ANOVA test of improvement of residual in GWR model; and spatial stationary index - the ratio of interquartile ranges of the standard error of coefficients in GWR model to twice of standard error of the coefficients in OLS model (Charlton et al, 2003).

At the last session, is cluster analysis of GWR results. The advantages of GWR models is provision of an extensive number of local coefficients. However, such an advantage is also a challenge where the summarization and interpretation of the results for the end users –e.g. policy makers- could be challenging (Mennis, 2013, Matthews & Yang, 2012). In this respect, in order to summarize the results of GWR in an interpretable format, *hierarchical clustering technique*, with Ward's method and squared Euclidean distance, on the local standardized coefficients of GWR model is conducted (insignificant coefficients are considered equal to zero). The study areas are subsequently clustered into two, three and four groups (see dendrogram in Fig 5.4a). The clusters are compared by one-way ANOVA test of the local coefficients and named after the effects which differentiate them the most from one another.

5.3 Results

5.3.1 Comparison between performance of OLS and GWR models

Comparison between adjusted R2 of the two models (see Table 5.2) show some 10% improvement of the estimation by deploying geographically weighted model (0.796 in GWR model compare to 0.691 of OLS). The spatial variation of the adjusted R2 is demonstrated in Fig. 5.2. The range of the local adjusted R2 (0.48 to 0.91) show that the goodness-of-fit of the estimation of some 76% of the studied areas is higher than that of OLS model. The geographic pattern of the values show a concentration of higher values of R2 around The Hague, Haarlemmermeer, Amsterdam west and Zoetermeer, Utrecht west and Barendrecht. in contrary, the goodness-of-fit in the areas of central Rotterdam, central Utrecht, Leiden and Dordrecht are the lowest values within Randstad. Presumably, the latent variables affecting HEC, such as detailed information on dwellings quality as well as individual habits, have a stronger impact in these areas.

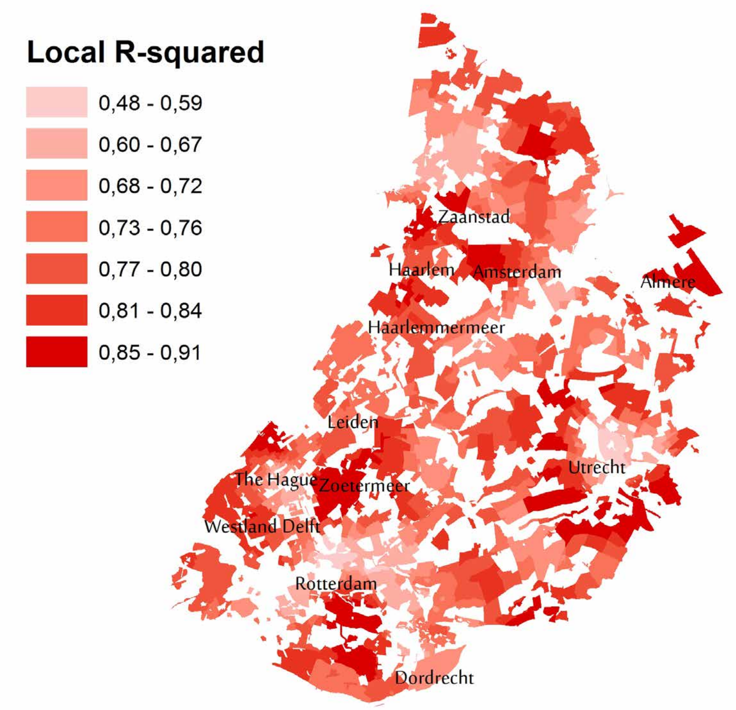


FIG. 5.2 Local adjusted R-squared of GWR estimation of HEC in the Randstad

AICc of the GWR model is substantially smaller than that of OLS (4780 of GWR compare to 5882 in case of OLS model), indicating remarkable better performance in this respect. In case of this study, Moran's I of the GWR model is substantially closer to 0, implying higher randomness of distribution of its residual compare to that of OLS model, -0.008 in case of GWR compare to 0.272 of OLS. As all the spatial stationary indices are greater than one, the results demonstrate that the impact of all the geographic factors are spatial non-stationary and therefore need to be locally studied. (Table 5.2).

TABLE 5.2 Estimated parameters and diagnostic statistics in the OLS and GWR models.

Variable	GWR results					OLS results
	β Mean	β Min	β Max	β SD	Stationary index	β
Intercept	-0,004	-0,537	0,507	0,199		0,000*
FAC1 population density & built-up areas	-0,178	-0,729	0,215	0,118	1,125	-0,199*
FAC2 Income & private tenure	0,459	-0,065	0,793	0,123	1,772	0,420*
FAC3 Household size & population younger than 14	-0,453	-0,848	0,062	0,124	1,142	-0,482*
FAC4 Building age	0,432	-0,141	0,861	0,143	2,263	0,361*
FAC5 Building density	-0,261	-1,069	0,247	0,183	2,622	-0,321*
R-squared	0,830					0,692*
Adjusted R-squared	0,796					0,691*
AICc	4780,15					5852,00
Residuals Moran's I	-0,0078					0,2715
Neighbours	108,000					

β: standardized regression coefficient
** p-value <0,05*

The ANOVA test of the residuals of GWR and OLS model show the significant improvement in case of the former (Table 5.3).

TABLE 5.3 ANOVA test of residuals of GWR and OLS models

	Df	Sum Sq	Mean Sq	F value
OLS Residuals	6.000	1083.53		
GWR Improvement	92.037	272.63	296.213	
GWR Residuals	3.415.963	810.90	0.23739	12.478*
**p-value* < 0,001				

Local coefficient of the FAC1 population density & built-up areas ranges from -0.729 to 0.215 where the global coefficient of the factor, obtained from OLS model, is -0,199 (Table 5.2). Study of the significance level of the local coefficient at p<0.05 level reveals that merely some 58% of the local coefficients of the FAC1 are significant. Almost all of the significant local coefficients are negative. In other words, in almost three fifth of the areas the higher values of the factor are associated with lower levels of HEC. The highest negative elasticity between FAC1 population density & built-up areas and HEC is observed in some areas of city of Utrecht. Some dispersed pockets of high negative elasticity are also identified in the so-called green heart areas (Fig 5.3a).

Local coefficients of FAC2 Income & private tenure range from -0.065 to 0.793 compare to 0.420 of the global model (Table 5.2). Some 99% of the local coefficients are found significant at the p<0.05 level, which are all positively associated with HEC. The elasticity between FAC2 Income & private tenure and HEC reaches its maximum in Haarlemmermeer and Harlem. The magnitude of the positive elasticity roughly resembles in case of Amsterdam, Utrecht and The Hague. Whereas, in case of Rotterdam either the coefficient estimate is not significant or the its magnitude is marginal (Fig 5.3b).

Although local coefficients of the FAC3 Household size & population younger than 14 range from -0.848 to 0.062 (compare to -0.482 in global model), however all of the significant coefficients, account for some 97% of the areas, are positive. Relatively high elasticity between FAC3 Household size & population younger than 14 and HEC is estimated in case of city center of Amsterdam and Leidn. No significant elasticity between the factor and HEC is estimated in city the centers of Utrecht. Though the estimated coefficient in case of Rotterdam is significant, however the magnitude is relatively modest (Fig 5.3c).

Local coefficient of the FAC4 Building age ranges from -0.141 to 0.861 (compare to 0.361 in global model). Some 95% of the estimated coefficients values are significant (at p-value< 0.05 level) which all are all positive. The largest elasticity between HEC and FAC4 Building age is estimated in some areas of the so-called green heart particularly in vicinity of Zoetermeer. FAC4 Building age is estimated to substantially increase level of HEC in vicinity of Zandaan and Dordrecht (Fig 5.3d).

In case of local coefficient of the FAC5 Building density, although the values are ranged from -1.069 to 0.247 (compare to -0.321 of the OLS model), however almost all the significant coefficients, observed in some 62% of the study areas, are negative. The concentration of the high values of estimated coefficient is central areas of Utrecht and Rotterdam. Also, high elasticity are estimated for areas north of Amsterdam and around port of Rotterdam (Fig 5.3e).

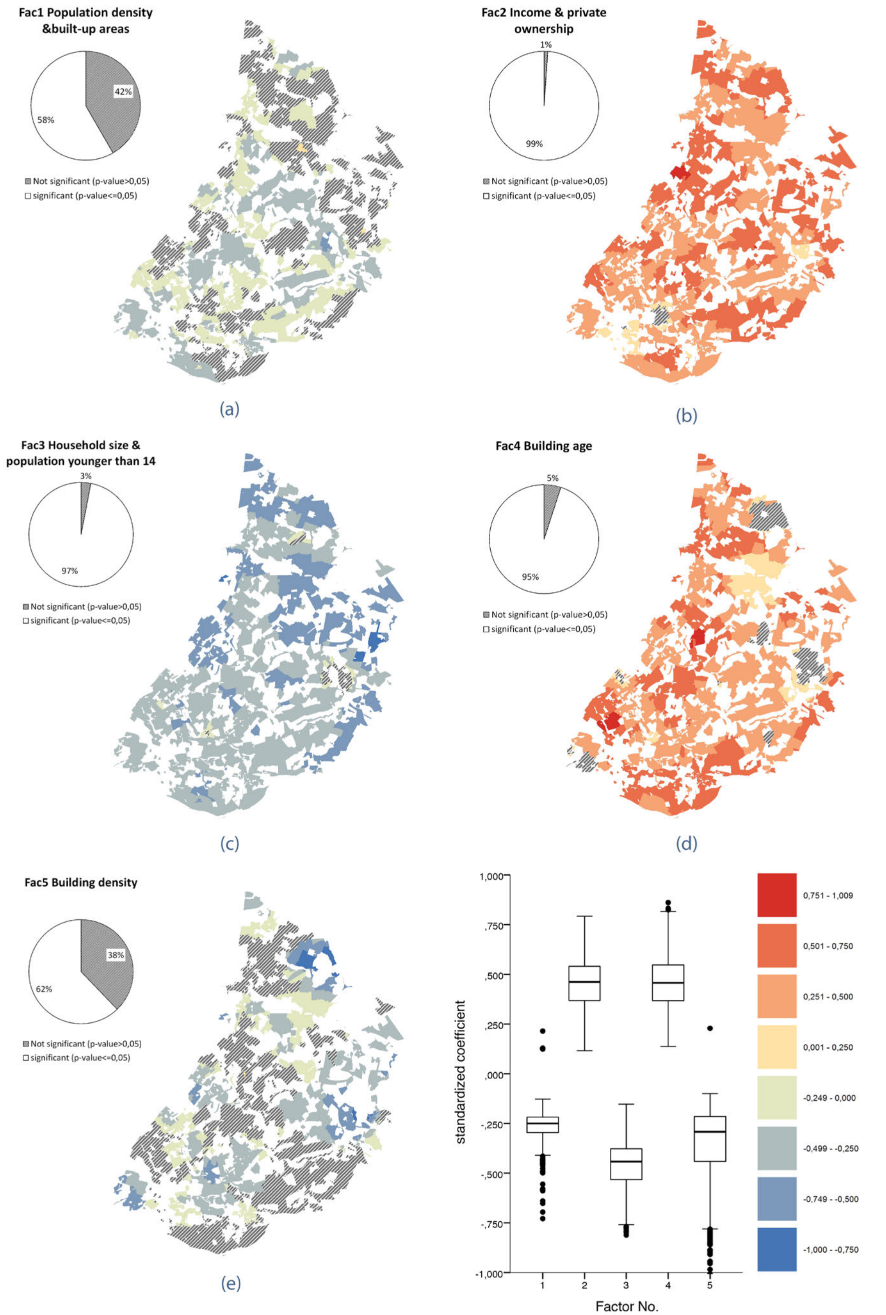


FIG. 5.3 Local standardized coefficient of the independent factors and their level of significance. The box plot illustrates the variability of the significant coefficients.

5.3.2 The typologies of local geographic impacts on HEC

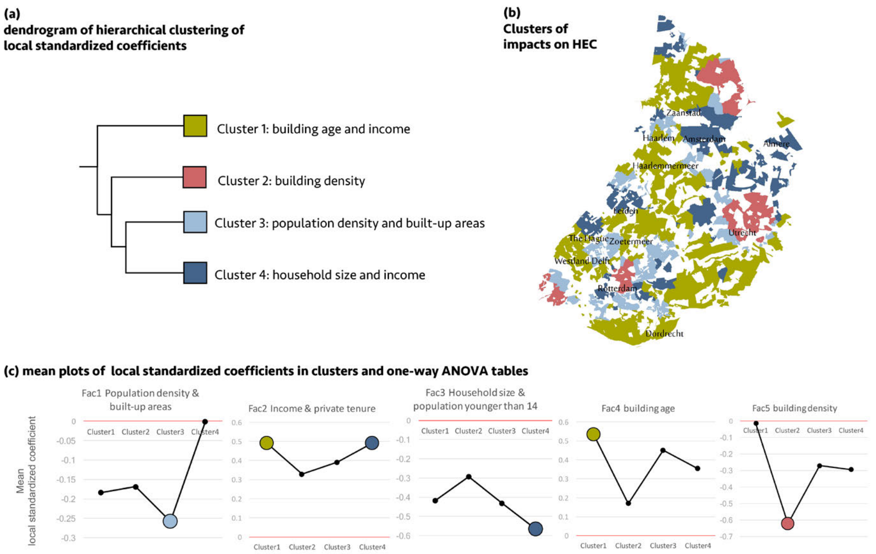
As result of hierarchical clustering of the local standardized coefficients of the independent factors, insignificant coefficients are considered to be equal to zero, four clusters are identified. ANOVA table show that all the clusters are significantly differentiated based on the mean value of local standardized coefficients (Fig 5.4).

The first impact-type, differentiated at the first stage of clustering (see dendrogram at Fig 5.4a) labelled “Cluster1 building age and income”, accounts for some 39,9% of the studied-areas. The areas of the type are differentiated from those of the other impact-types according to substantial positive coefficients of FAC4 Building age and FAC2 Income & private tenure. The impact of FAC1 population density & built-up areas and FAC3 Household size & population younger than 14 are roughly at the average level of local coefficients in the Randstad. The impact of FAC5 Building density on HEC in the areas of this type is marginal (Fig 5.4c).

The areas of the second impact-type, differentiated in the second stage of clustering, account for 11,1% of the areas, are identified as “Cluster2 building density” as FAC5 Building density show the largest negative coefficient value. The impact of FAC1 population density & built-up areas is roughly at the average level of local coefficients in the Randstad. That of FAC2 Income & private tenure, FAC3 Household size & population younger than 14 and FAC4 Building age are lower than other clusters.

Two clusters are identified in the third stage of clustering. In the areas of the third impact-type, labelled as “Cluster3 population density and built-up area”, accounting for 23% of the study areas, merely one factors have remarkable impact on HEC: FAC1 population density & built-up areas. Whereas, the impact of other factors is almost at the average of the Randstad areas.

The fourth impact-type, account for 26% of the areas, is identified as “Cluster4 household size and income” are differentiated by substantial impact of two factors: FAC2 Income & private tenure, FAC3 Household size & population younger than 14. The impact of FAC1 population density & built-up areas on the areas of this cluster is almost zero, and that of FAC4 Building age and FAC5 Building density stands at average level.



	Sum of Squares	df	Mean Square	F	Sum of Squares	df	Mean Square	F	Sum of Squares	df	Mean Square	F	Sum of Squares	df	Mean Square	F	Sum of Squares	df	Mean Square	F
Between Groups	21,3	3	7,11	657,3*	8,6	3	2,87	192,4*	16,3	3	5,43	458,2*	32,7	3	10,89	812,4*	89,1	3	29,71	3512,6*
Within Groups	26,1	2409	0,01		35,9	2409	0,01		28,5	2409	0,01		32,3	2409	0,01		20,4	2409	0,01	
Total	47,4	2412			44,5	2412			44,8	2412			65,0	2412			109,5	2412		

* p-value<0,001

FIG. 5.4 Four types of impact of geographic drivers on HEC obtained by hierarchical clustering of local standardized coefficients

5.4 Discussion

The core aspect of this exploration was whether the impacts of geographic drivers on HEC are spatially non-stationary or not, and whether GWR models provide a better understanding of HEC rather than conventional OLS. As illustrated by the comparison between conventional OLS model and GWR model on HEC, the latter model significantly improves our understanding of HEC's drivers in different aspects: goodness-of-fit of estimate is some 10% higher (measured by R2); AIC is substantially lower; and the residual of the model is smaller and more randomly distributed (tested by means of ANOVA and Moran's I test on residual). In addition, verified by spatial stationary index, it is demonstrated that the impacts of all the geographic factors on HEC vary over the study areas.

TOC

Considering the second research question, how the impacts of geographic drivers on HEC differ across the urban areas of the Randstad urban region, subsequent to application of GWR model, four types of impacts on HEC are identified: building age and income impact, building density impact, population density and built-up area impact, and household size and income impact. However, the output of GWR models is limited into discovering the associations and does not disclose the causal mechanisms. in this section, for sake of opening up new discussion and stimulating further studies, some speculations of the causal mechanisms are presented.

The first type of impact, called as “building age and income”, highlights the areas in which HEC is the most increased by building age, inhabitants’ income and property value. The neighbourhoods of this cluster are mainly less urbanized areas of the Randstad. Presumably, considering the higher amount of free standing dwellings, the impact of quality of buildings on HEC is remarkably higher compare to other clusters. In a similar fashion, higher income and private tenure, which presumably is associated with larger dwelling size and possession of more appliances, has a substantial impact on increasing HEC. Observed positive elasticity of income shows that though the more affluent inhabitants can afford better maintenance and insolation for their dwellings, however, due to different life style, ultimately their energy consumption outnumber that of those with lower income.

The second type of impact, labelled as “building density”, is mainly identified by remarkable impact of high FAR and low solar radiation and wind intensity (associated with high values of ARL) on decreasing HEC. The areas of this cluster are mainly located in Rotterdam and Utrecht. Presumably the remarkable impact of these indicators in these cities is related to higher variability of building density compare to rest of the neighbourhoods. One possible reason for impact of FAR on decreasing HEC is compactness of dwellings and higher heat exchange between them. FAR could be also associated with formation of urban-heat-islands (UHI) which can result in higher air temperature and thus decrease HEC (similar to conclusions drawn by Ewing and Rong, 2008). The association between lower HEC and lower solar radiation and wind intensity could be due to two causal mechanisms. First, higher solar radiation presumably raises electricity use for cooling and ventilation in warm and sultry months, whereas it is supposedly not intense enough to decrease the amount of energy used for warming in cold seasons. Second, presumably high wind intensity increases thermal loss of the buildings due to higher levels of infiltration and exfiltration – which can raise gas use (Sanaiean et al., 2014, van Moeseke et al., 2005). Apparently, such energy loss offsets the thrift gained by better ventilation in windy areas.

The third impact-type, labelled as "population density and built-up areas", highlights the areas in which HEC is the most affected by population density and presence of built-up areas. The areas of this cluster are mainly located in the fringes of the big cities of the Randstad. Such areas could vastly vary in population density as they include different types of developments ranged from populated modernist developments (as Zoetermeer) to suburban areas with villas (as Vrijenburg located in North of Barendrecht). Higher population density in the fringe areas is presumably associated with more vital urban environment which, according to a study by Heinonen et al. (2013), could increase participation of residents in outdoor activities and thus reduce amount of time spent at dwellings and HEC.

The last impact-type, labelled as "household size and income", point out the areas in which HEC is remarkably affected by presence of larger households with children and adolescences (negative coefficient) as well as higher income of the residents (positive coefficient). The areas of this cluster are mainly located in highly urbanized areas of Amsterdam, The Hague, Leiden and Almeer. Decrease in level of HEC in response to presence of larger households is supposedly due to economies of scale (similar to the conclusion drawn by O'Neill and Chen, 2002). Presumably, the remarkable impact of household size and younger age groups on HEC is due to distinguished life style of such families from that of retired citizens living in small households.

5.5 Conclusion

HEC has been a hot topic in the policy-making and scholar circles in the last decades. However, one knowledge gap in the existing body of literature on HEC is eminent: all the previous studies implicitly presumed that the influence of geographic drivers on HEC resemble across the study areas. Therefore, deploying conventional statistical method, merely the average global impact of geographic drivers on HEC has been estimated, where location specific relations has remained unexplored.
The main conclusion of this study is: HEC is vastly affected by location specific impacts and thus understanding of such impacts is essential for enhancing further understanding of HEC.

This result of this study has also two policy implication. First, it is established that the effects of socioeconomic, housing, land cover and morphological indicators on HEC are spatially variant. In this case, a certain set of policy guidelines would not fit the circumstances of all the areas and thus one-size-fits-all type policies need to be completed with location-specific strategies. By proposing location-specific strategies, decision makers could prioritize different incentives and obligations in different areas of the region. Secondly, the results show that the effect of energy efficiency of buildings on reduction of HEC is not necessarily the only effective determinant of HEC in all the areas. Thus, the policies need to add socioeconomic and morphological angles to their approach.

This study also has one major limitations: there are some latent variables which potentially affect HEC such as behavioural habits of the inhabitants or detailed data on building quality. Although obtaining such data on the scale of an urban region in size of the Randstad is practically impossible, however the potential “omitted variable bias” need to be acknowledged. Finally, further study on HEC could chase the possibilities for application of geographically weighted structural models, such as path analysis -which are typically used for studying HEC.

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6 Local determinants of household gas and electricity consumption in Randstad region, Netherlands: application of geographically weighted regression

ABSTRACT The previous studies on household energy consumption (HEC) are based on an implicit assumption: the impact of geographic determinants on HEC is uniform across a given region, and such impacts could be unveiled regardless of geographic location of households in question. Consequently, these studies have searched for global determinants which explain HEC of all areas. This study aim at examining validity of this assumption in Randstad region by putting forward a question regarding households' gas and electricity consumption: are the determinants global, stationary across all the areas of the region, or local, varying from one location to another? By application of geographically weighted regression, impact of

socioeconomic, housing, land cover and morphological indicators on HEC is studied. It is established that the determinants of HEC are local. This result led to second question: what are the main determinants of gas and electricity consumption in different neighbourhoods of Randstad? The results show that variety of factors could be the most effective determinant of gas consumption in different neighbourhoods: building age, household size and inhabitants' age, inhabitants' income and private housing tenure, building compactness. Whereas, in case of electricity consumption the picture is more deterministic: in most of the neighbourhoods the most effective factors are inhabitants' income and private tenure.

KEYWORDS Household energy consumption, Geographically weighted regression, Gas, Electricity, Randstad, Netherlands

6.1 Introduction

The level of household energy consumption (HEC) in Netherlands is high and unsustainable: Calculated per capita and adjusted for climate, in 2013 HEC in Netherlands was about 8% higher than average EU-28 [1-2]; Dutch households' greenhouse gas emission per capita was 37% higher than the EU-28 average [3]; and sales of gas in the residential and commercial sectors per capita was 202% higher than EU average [4-5]. Three geographical factors could be accounted for high level of HEC in Netherlands. First, the substantial dependency of HEC on natural gas largely due to the existence of the large amount of natural gas in the northern parts of the Netherlands, in particular the so-called 'Groningen' or 'Slochteren' gas field which, on its discovery in 1959, seemed abundant enough to satisfy Dutch (and other European countries') needs for natural gas. This assumption led to a nationwide implementation of natural gas infrastructure; all the households of the country has access to gas and electricity grid. Additionally, given the highly liberalized and competitive energy retail market, the price of energy for household, gas and electricity, is relatively low in Netherlands. In 2012 energy prices for households was 5% lower than the European average [6], whereas GDP per capita was more than 30% higher [7]. In this respect, given the substantial share of HEC from total emission, 16% of total in 2015 [8], policies of Netherlands targeted reduction of HEC by introduction of in Third National Energy Efficiency Action Plan for the Netherlands [9]. The policy document introduces variety of incentives and regulation for curbing HEC which are applicable for all the locations of the Netherlands. The main focus of the introduced measures is improvement of dwellings' energy efficiency e.g. low interest loans for building insolation, tighter standards for new constructions, restrict measures for efficiency of heating and ventilation systems.

The necessity of reduction of HEC is also reflected between scholars. The existing body of literature on HEC is rich as plenty of previous studies have established links between HEC and variety of determinants among them socioeconomic characteristics, urban form, urban microclimate, housing. However, these studies are limited in scale. Most of the previous studies on HEC use surveys conducted at scale of individual dwellings. Therefore, the larger geographic pattern of HEC, and its geographic drivers, is barely studied. In this respect, missing the larger geographic patterns, all the previous studies are conducted based on an implicit assumption: determinants of HEC are identical in every and each dwelling regardless of its geographic location. In other words, it is assumed that the impact of geographic determinants on HEC is uniform across a given study area, and such impacts could be unveiled by application of aspatial methods. In this respect, vast majority of previous studies have ignored the fact that impact of a given determinant could vary from one location to another. Consequently, these studies bring forward one-size-fits-all type of recommendation for all the areas in question instead of location-specific ones.

The core objective of this study is to bridge this knowledge gap by putting forward two research questions: (a) are the effects of geographic determinant on households' gas and electricity consumption vary across the neighbourhoods of Randstad region? In other words, are the determinants global, stationary across all the areas of the region, or local, varying from one location to another? (b) if the determinants are local, what are the main determinant of gas and electricity use in different neighbourhoods of the region? To chase answers to these questions, this study apply geographically weighted regression (GWR) to examine the effect of a variety of socioeconomic, housing, land cover and morphological properties on household's gas and electricity consumption. In the next parts, first the previous studies on HEC are briefly reviewed. Then after, the methodology, case study and data of this research are described. Subsequently, results are presented and discussed. The paper ends up with a brief conclusions regarding scientific studies and policies on HEC.

6.2 Previous studies on HEC

Most of the previous studies on HEC are conducted at the scale of individual dwellings i.e. using household survey regardless of larger geographic pattern of HEC. At this scale, previous studies have shown that variety of factors can affect level of HEC: Inhabitants with higher income have a higher consumption [10-11]; due to economies of scale, larger household size is associated with lower HEC [12-13]; age of the inhabitants, particularly presence of senior residents and children, affect HEC [10, 14]; presence of retired or disable inhabitants boost level of HEC [12]; HEC in different housing tenure, due to various systems of paying for energy bills as well as different level of investment in buildings, is significantly different [11, 15]; HEC soar in the building with higher age [10-11]; land-cover of the neighbourhoods can affect land surface temperature and consequently HEC [16-17]; Wind intensity affect air infiltration and exfiltration of buildings and thus HEC [18-19]; building density alter HEC by its effect on compactness of dwellings [20-21]; Rugosity affect effective wind speed and HEC in the neighbourhoods [22]; buildings' surface-to-volume ratio impact HEC by affecting thermal exchange between dwellings [23-24]; Population density affect HEC via altering level of urbanity and behaviour of residents [14, 25]; and solar radiation affect HEC via impacting indoor temperature [26-27].

Studies on geographic determinates of HEC (conducted on aggregated HEC in neighbourhoods, cities, regions, etc.) are few in numbers, however plentiful in amount of information. These studies enhance a geographic understanding of HEC: the locations-specific determinants of HEC at different locations. For instance, a study on rural Chinese areas show that energy price and energy transportation (i.e. distance from coal sources) are among the main determinants of HEC. Furthermore, the study show these effect of vary in different geographies: energy transportation is significant only if the distances is greater than 20 km; impact of energy price soar in high mountains [28]. A study on determinants of HEC in 64 European regions, so-called NUTS2 regions concluded that socioeconomic (income, education, unemployment, poverty) and contextual (e.g. climate) variables significantly affect HEC. The study show that impact of some determinates, e.g. disposable income, is common for all the regions. However that of some determinates vary due to regional development. For example, GDP has a positive effect on HEC of less developed region, due to achieving higher living standard, whereas it has a negative impact on HEC of more developed region, due to achieving higher energy efficiency [29]. A regional study on household's final energy use in the Netherlands show that quality of buildings and income has a greater impact on HEC of rural areas than urbanized areas. The study conclude that in the suburban areas population density is a

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significant determinant of HEC, whereas in highly urbanized areas household size or building density are the prominent determinants [30].

6.3 Methodology

Prior to application of GWR models, in order to examine the generalizable effects of the geographic determinants on HEC, two conventional linear regression models (OLS) are developed:

$$y_i = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i \qquad \text{EQUATION 6.1}$$

Where y_i represents the estimated value of HEC (gas or electricity consumption) in the location $\boldsymbol{i}$, β_0 shows the intercept, β_k denotes the coefficient slope of the independent variable k, x_{ik} represents the value of independent variable k in location $\boldsymbol{i}$. ε_i accounts for the random error term in location $\boldsymbol{i}$. Subsequently, in order to examine the location-specific effects, two GWR models (equation 2) are applied.

$$y_i = \beta_0(\mu_i, \vartheta_i) + \sum_k \beta_k(\mu_i, \vartheta_i) x_{ik} + \varepsilon_i \qquad \text{EQUATION 6.2}$$

Where (μ_i, ϑ_i) represents the geographic coordination of location $\boldsymbol{i}$, $\beta_k(\mu_i, \vartheta_i)$ and $\beta_0(\mu_i, \vartheta_i)$ are the local coefficient and intercept of independent variable k estimated specific to location $\boldsymbol{i}$. The local coefficients at location $\boldsymbol{i}$ is calculated by (equation 3):

$$\hat{\beta}(\mu, \vartheta) = (X^T W(\mu, \vartheta) X)^{-1} X^T W(\mu, \vartheta) y \qquad \text{EQUATION 6.3}$$

Where $W(\mu, \vartheta)$ is the spatial weighting matrix which conceptualize the importance of adjacent neighborhoods of location $\boldsymbol{i}$:

$$W_{ij} = \begin{cases} e^{(-d_{ij}^2/\theta_{i(k)}^2)}, if\ d_{ij} < \theta_{i(k)} \\ 0, otherwise \end{cases} \qquad \text{EQUATION 6.4}$$

Where W_{ij} denotes the weight of location j for the estimation of the location $\boldsymbol{i}$ coefficients, d_{ij} is the geodesic distance between location $\boldsymbol{i}$ and j. $\theta_{i(k)}$ is an adaptive bandwidth denoting distance from the kth nearest neighbor. Using ArcGIS (version 10.2), the bandwidths of the models are specified so as to minimize the Akaike Information Criterion (AIC) of the GWR models.

The performance of GWR and OLS models are compared by means of five tests. First, adjusted R2 of the two models are compared. Second, by comparison between the AICc (corrected Akaike's Information Criterion) of the models. Typically, at least three points decrease in AICc is seen as a significant improvement (e.g. [31-32]). Third, comparison of randomness of the distribution of the residuals of the models – validated by Moran's I Index. The index is a measure of spatial autocorrelation ranged between -1 and +1; value closer to zero shows more random distribution. Fourth, in order to examine whether the effect of the determinants on HEC vary across the study areas, stationary indices - proposed by Charlton, Brunsdon, and Fotheringham [33] - of independent variables are calculated. To do so, interquartile ranges of the standard error of coefficients in the GWR model are divided by twice the standard error of coefficients in the OLS model. If value of the stationary index is equal to or greater than one , it indicates that the effect of the given independent variable on HEC is spatially non-stationary. Fifth, ANOVA tests, to compare residuals of GWR and OLS models, are applied.

6.4 Case study and Data

6.4.1 Case study area and analysis area

The spatial element used in this study are the ‘buurten’, spatial divisions defined by the Dutch central bureau of statistics (CBS) - what we call as neighbourhood. The case study of this research – what we call as “study area”- is consisted of neighbourhoods of the Randstad region. The Randstad is a highly urbanized metropolitan area located in the south west of the Netherlands consist of the four major cities of Amsterdam, Rotterdam, The Hague and Utrecht, and the areas between them – the so-called “green heart”. In order to avoid the boundary-effect problem in GWR models, all the calculations are carried out on the “study area” plus a 20 km buffer – what we call as “analysis area”. Although all calculations are carried out on the analysis area, ultimately merely the results obtained for “study areas” are taken into consideration (Figure 6.1).

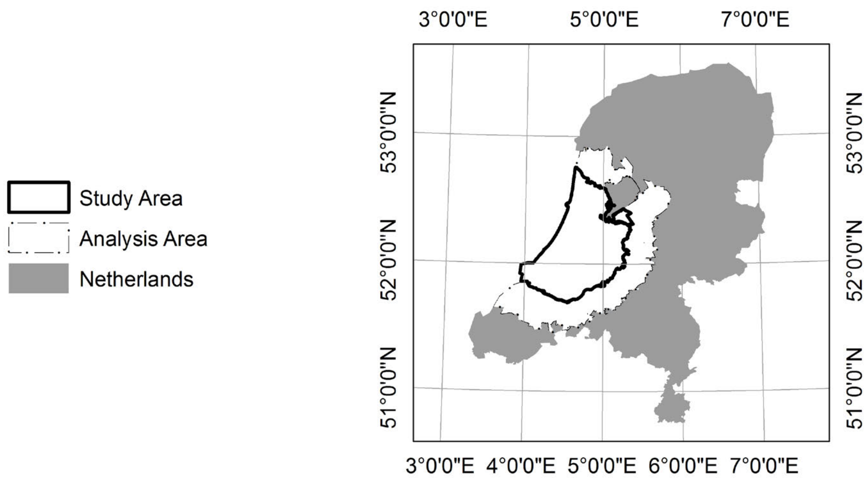

FIG. 6.1 Location map of study area and analysis area

6.4.2 Dependent variables

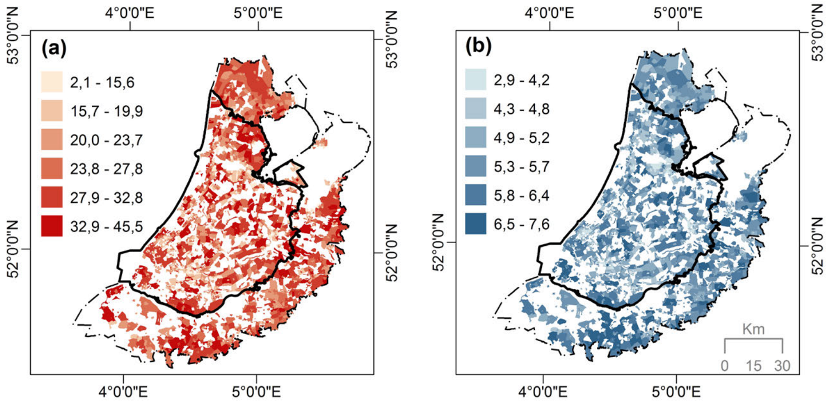

FIG. 6.2 Dependent variables of study: a annual gas consumption per capita 2013 (Mega Joule), b annual electricity consumption per capita 2013 (Mega Joule)

The dependent variables of the study are gas and electricity consumption per capita within dwellings [34]. As the available data does not show the areas equipped with solar energy supply or district heating, the abnormal values of gas and electricity use needed to be filtered out (incidents with z-value <= -2.5 or z-value >= +2.5) Ultimately, the “analysis area” consists of 3514 neighbourhoods and the “study area” of 2413 (Figure 2a and 2b). The Moran’s Index test show that high values of gas and electricity consumption (both in study and analysis area) are spatially clustered across the region. The respective Moran’s I z-score is well beyond the threshold of 2.58 (which indicate spatially clustered pattern): 36.8 (in case of gas use in study area), 49.7 (in case of gas use in analysis area), 42.3 (in case of electricity use in study area), 57.6 (in case of electricity use in analysis area). Thus, as spatial variation is significant, application of GWR is essential for enhancing better understanding of such geographic pattern (figure 6.2).

6.4.3 independent variables

This study use five dependent variables. The variables compress the effect of 21 indicators by means of factor analysis. By choice of the 21 indicators, we tried to include all the potential effective factors without a priori selection (see Table 6.1). Socioeconomic and housing variables are taken from CBS, 2013 [26]. Land cover

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variables are extracted from a Bodemgebruik database, 2012 [35]. Building height database in the Netherlands, 3D BAG [36], is used to prepare a digital elevation model (DEM). Cell size of DEM is 10m. The latter in utilized to prepare urban form indicators. In the next part, a more detailed explanation of some of the variables is presented.

According to Adolphe [22], the variation of building height, or what he calls as rugosity, could have a significant effect on the urban microclimate. We calculated rugosity as the standard deviation of height values (including those with zero height) of DEM. The frontal area index (λf) is the ratio of the total area of external building walls to the total area of the neighbourhood. In order to calculate λf , firstly external walls need to be identified. To do so, using ArcGIS 10.2 Focal Flow tool, 3 x 3 immediate neighbours of each DEM cell is studied. it is determined that which sides of each DEM cell are external wall (i.e. are not occupied with a building cell or are occupied with a shorter building). The obtained information is used for calculation of total amount of external walls at each DEM cell. This has been instrumented for calculation of λf and subsequently aerodynamic roughness length (ARL). ARL is the height in which the effective wind speed is theoretically zero. Higher values of ARL correspond with lower wind intensity [37]. The morphometric model introduced by Macdonald et al. [38], one of the most comprehensive models according to a review by Grimmond and Oke [39], is used:

$$\frac{Z_d}{Z_H} = 1 + \alpha^{-BCR}(BCR - 1)$$ EQUATION 6.5

$$\frac{Z_0}{Z_H} = \left(1 - \frac{Z_d}{Z_H}\right) \exp\left(-\left(\frac{0.5\beta C_D \lambda_f}{k^2}\left(1 - \frac{Z_d}{Z_H}\right)\right)^{-0.5}\right)$$ EQUATION 6.6

Where Z0 is aerodynamic roughness length for momentum, Zd is zero-plane displacement height, ZH is height of roughness element (m), BCR is building coverage ratio, lf frontal area index, α = 4.43, β = 1.0, k = 0.4, and CD @ 1.

Deploying the Arcgis 10.2 solar radiation toolbox, the DEM model is used to calculate solar radiation (SLR) on summer (21 June) and winter (21 December) solstice of 2013. The average value of the two days is used to calculate two variables: solar radiation per square meters of neighbourhoods' surface (solar radiation on neighbourhood (WH/m2)) and per cubic meters of the buildings (solar radiation per building volume (WH/m3)).

To address the potential multicollinearity between the 21 indicators, factor analysis, with extraction method of principal component analysis and rotation method of Oblimin with Kaiser Normalization, is deployed. As result, the effect of the indicators is compressed in five factors (Table 1). As the extraction method is principal component analysis, a small level of independence between the obtained factors is tolerated. Consequently, one of the initial variables, FAR (floor area ratio), has made contribution to two of the factors. Whereas the rest of 20 variables have merely contributed to one factor. The factors explain almost 75% of the total variance of the 21 variables. The first factor, FAC1 Population density & built-up areas, is positively loaded onto built up coverage (%), BCR, lf, population density and floor area ratio (FAR), and negatively on green-coverage (%).FAC2 Income & private tenure, is positively loaded onto income per capita and property value, and negatively loaded onto disability (%), unemployment (%) and public rental (%). FAC3 Household size & population younger than 14 y/o, is positively loaded onto population ages 0–14 (%) and household-size, and negatively loaded onto population ages 65+ (%). FAC4 Building age, is positively loaded onto building median age, and negatively onto floor area after introduction of 1988 building standards (%). FAC5 Building compactness, is and positively onto FAR, rugosity and ARL and negatively onto solar radiation per building volume (WH/m3) and solar radiation on neighbourhood (WH/m2).

TABLE 6.1 The five Independent variables of the study compress the effect of 21 indicators. The pattern matrix show the loading of independent variables on the indicators. Coefficients with absolute value greater than 0,400 are marked bold.

Factors	FAC 1	FAC2	FAC3	FAC4	FAC5
Variables	Population density & built-up areas	Income & private tenure	Household size & population younger than 14 y/o	Building age	Building density
built-up coverage (%)	**,977**	-,089	-,091	-,177	-,067
building coverage ratio (%)	**,905**	,075	,005	,177	-,005
green-coverage (%)	**-,891**	,086	,075	,216	-,065
frontal area index	**,750**	,021	,064	,201	,291
population-density (persons per sq km)	**,621**	-,165	,231	,125	,270
income per capita (euro)	,126	**,892**	-,304	-,113	,121
public-rent (%)	,050	**-,780**	-,070	-,047	,183
property-value (euro)	-,276	**,739**	-,058	,020	-,085
disability (%)	-,147	**-,631**	-,266	-,024	,088
unemployment (%)	,221	**-,481**	-,056	-,040	-,014
population ages 65+(%)	,019	,037	**-,891**	-,067	-,064
population ages 0-14 (%)	-,020	,002	**,748**	-,343	-,125
household-size	-,167	,218	**,478**	-,338	-,380
building median age	-,061	,110	,046	**,855**	,119
floor area after introduction of 1988 building standards (%)	-,013	,205	,283	**-,674**	,267
solar radiation per building volume (WH/m³)	,028	,089	-,055	,002	**-,919**
Rugosity	,288	-,021	,026	,139	**,751**
solar radiation on neighbourhood (WH/m²)	-,260	-,031	-,066	-,273	**-,741**
aerodynamic roughness length	,175	-,168	-,001	-,143	**,721**
floor area ratio (%)	**,484**	,099	,067	,306	**,532**
Buildings' surface to volume ratio (m^{-1})	,067	-,005	,191	,138	-,379

6.5 Results

6.5.1 comparison between performance of GWR and OLS models

A comparison between adjusted R^2 of the two OLS and GWR models, shows that all three of the GWR models have a better goodness-of-fit (Table 6.2). The adjusted R^2 of the GWR model of gas consumption is some 15% higher than that of OLS. The corresponding number for the electricity consumption models is about 17%. The local R^2 of the GWR models (Figure 6.3) show that in more than 76% of the areas estimation of gas and electricity consumption produced a better R^2 than OLS model.

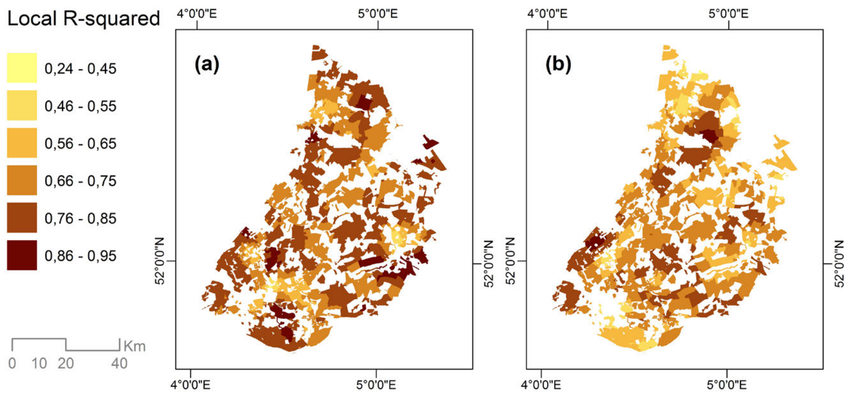

FIG. 6.3 Local adjusted R-squared of GWR estimation of: **a** gas consumption, **b** electricity consumption.

The comparison between the AICc (corrected Akaike's Information Criterion) of the GWR and OLS models shows a remarkable improvement in the case of GWR models. The results show that the residuals of GWR models are more randomly distributed rather than those of OLS models; the Moran's Indices of the GWR models are substantially closer to zero than those of OLS models. The stationary indices of all the independent variables of the GWR models are greater than 1. This indicates that the effect of the variables on HEC is spatially non-stationary (Table 6.2).

TABLE 6.2 Diagnostic statistics in GWR and OLS models.

Independent variables	Dependent variable					
	gas consumption			electricity consumption		
	GWR β mean	OLS β	stationary index	GWR β mean	OLS β	stationary index
FAC1 population density & built-up areas	-0,173	-0,193***	1,118	-0,150	-0,211***	1,195
FAC2 Income & private tenure	0,431	0,400***	1,770	0,594	0,560***	1,751
FAC3 Household size & population younger than 14 y/o	-0,433	-0,477***	1,141	-0,396	-0,405***	1,132
FAC4 Building age	0,451	0,377***	2,262	0,072	0,024*	2,239
FAC5 Building density	-0,250	-0,321***	2,620	-0,108	-0,222***	2,616
R-squared	0,8237	0,6787		0,7915	0,6272	
Adjusted R-squared	0,7880	0,6782		0,7502	0,6266	
AICc	4918,83	5995,77		5486,74	6518,44	
Residuals Moran's I	-0,0065	0,2709		0,0082	0,2349	
Neighbours	108			110		
β denotes standardized coefficient						

** p-value < 0,05, **p-value < 0,01, ***p-value < 0,001*

ANOVA test of the residuals in GWR and OLS models indicate a significant improvement in case of GWR models (Table 6.3).

TABLE 6.3 ANOVA test of residuals of GWR and OLS models.

	Dependent variable							
	gas consumption				electricity consumption			
	Df	Sum Sq	Mean Sq	F value	Df	Sum Sq	Mean Sq	F value
OLS Residuals	6	1128,78			6	1309,8		
GWR Improvement	92,037	285,03	3,0969		90,297	287,78	3,187	
GWR Residuals	3415,963	843,75	0,247	12,538	3417,703	1022,02	0,299	10,658

F values are significant at p-value < 0,001

6.5.2 local determinants of HEC

Figure 3 shows the estimated local standardized coefficients of the independent variables in the two GWR models. According to the results of the GWR models, the percentage of the areas with a significant coefficient of FAC1 Population density & built-up areas is rather small (Figure 6.4a and Figure 6.4f). In the case of the gas consumption model the impact of the factor is significant – at p-value <0.1 level – in 63% of the areas. In case of electricity usethe percentages is 45%. However, the magnitude of the significant coefficients is considerable in a substantial portion of the areas, the significant coefficients are negatively signed. The magnitude of the coefficient is almost similar in case of the two models.

The results of the GWR models of gas and electricity consumption show that in almost all of the areas, the coefficients of FAC2 Income & private tenure are significant (Figure 6.4b and Figure 6.4g). Roughly speaking, signs of all the significant coefficients are positive. The largest effect of the factor is observed in the case of electricity consumption model (according to the mean standardized coefficient of the GWR model).

The results of GWR models of gas and electricity consumption show that in more than 97% of the areas, the coefficients of FAC3 Household size & population younger than 14 y/o are significant (Figure 6.4c and Figure 6.4h). The sign of all the significant coefficients is negative. The magnitude of the coefficients is almost similar in the two models.

The results show FAC4 Building age has significant effect on a gas consumption in more than 95% of the areas (Figure 6.4d and Figure 6.4i). However, In case of electricity consumption the factor is not effective in almost 70% of the areas. The magnitude of the coefficients (assessed by the mean value of the GWR models) is remarkably high in the case of gas consumption model. The sign of all the coefficients is positive. in the electricity consumption model, though positive, the magnitude of the coefficients is close to zero.

According to the results of the GWR models, in the case of the gas consumption model, the impact of FAC5 Building compactness is significant in 70% of the areas (Figure 6.4e and Figure 6.4j). In the case of electricity consumption, the corresponding number is 44%. The coefficients, except in the case of 5% of the areas in electricity consumption model, are negative. The largest magnitude of the effect is observed in the case of the gas consumption model.

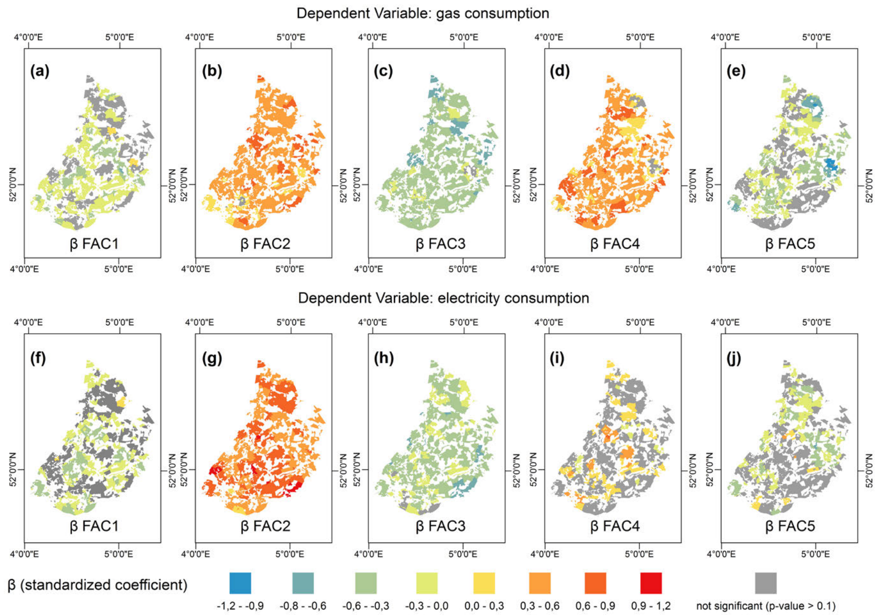

FIG. 6.4 Local standardized coefficients: **a-d** gas consumption model, **f-j** electricity consumption model

Figure 4 illustrates the largest local standardized coefficients (in absolute value) – what we call as the most effective local determinant – in different neighbourhoods of the study area. The results show that, variety of factors could be the most effective determinant of gas consumption in different neighbourhoods: FAC4 Building age in 37% of the neighbourhoods, FAC3 Household size & population younger than 14 y/o in 29% of the neighbourhoods, FAC2 Income & private tenure in 23% of the neighbourhoods, FAC5 Building compactness in 11% of the neighbourhoods (Figure 6.5a). In case of electricity use model, the picture is more deterministic: in 84% of the neighbourhoods FAC2 Income & private tenure is the most effective factors. In the rest of the areas FAC3 Household size & population younger than 14 y/o is found to be the most effective (Figure 6.5b).

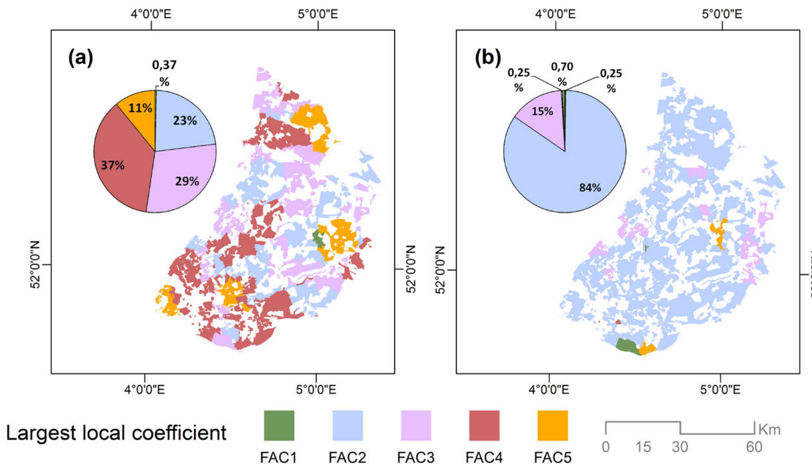

FIG. 6.5 The most effective local determinants of - largest local standardized coefficients (in absolute value)- of: **a** gas consumption, **b** electricity consumption

6.6 Discussion

The results of GWR models of gas and electricity consumption show that, in almost all the neighbourhoods, sign of the coefficients is similar. However, the magnitude of the coefficients remarkably vary across the neighbourhoods. The coefficients of FAC1 Population density & built-up areas are negative in almost all the areas. This could be due to higher air temperature, consequent to higher surface temperature, in the neighbourhoods with higher percentage of built-up areas (similar to what is suggested by [21]). Also the residents of areas with higher population density, say more urbanized, could be more engaged with outdoor activities and spend less time within their dwellings. This could significantly reduce HEC (similar to the conclusion drawn by [40-41]). The coefficients of FAC2 Income & private tenure are positive in all of the neighbourhoods. Presumably, high-income residents live in larger dwellings and possess more appliances at their homes (similar to conclusion drawn by [42]). All the local coefficients of FAC3 Household size & population younger than 14 y/o are negative. This could be due to economies of scale – as suggested by variety of previous studies (e.g. [43]).

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Increase in FAC4 Building age has a large impact on increasing gas consumption. This is presumably due to lower energy efficiency of buildings (as concluded by variety of previous studies e.g. [24]). The effect of the factor on electricity consumption is not significant in most of the neighbourhoods. However, if significant, the sign of coefficients is positive. Almost all of the local coefficients of FAC5 Building compactness are negative. This could be due to compactness of buildings and higher heat exchange between the dwellings in the neighbourhoods with higher FAR (as concluded by variety of authors among them [11]). It also could be due to lower wind intensity (associated with high ARL) which reduce air infiltration /exfiltration and therefore buildings' thermal loss [44]. Additionally, lower solar radiation in the neighbourhoods with higher FAC5 Building compactness, could reduce electricity consumption for cooling and ventilating [45].

The results show that variety of factors could be the most effective determinant of gas consumption in different neighbourhoods. Whereas, in case of electricity useFAC2 Income & private tenure is the most effective determinant in vast majority of the neighbourhoods. This could be explained by different final end-uses of gas and electricity in residential sector.

Eurostat data on final energy consumption of Dutch households in in 2015 [46], show that gas was the main source for space heating (87%) and warm water (90%). In this respect, the results of this study is in line with those of previous studies which show space and water heating could be affected by variety of determines among them occupant characteristics (e.g [47]), building characteristics (e.g [48]), housing tenure (e.g [49]), urbanization rate (e.g [50]), and number of dwellings per buildings (e.g [51]). When it comes to electricity consumption, more than 50% of households' consumption is for lightening and appliances [46]. In this respect the results of this study is in line with previous studies which suggest that households with higher income consume more electricity for lightening - due to owing larger dwellings - and appliances - due to possession of greater number of devices (e.g. [42]).

6.7 Conclusion

HEC has been of interest of many researchers and policy makers in the last decades. However, there is an eminent knowledge gap in the existing body of literature on HEC: all the previous studies have implicitly presumed that HEC could be explained by set of spatial stationary reasons and therefore has tried to unveil such everywhere-true reasons. The results of this study show that such presumption is questionable. It is obtained that, in the Randstad region, the of effects of socioeconomic, housing, land cover and morphological indicators on HEC vary from one location to another. In this respect, the main conclusion of this research is: in order to provide a better understanding of HEC, studies in this field need to search for the location specific factors which affect HEC in a given neighbourhood.

It is also obtained that GWR models provide a better estimation of HEC rather than the OLS models. Previous studies on HEC have applied a wide range of aspatial techniques e.g. machine learning, linear regression, structural equation models, simulation models (see the review [52]). However, HEC studies lag behind in application of spatial econometrics methods. This studies concludes that HEC studies need to be enriched by further application of spatial statistics.

The results of this study also has a policy implication. By application of GWR, It is established that variety of factors could be the main determinants of level of gas and electricity consumption in different neighbourhoods. Additionally, the policies as like Third National Energy Efficiency Action Plan [9] need to break through the narrow perspective of building energy efficiency, and take socioeconomic and morphological aspects into their consideration. Another policy implication regards the effect of FAR (floor area ratio) on household energy consumption, particularly gas use, within dwellings. it is obtained that FAR has a dual impact on consumption: On one hand FAR is associated with level of urbanity (i.e. more population density and built up surfaces), on the other hand FAR affect level of compactness (i.e. lower wind speed and solar radiation). Considering construction of 500,000 new dwellings in Randstad region according to 2014 vision [53], further studies need to assess the impact of this extra FAR on energy household energy consumption.

Further studies need to adopt the existing methods for studying microclimate factors –i.e. air and surface temperature, humidity - to enrich the estimates of HEC (similar to what is applied by [54-56]). Additionally, the effect of ever growing urbanization patterns (similar to that of [57-58]) on HEC need to be further studied. Further research could also seek for a comprehensive framework which combine HEC with potential locations for energy production (similar to the study by [59]). The last, in this study the determinant of gas and electricity consumption have been independently studied, the further studies could investigate the spatial autocorrelation between the two (similar to the methodology used by [60]).

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7 Conclusion

7.1 Summary of findings: local and global determinants HEC

The objective of this study is to identify both the global determinants of HEC (i.e. factors which trigger the same response across the whole country, or part of it) and the local determinants of HEC (i.e. factors which trigger different responses across the country or part of it).The results of two studies carried out at the scale of all neighborhoods of the Netherlands (Article#1 and Article#3) show that most of the determinants of HEC are local, while only a few are global. in contrary, a study on the urbanised neighbourhoods of the Netherlands (Article #2), most of the determinants are global, and only some are local (Table 7.1).

The results of the two studies carried out on the neighbourhoods of the Randstad indicate that all the determinants are local. This implies that when neighbourhoods of a highly urbanized region are compared, all the measured effects are highly location-specific (Table 7.2).

TABLE 7.1 Geographical variability on the estimated impact of determinants in all the neighbourhoods of the Netherlands. Negative values of "DIFF of Criterion" indicate local impacts.

	Article #1		Article #2		Article #3	
Variable	Local / Global	DIFF of Criterion	Local / Global	DIFF of Criterion	Local / Global	DIFF of Criterion
Dependent variable	HEC (euro) in all neighbourhoods of the Netherlands		HEC (joule) in urbanised neighbourhoods of the Netherlands		Share of HEC of income in all neighbourhoods of the Netherlands	
Income	Local	-16,96	Global	5,84		
Low-income (%)					Global	2,84
Household-size	Local	-60	Global	8,76	Local	-54,14
Building-age	Local	-18,79	Local	-22,42	Local	-22,58
Private-rent (%)					Local	-297,64
Unemployment (%)					Local	-22,89
Pensioner (%)					Global	4,61
Surface-to-volume	Local	-8,62	Global	6,69		
Population-density	Local	-48,36	Local	-43,44		
Summer-days	Local	-97,16	Global	3,59	Local	-13,68
Frost-days	Global	3,84	Global	5,32	Local	-23,3
Wind-speed	Local	-11,89	Global	10,66		
Land surface temperature	Global	42,79	Local	-14,97		
Humidity (%)			Global	5,49		

TABLE 7.2 Geographical variability on the estimated impact of determinants in the neighbourhoods of the Randstad Area. Values of "Stationary-index" greater than 1 indicate local impacts.

	Article #4		Article #5		Article #5	
Variable	Local / Global	Stationary index	Local / Global	Stationary index	Local / Global	Stationary index
Dependent variable	HEC (euro) in all neighbourhoods of the Randstad region		Gas consumption (Joule) in all neighbourhoods of the Randstad region		Electricity consumption (joule) in all neighbourhoods of the Randstad region	
FAC1 population density & built-up areas	Local	1,13	Local	1,12	Local	1,2
FAC2 Income & private tenure	Local	1,77	Local	1,77	Local	1,75
FAC3 Household size & population younger than 14 y/o	Local	1,14	Local	1,14	Local	1,13
FAC4 Building age	Local	2,26	Local	2,26	Local	2,24
FAC5 Building density	Local	2,62	Local	2,62	Local	2,62

These findings implies that it is necessary to study the local circumstances of the neighbourhood in question (e.g. socio-economic, urban form, housing, and macro/micro climate issues) in order to understand the determinants of household energy consumption in a given neighbourhood. It is also necessary to acknowledge that HEC of each and every neighborhood is shaped by its own original circumstances. A vast majority of previous studies on HEC, are based on an underlying presumption that there are some generic rules applicable to HEC all neighbourhoods. The core conclusion of this study is that the validity of this presumption is questionable, and future studies on HEC need to acknowledge that there is no divine rule when it comes to HEC.

7.2 Reflection on data and methods

7.2.1 comparison between performance of spatial and aspatial models of HEC

In all five studies reported in this manuscript, one aspatial model, ordinary least square regression (OLS) and one spatial model, geographically weighted regression model (GWR), are employed. In the articles on Netherlands scale, chapter 2 to 4, an extra spatial model is adopted: semi parametric geographically weighted regression (SGWR). In this section performance of the aspatial models and the best spatial model in the studies is compared by means of three statistical tests: adjusted R2; AICc (corrected Akaike's Information Criterion) of the models; spatial distribution of the residuals –assessed by Moran's I Index. The results of the studies showed that spatial statistical models significantly outperform aspatial models. This finding show that in all the cases the aspatial models significantly outperform the spatial models, and that in order to understand the determinants of household energy consumption in a given neighbourhood, it is necessary to study the local circumstances of the neighbourhood, i.e. socioeconomic, urban form, housing, macro and micro climate. Comparison between distribution of the residuals of aspatial and spatial models show that those of latter are more randomly distributed. In the next parts performance of the spatial and aspatial models is presented and compared.

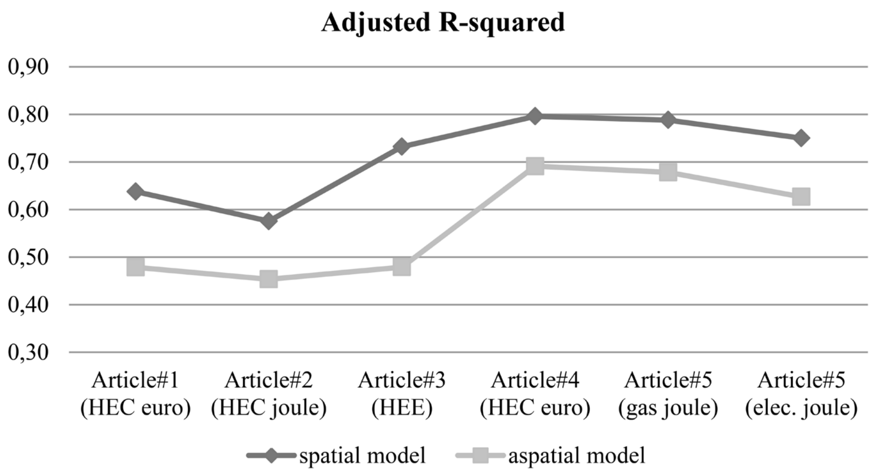

FIG. 7.1 Comparison between R-squared of spatial and aspatial models

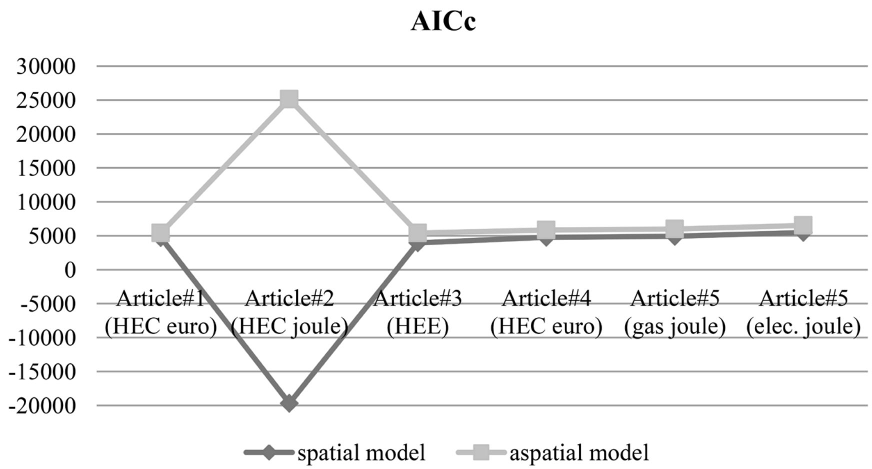

FIG. 7.2 Comparison between AICc of spatial and aspatial models.

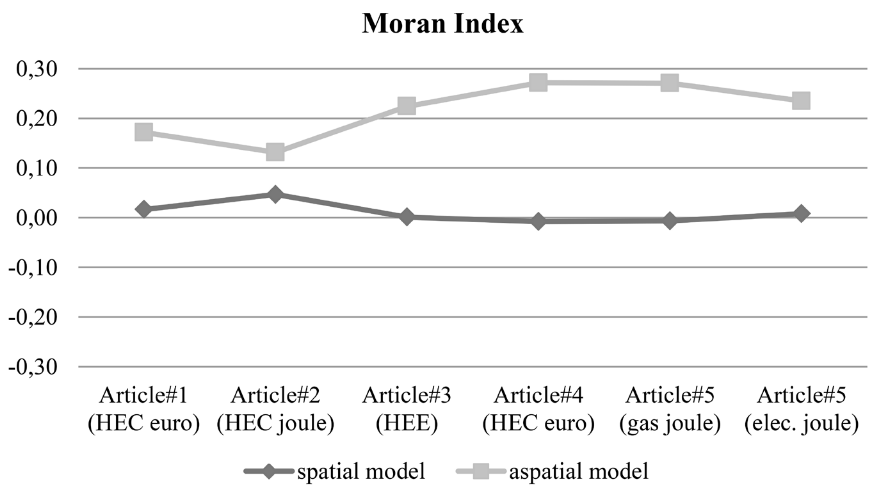

FIG. 7.3 Comparison between spatial distribution of the residuals of spatial and aspatial models

The comparison between R-squared, measures goodness-of-fit (i.e. the percentage of the variance of the dependent variable explained by the independent variables) of aspatial and spatial models show that the latter remarkably outperform the former. The R-square measures of aspatial models range from 45% to 67%, whereas those of spatial models is between 57% and 80%. The results show that by employing a spatial model, R-square of estimation increase between 10% and 25% – 14% in average (Figure 7.1).

The results show that in the models AICc is reduced by at least 660 points. A decrease more than three points in AICc is typically seen as a significant improvement. In this case, spatial models have a remarkably better performance (Figure 7.2).

Comparison between spatial distribution of residuals of the aspatial and spatial models, results of *Moran Index* test (a test in which the numbers closer to zero indicate more random spatial distribution), show that residuals of all spatial models are more randomly distributed than those of spatial models (Figure 7.3). It is found that residuals of all the spatial models is perfectly random whereas those aspatial models are spatially concentrated.

TOC

7.2.2 Bandwidth type, number of samples and coefficient of variations in spatial model

The spatial elements of the studies at the Netherlands scale are different from those in of the Randstad-scale studies. In the studies at the Randstad scale (chapter 5-6), the spatial elements are more fine-grained, i.e. *buurt*; whereas at the Netherlands-scale studies (chapter 2,3,4), the spatial elements are *wijk* (which is roughly consisted of 5 to 6 *buurt*). The reason for using a larger spatial element in the Netherlands-scale studies is that, if all the *buurts* of the Netherlands were fed into a GWR model, that is more than 10.000 *buurt* across the Netherlands, none of the software which are used, Arc GIS and GWR 4.0, would possibility be able to handle the analysis. Moreover, using 10.000 of *buurts* for a GWR study would result in high level of local multicollinearity which affect the quality of the results.

The difference between the spatial elements of the studies has resulted in use of two different bandwidth types for these studies:

The first type of bandwidth is Adoptive Bandwidth (in the case of the Randstad scale studies in chapter 5,6), that is the fixed number of closet neighbourhoods of the location in question. In the other words, in these studies number of locations included in every and each regression analysis of the GWR model is the same: 108 neighbourhoods (chapter 5.6.1, Table 5.2, page 201); 108 and 110, in case of gas use and electricity use models (chapter 6.7.1, table 6.2, page 229). The reason for use of adaptive bandwidth in case of the Randstad-scale studies is to ensure that every neighbourhood is compared with sufficient number of other neighbourhoods (buurt).

The second type of bandwidths are Fixed Bandwidth (the case of the studies on the Netherlands scale in chapters 2,3,4), that is a fixed metric distance from the location in question. In other words, in these studies the adjacent area of the location in question is consisted of the neighbourhoods which are no further than a specific metric distance: 13km and 11km (in case of GWR and SGWR models in Chapter 2.7.2, Table 2.5, page 108), 39km (Chapter 3.6.2, Table 3.3, page 142), 40km and 29km (in case of GWR and SGWR models, Chapter 4.5.2, Table 4.4, page 170). The reason for use of fixed bandwidth in case of the Netherlands-scale studies is that as the size of the *wijks* are significantly different in rural and urban areas, use of adaptive bandwidth would result in analysis of a very large area in case of the former, and a small area in case of the latter, and thus would bias the results.

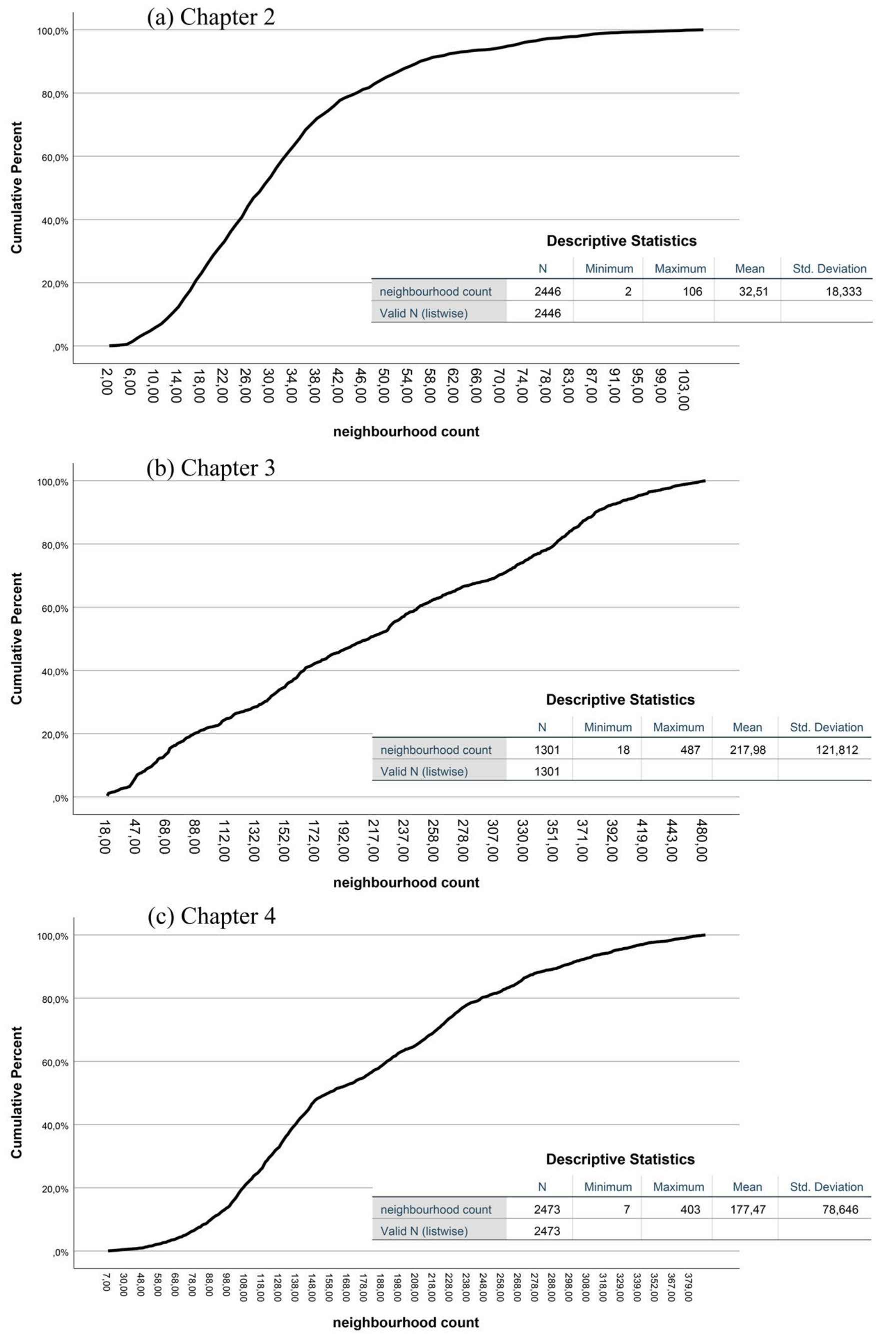

FIG. 7.4 Number of neighbourhoods (wijk) included in local regressions of the GWR models in the studies at the Netherlands scale in chapter 2 (a), chapter 3 (b), and chapter 4 (c).

Consequently, to use of Fixed Bandwidth type in the studies at the Netherlands scale, the number of wijk included in the local regression models vary from one location to another (see Figure 7.4). The average number of studied neighbourhoods in case of the studies in chapter 3 and 4 are large in size (218 and 177). The corresponding number in case of the study of chapter 2, however, is smaller in size (33).

The number of neighbourhoods in local regression models (buurt or wijk) raise another question about the performance of GWR models: how diverse are the values of independent variables within the bandwidth of a neighbourhood in question? And, whether or not such a diversity is large enough to draw conclusions considering the local impact of variables?

In order to search answers to these questions two measures are used:

$$Global\ CV(x) = \frac{SD(x)}{Average(x)}$$

EQUATION 7.1

$$Local\ CV(x_i) = \frac{SD(W_{ij}x_j)}{Average\ (W_{ij}x_j)}$$

EQUATION 7.2

where CV denotes coefficient of variation, as a measurement of diversity of the variable in question. x denote an independent variable in global model, and x_i denote that in location $\boldsymbol{i}$. x_j is magnitude of variable x in location j (within the bandwidth of location $\boldsymbol{i}$) and W_{ij} is the spatial weight denoting impact of location j on location $\boldsymbol{i}$. The measurement of the global and local CV values show that expect in case of the climate variables, the diversity of the variables in the local models in not smaller than those in global models (see Table 7.3).

TABLE 7.3 Coefficient of variation in the global models (orange cells), local variables in the local models (white cells) and global variables in local models (grey cells).

Chapter 2 (local and national determinants of HEC)										
	Income per capita	house-hold size	Building age	Surface to volume	Popu-lation density	Summer days	Frost days	Wind speed	LST	
N	2444	2444	2444	2444	2444	2444	2444	2444	2444	
Global CV	0,165	0,129	0,383	0,129	1,455	0,345	0,091	0,133	0,047	
Local CV Mean	0,124	0,111	0,324	0,115	1,182	0,040	0,010	0,128	0,035	
Local CV Median	0,115	0,108	0,304	0,113	1,128	0,040	0,010	0,127	0,035	
Local CV Minimum	0,022	0,017	0,053	0,019	0,280	0,002	0,001	0,033	0,004	
Local CV Maximum	0,340	0,296	0,694	0,251	3,050	0,106	0,030	0,300	0,095	
Chapter 3 (urban heat islands and HEC)										
	Income per capita	House-hold size	Popu-lation density	Building age	Surface to volume	Summer days	Frost days	Humidity	Wind speed	LST
N	1301	1301	1301	1301	1301	1301	1301	1301	1301	1301
Global CV	0,190	0,139	0,917	0,464	0,160	0,338	0,090	0,009	0,165	0,051
Local CV Mean	0,169	0,137	0,834	0,446	0,158	0,103	0,026	0,003	0,086	0,043
Local CV Median	0,169	0,135	0,794	0,460	0,156	0,110	0,028	0,003	0,091	0,043
Local CV Minimum	0,079	0,087	0,500	0,199	0,099	0,009	0,004	0,000	0,020	0,020
Local CV Maximum	0,268	0,213	1,429	0,596	0,198	0,228	0,057	0,008	0,165	0,055
Chapter 4 (energy poverty)										
	house-hold size	Private rent (%)	Low income (%)	Unem-ployment (%)	Pension-er (%)	Building age	Summer days	Frost days		
N	2472	2472	2472	2472	2472	2472	2472	2472		
Global CV	0,131	0,431	0,137	1,640	0,300	0,389	0,342	0,096		
Local CV Mean	0,122	0,406	0,121	1,360	0,290	0,356	0,079	0,021		
Local CV Median	0,118	0,394	0,112	1,272	0,283	0,340	0,084	0,021		
Local CV Minimum	0,058	0,250	0,054	0,637	0,153	0,161	0,006	0,003		
Local CV Maximum	0,202	0,567	0,222	2,614	0,485	0,609	0,175	0,051		

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TABLE 7.3 Coefficient of variation in the global models (orange cells), local variables in the local models (white cells) and global variables in local models (grey cells).

Chapter 5-6 (Randstad-scale: energy expenditure, gas use, electricity use)					
	FAC1: Urbanity	Fac2: Income	FAC3: house-hold size	FAC4: building age	FAC5: building compact-ness
N	2413	2413	2413	2413	2413
Global CV	6,240	61,318	-25,129	17,592	-5,354
Local CV Mean	3,225	40,884	-6,650	0,164	-40,685
Local CV Median	1,918	1,796	-2,179	1,813	-1,480
Local CV Minimum	-773	-62243	-2980	-3741	-97624
Local CV Maximum	4899	171060	1240	1132	915

Figure 7.5 shows the local coefficient of variations (CV) in case of the study of chapter 2, the study with in average 33 neighbourhoods included in every local regression, the smallest value between the studies. The result show that in more than 99% of the cases, local CV is larger than 1%, and thus independent variables in the local models are diverse (Figure 7.5).

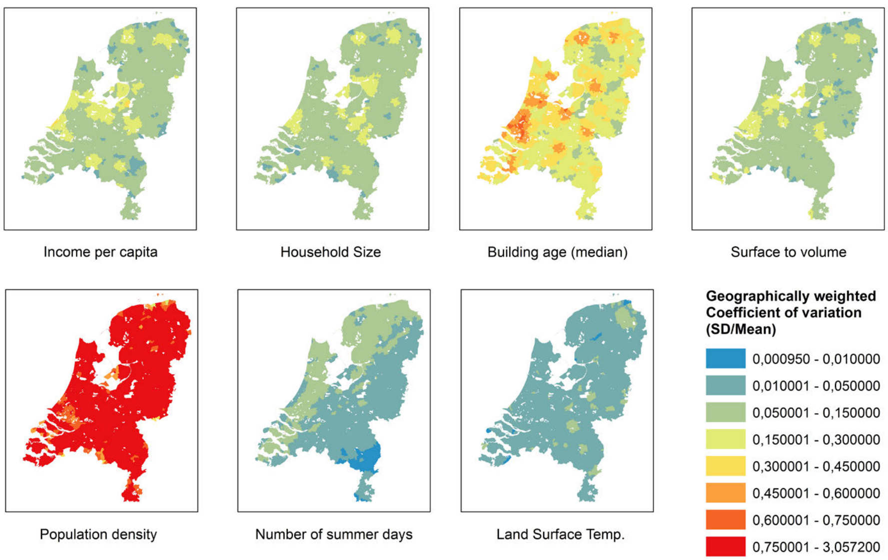

FIG. 7.5 Local coefficient of variation (CV) in the study of chapter 2.

7.2.3 Climate measures

The air temperature in the studies in the chapter 2, 3, 4 is quantified by means of two measurements: Summer day, that is the number of days with maximum temperature higher than 25 degrees, and frost days, that is number of days with minimum temperature below zero. The reason for use of these measurements instead of number of Cooling Degree Days (CDD) and Heating Degree Days (HDD) was the sensitivity of the latter measures to the so-called reference temperature.

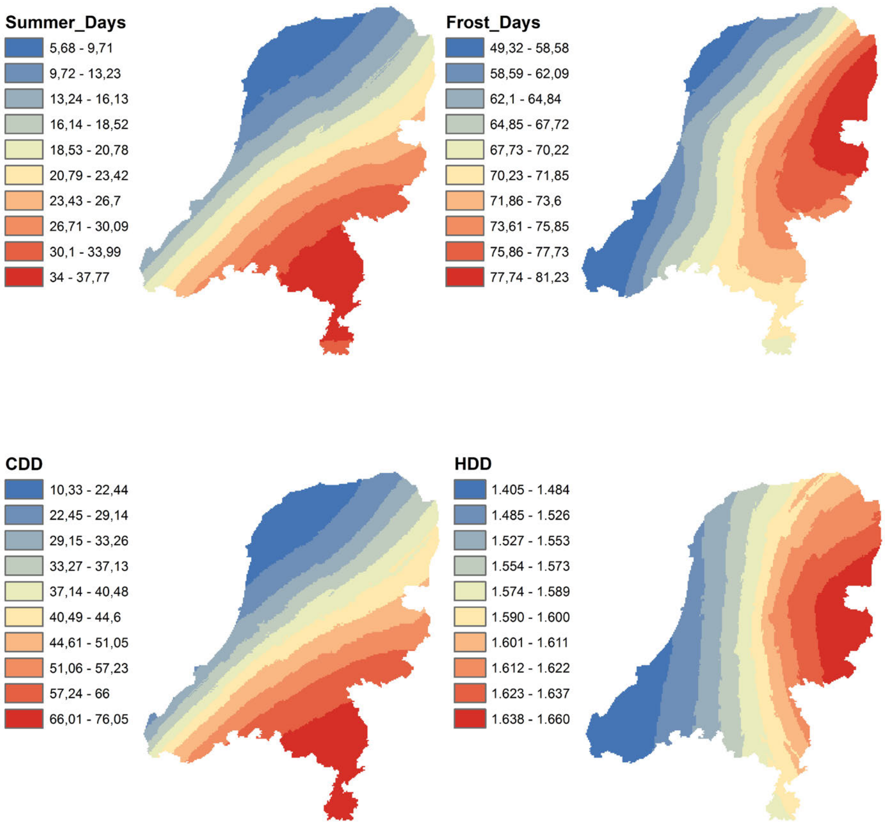

FIG. 7.6 Comparison between different measurements of air temperature summer day, frost days, cooling degree days (CDD), heating degree days (HDD).

Figure 7.6 show that in case the reference temperature for heating is set at 15,5 degrees, and that for cooling is set at 25 degree, the spatial distribution of the four measurements are similar to a large degree (i.e. CDD is similar with summer days, and HDD with frost days). The variation of the values of CDD and HDD however is very large across the country. The values of summer days and frost days are more homogenous. They, however, merely reflect the extreme cases, future studies could employ HDD and CDD by use of reference temperature specific to Netherlands.

In order to measure the intensity of wind, different measures are employed. In the studies at the Netherlands scale, chapter 2, ,3, 4, using the records at the 28 meteorological stations of KNMI, the wind speed at 10 Meters height is estimated. In the studies at the Randstad scale, given the fine-grained size of the spatial elements and the relatively fewer number of meteorological stations, see Figure 7.7 a, two morphological measurements are used as proxies for wind speed: (1) aerodynamic roughness length, calculated based on frontal density of buildings (Figure 7.7 b, c); (2) rugosity, i.e. the variation of building heights in a neighbourhood (Figure 7.7 d). The further studies could combine the meteorological and morphological measurements to address the wind intensity in a more detailed manner. The studies, in this regard, could use the data of meteorological stations to indicate the wind speed at 100 meters, and combine that with the detailed morphological data over aerodynamic roughness length and rugosity.

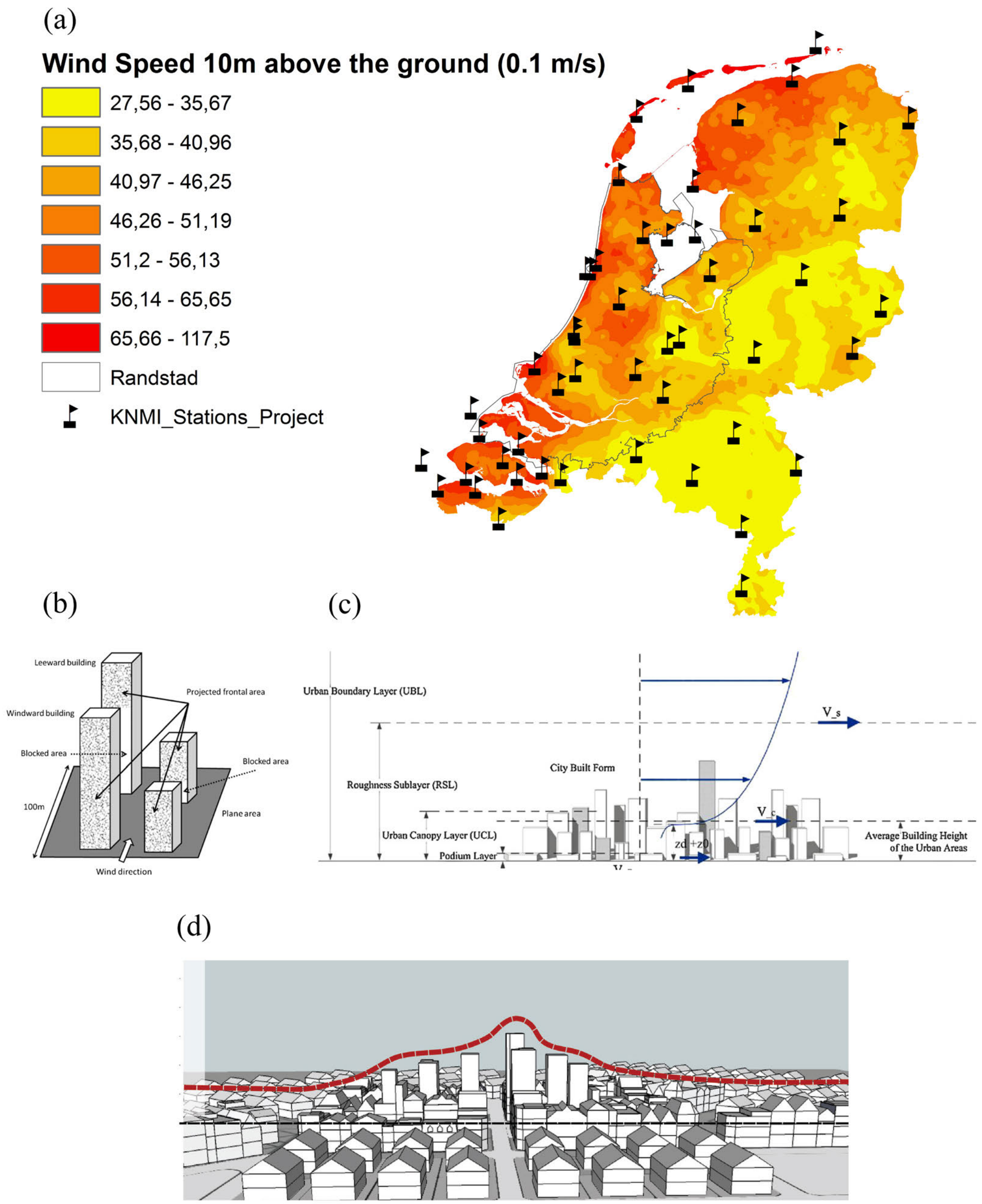

FIG. 7.7 Meteorological approach for calculation of wind speed (a) versus morphological measures: frontal density (b), aerodynamic roughness length (c), and rugosity (d).

7.2.4 Variation of energy price

Two of the studies are based on the energy prices in the Netherlands (chapter 2) and Randstad region (chapter 5). The studies are based on the average gas and electricity prices. Such prices, however, vary across different areas of the Netherlands as different energy companies and network companies offer different tariffs. The variation of tariffs is partially due to the different so-called gas and electricity regions where the different network companies are in charge of distribution of energy. Additionally, in a same neighbourhood the tariffs offered by different energy companies could differ up to 10%. Such a variation could have an effect on the results of the studies. However, as no source is available that indicates the average of price paid by the households of different neighbourhood, measuring such an impact is not possible. In order to improve the studies on the household energy expenditure and energy poverty in the Netherlands, a future survey on the price paid for energy across the Netherlands is essential.

7.3 Discussion: how to approach household energy consumption in the Netherlands

The results of the studies presented in this manuscript indicate that the effects associated to the majority of the determinants of HEC are local-specific. In the following sections, four implications developed by this finding for dealing with issues of HEC in the Netherlands will be elaborated.

7.3.1 Location-specific strategies in addition to one-size-fits-all policies

The national-scale policies regarding HEC in the Netherlands, which are defined by the Third National Energy Efficiency Action Plan for the Netherlands (2014), introduce an identical set of incentive and regulations for all areas of the country as that the stimuli of ....HEC are similar in every location of the Netherlands, and therefore it is possible to formulate an identical set of incentives and regulations which is optimally suitable throughout all the locations of the country. The results of the five studies show that validity of such a presumption is questionable at best. It is therefore established that determinants of HEC and HEE in the Netherlands could be categorised in two types: global determinants and local determinants. It is also established that the nature and magnitude of the impact of the local-specific determinants varies across the neighbourhoods of the Netherlands. Therefore, these policies need to be amended in order to accommodate this fact, which is that a rigid set of policies could not optimally be suitable for all local circumstances of the country. The most effective way to reduce the HEC of a neighbourhood can differ due to location-specific circumstances such as socioeconomic patterns, climate, levels of urbanization, land cover, and housing stock. These policies that aim at reduction of HEC and HEE need a shift in their perspective: that these one-size-fits-all policies (which are suitable for addressing the global determinants of HEC) need to be completed by location-specific strategies (which are designed for location-specific circumstances).

This finding also urges for the diversification of policy instruments regarding to the reduction of HEC in the Netherlands. These instruments make measurements that are based on the energy efficiency of buildings, which is the keystone of almost all of their introduced incentives and regulations. Policies need to break through their narrow perspective regarding building energy efficiency and take more multidimensional approaches in addressing energy poverty, urban microclimate, sociodemographic trends, and urban form. Household energy consumption within dwellings is not only just about the dwellings, therefore policies that manage them should not be either. In the next parts of the report, some points of focus for the elaboration of policies regarding the reduction of HEC will be discussed.

7.3.2 Energy poverty, a neglected dimension

Policies regarding HEC in Netherlands turn a blind eye on the affordability of energy expenditures for households, just as far as their access to energy is not denied. Energy policies in most of the EU states have considered both the vulnerability of households to meet their primary needs, as well as the affordability of energy expenditures. Dutch policies, however, have not followed suit. Policies in the Netherlands merely differentiate between consumers that are vulnerable from others that are not. A vulnerable consumer is designated as a person whose supply of electric or gas has been halted by an energy supplier, and thus her/his health is being put at risk. The result of this study shows that there is a strong association between the household energy expenditure (HEE) in the neighbourhoods of the Netherlands and the presence of potentially vulnerable social groups. This result marks bringing the issue of energy affordability into the policies regarding household energy consumption in the Netherlands an urgent matter. The current policies merely spread a safety net for vulnerable consumers whose health is in danger caused by a lack of access to energy. This net needs to be spread further in order to protect all households whose well-being has been affected by the heavy burden of energy expenditures. Currently, the underlying objective of the Third National Energy Efficiency Action Plan is to reduce the environmental damages related to energy consumption. This perspective is way too narrow, and future policies need to add a reduction of social damages to their approach.

It is found that there is a global association between HEE and presence of two social groups: low-income inhabitants and pensioners. The results indicate that there are some local associations between HEE and four characteristics of neighbourhoods: household size, percentage of unemployment, building-age, and percentage of privately rented dwellings. Policies need to accommodate this fact: as determinants of HEE could be global or local, policy measures need to be more diverse in their spatial definitions and intended implications. To do so, two types of policy measures could be adopted: first, policy measures need to aim to protect particular vulnerable groups (i.e. low income and pensioners) of all the neighbourhoods of the country; second, policy measures should aim to offer support which is more specific to some neighbourhoods. In order to implement the latter, it is essential to monitor whether particular social groups in a neighbourhood (i.e. larger households, renters of private tenures, unemployed, and dwellers of low energy efficient buildings) spend a large portion of their income to meet their energy expenses.

A potential notion is that HEE could be employed in order to prioritise neighbourhoods for implementation of the actions introduced by the Third National Energy Efficiency Action Plan for the Netherlands (Ministry of Economic Affairs, 2014). For instance, the policy has allocated a €400 million fund towards the improvement of the energy efficiency of privately rented buildings. A new policy regime could bring a spatial dimension to this allocation by prioritising dwellings in which HEE is high. Other potential polices which could be put forward could use HEE as a basis for the spatial prioritisation of the block-by-block approach, large scale projects proposed by the policy document intended to improve energy efficiency of the existing housing stock.

7.3.3 Aging population and mitigation of lonely at home hours

The results of all five studies indicate that household size and an inhabitant's age have a considerable impact on both HEC and HEE. The results show that in a majority of neighbourhoods, the presence of larger households with children younger than 14 years old are associated with lower levels of energy consumption per capita. The other side of this coin states that the presence of single-person households and/or senior citizens could raise the level of consumption.

In this respect, given the projected demographic trends in the Netherlands that shows an increasing number of single-person and retired households, HEC is set to rise in the future. According to Dutch Central Bureau of Statistics (CBS) projection, the average household size in 2060 will be around 2.08 persons (compared to 2.25 in 2011), while single-person households will account for 44% of all households (compared to 36% in 2011). Furthermore, nearly half of one-person households are expected to be older than 65 by the year 2050 (compared to just 31% in 2011) (Centraal Bureau voor de Statistiek, 2011).

These trends could bind HEC policies and urban planning together, as the latter could contribute to altering the time-use of these ever shrinking and aging households by encouraging co-presence in so called 'third places'. A 'third place,' which is a coined term found in the book *The Great Good Place* written by an American sociologist named Ray Oldenburg, refers to places other than one's living place (termed 'first place') or place of work (or 'second place') that "hosts the regular, voluntary, informal and happily anticipated gathering of individuals" (Oldenburg, 1999, p. 16). In addition to major social impacts such as overcoming loneliness and the related improvement of mental health (Oldenburg, 1999), which is a significant problem particularly found among senior citizens (Rosenbaum et al, 2009), a regular co-presence in third places could decrease HEC due to issues dealing with economies of scale. Given that a range of urban functions can serve as third places, such as cafés, restaurants, and health clubs (Rosenbaum et al, 2009), proposing clear-cut planning advice for promoting third places is complicated, as requirements for diversity shift from one place or target group to another (Oldenburg, 1999). In collaboration with local communities, planning documents need to be developed that introduce location-specific incentives which could facilitate the emergence of third places.

7.3.4 Bringing urban heat island effect into HEC policies

It is established that land surface temperature (LST) significantly affects HEC of almost one third of Dutch urbanised neighbourhoods: HEC of 31% of Dutch urbanised neighbourhoods is significantly affected by LST, and LST account for 6% of total energy consumption in these neighbourhoods. Given projected climate scenarios prepared by the Royal Netherlands Meteorological Institute (KNMI, 2015), the effect mentioned above could see an increase in the coming years. Scenarios suggest that average temperatures in Netherlands could increase up to 2,3 degrees Celsius, and exposure to solar radiation may increase up to 1,6 %. Coupled with the rise of population groups that are more sensitive to heat waves, HEC policies need to address the issue of urban heat islands: tackling LST desperately needs to be part of the solutions that have been proposed by HEC policies.

The policies aimed at reducing HEC need to find an appropriate approach to accommodate the reduction of LST. On one hand, the impact of LST on HEC is not as important as that of building energy efficiency and building regulations. It is because of that that their position in the policy documents should not be as prominent. However, in particular situations where LST largely affects HEC, as well as the health of inhabitants who are particularly susceptible in heat waves, some of the resources assigned for the reduction of HEC could be used for the alleviation of LST. The resources assigned by the Third National Energy Efficiency Action Plan for the Netherlands (2014) are considerable, among them being a €400 million fund allocated for the improvement of subsidized rental private sectors, and around €185 million worth of central government low-interest loans for the owners of the buildings themselves. A reduction of LST could be achieved at a relatively low cost, and could be done by just simply increasing both green and permeable surfaces in the cities of the Netherlands (Mushore et al., 2017; Hang and Rahman, 2018; Garuma et al., 2018). This could be achieved by using a small part of the allocated funds that in extreme cases could be assigned for this purpose. The approach to urban planning and design, respectively, could be altered in order to accommodate mitigation of urban heat islands as one of the priorities (e.g. Echevarría Icaza et al., 2016).

7.4 Conclusion

The results these five studies indicate that impact of most of the determinants of HEC are local and vary across different neighbourhoods in the Netherlands and Randstad region. The significant presence of location-specific determinants is likely to be due to the interaction between the different determinants of HEC, meaning that not only do the determinants affect HEC, but also they affect one another in one way or another. To conceptualize these various interactions among the determinants, the following eleven links could be established in order to explain them (Figure 7.8):

1. Housing typologies are affected by land parcellation and building density in a neighbourhood (Smith et al., 2005).
2. Residential location choice of households is affected by properties of the urban form, such as urbanity, accessibility, and green spaces (Bayoh et al., 2006).
3. The time use of residents (e.g. hours spent at home) differ between urban and rural areas (Heinonen et al., 2013; Yu et al., 2013).
4. Building densities and street patterns affect population density, travel behaviour, and consequently the functional mix of neighbourhoods (Hoppenbrouwer and Louw, 2005; Hillier, 2007);.
5. The geometry of buildings and the land cover they provide affect the characteristics of the urban microclimate, such as wind, land surface temperature, and humidity (Sanaieian et al., 2014; Erellet al., 2012).
6. The architecture of buildings could facilitate (or block) the mixing of functions at both the block and neighbourhood scales (Kliment and Barr, 2004).
7. The attributes and prices of dwellings attract different types of households (Kim et al., 2005), and therefore can determine the socioeconomic status of these households which, in turn, affecti the size of investment in the buildings (Bouzarovski, 2009).
8. The location choice of different socioeconomic groups is affected by the accessibility to various amenities in their context. In turn, location choice of these amenities is associated with the social patterns of neighbourhoods (Guo and Bhat, 2007).
9. The time-use of households differs in response to family size, age group, income, employment, etc. (Kang and Scott, 2010; Lee et al., 2007).
10. The mix and use of land affects the time which is used for different social and recreational activities outside of dwellings (Bhat, 2005).
11. The urban microclimate affects the comfort of outdoor spaces and alters how residents use their time (Nikolopoulou, 2001).

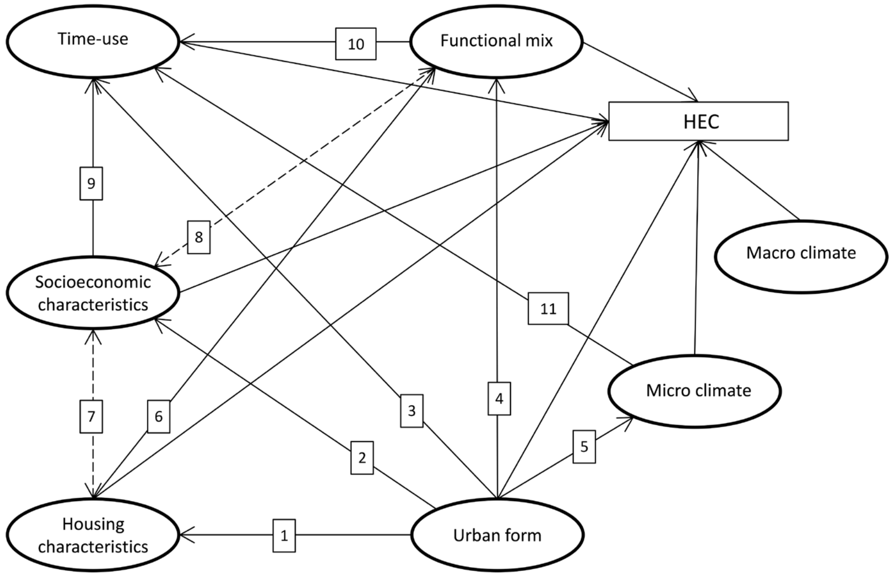

FIG. 7.8 Interactions between the determinants of HEC.

Given all the interactions that exist among the determinants of HEC, there is a need to explain the variety of impacts that HEC determinants can have in different neighbourhoods. These effects can be understood and elaborated by making the following two mechanisms:

1 The interactions between different determinants of HEC may vary in different geographic contexts. For instance, the associations between socioeconomic characteristics and housing characteristics could be different, or even opposite, in different cities. Take housing choice of high income household as an example. in the city of Amsterdam, the buildings with the lowest energy levels of energy efficiency, located by the canals in the historic city center, could be attractive to the household with the highest levels of income. In contrary, in the south parts of the city of Rotterdam, the most energy efficient buildings, high rise buildings constructed through a process of gentrification initiated in the 90s, are presumably the only buildings attractive to high income residents. In this respect, under different circumstances, the interactions between two of the most influential determinants of HEC could be entirely opposite: attraction of high income to low energy efficient buildings, in case of the former, and attraction of high income households to high

energy efficiency buildings, in case of the latter. This could potentially result in different associations between HEC and income. In the former case, HEC of the high income residents of the neighbourhoods in question may widely outnumber that of other residents. Whereas, in case of the latter, this gap may be narrowed or even closed.

2 Every determinant of HEC has multiple, and sometimes opposite, impacts on HEC –i.e. some of the impacts may contribute to higher level of HEC, whereas some could contribute to lower levels. The overall impact of a determinants, the trade-off between its contradicting effects, could result from the locality of HEC determinants. For instance, higher building density is associated with a higher compactness of building volumes, which is associated with lower levels of HEC. Meanwhile, higher building density could be coupled with a lesser amount of sunlight hitting the buildings, which can have two opposite impacts: it may boost the energy consumed for space heating, or it may also decrease the energy consumed for space cooling. The density factor could also potentially affect wind speed in a neighbourhood, which could also lead to two contradicting effects. Higher levels of wind speed could result in increased air infiltration and exfiltration of buildings, consequently supressing their ability to mitigate heat loss. Meanwhile, a lower wind speed could increase energy consumption for the ventilation of houses. The overall impact of building density, therefore, could vary from one location to another, as the trade-off between its contradicting effects of HEC does.

7.5 Final reflection

In the last few decades, many studies, including this thesis, have examined the geographical factors which contribute to reduction of household energy demand. However, one crucial point is often forgotten: the reduction of energy demand should not be the objective per se. The objective should be to reduce the environmental burdens of energy consumption, such as harmful emissions (particularly CO2 but other pollutants as well). In this respect, future empirical studies need to focus on the overall potential for the reduction of emissions through various mechanisms, particularly in terms of the management of energy demand, and shifts in energy sources. To do so, the main factors which influence energy consumption in different neighbourhoods need to be detected, and location-specific solutions for more energy efficient consumption need to be elaborated. Second, the potentials for low-emission energy supply (including heat pumps, AC electricity, DC electricity produced by solar panels, and industrial waste heat recovery) need to be assessed and implemented. Life Cycle Analysis is one means of assessing the embedded emissions associated with the production, implementation, and performance of such changes. By addressing both the embedded emissions of energy sources and the management of energy demand, future studies need to identify solutions to achieve reductions in total emissions within certain reasonable costs. As a result, location-specific strategies need to be developed which offer a phasing for the reduction of emissions in different locations of the country, region and city. This approach is crucial for reducing the environmental burdens of energy consumption and promoting more sustainable cities.

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Curriculum Vitae

Bardia Mashhoodi

Date of Birth: 24 November 1980
Place of Birth: Tehran, Iran
Citizenship: Iranian / Dutch

Willebrordusstraat 34D
3037 TS Rotterdam, Netherlands
+31 - (0)6 34 91 68 83
b.mashhoodi@tudelft.nl

Education

2010 – 2019 Delft University of Technology, Delft, Netherlands
PhD, with a thesis entitled *spatial Dimension of Household Energy Consumption.*

2008 – 2010 Delft University of Technology, Delft, Netherlands
Master of Science in Urbanism

1999 – 2007 Azad University, Central Tehran Branch, Tehran, Iran
Bachelor of Science in Architecture Engineering

1999 – 2005 Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran
Bachelor of Science in Industrial Engineering, specialized in system analysis and programming

Research Experience

	Project	Role
2010	*An analysis of the optimum location for new bridges on the river Maas* TUDelft (funded by the municipality of Rotterdam)	Member of research team
2011 – 2013	*RDSS (Rotterdam Decision Support System)*, developing a GIS-based decision support system for Rotterdam South TUDelft (funded by the municipality of Rotterdam)	Researcher in charge of the project
2013 – 2014	*Better Airport Regions* TUDelft (funded by NWO)	Member of research team
2014 – 2015	*Understanding residential energy consumption and energy poverty in the Randstad region* TUDelft (3TU-funded) PdEng thesis, as a pilot test for the adaption of PdEng degree in the Faculty of Architecture and the Built Environment	PdEng researcher (pilot PdEng thesis for Faculty of Architecture and the Built Environment)
2017 – 2018	*COHESIFY*, studying the impact of EU cohesion policy on European identification TUDelft (funded by Horizon 2020)	Member of research team
2016 – 2019	*DCSMART*, studying Distribution Smart Grids TUDelft (funded by ERA-NET Horizon 2020 programme)	Member of research team
2019 –	Post-doctoral researcher and lecturer (TU Delft)	

Teaching

	Institution	Course
2016 – 2018	TUDelft, Faculty of Architecture and the Built Environment	Course of *Design and Planning Support Tools* as part of the curriculum of postgraduate master of urbanism (EMU) and part of the graduate school courses for PhD candidates
2016 – 2018	TUDelft, Faculty of Architecture and the Built Environment	Course of *An introduction to GIS Analysis*, a supplementary course for MSc graduation students
2016 – 2018	TUDelft, Faculty of Architecture and the Built Environment	Course of GIS and cartography in the fifth semester of bachelor studies, minor programme of Neighbourhoods of Future
2016 – 2017	Erasmus University Rotterdam, IHS Institute	A two-session course of *An introduction to Road Network Analysis*, part of a lecture series for MSc graduation students
2018 –	Erasmus University Rotterdam, IHS Institute	A two-session course of *An introduction to Spatial Statistics and Geographically Weighted Regression*, part of a lecture series for MSc graduation students

Mentoring Experience

	Institution	Role
2018	Erasmus University Rotterdam, IHS Institute	Masters graduation thesis of Alam Wijaya Senopati, entitled *The Impact of Street Connectivity and Public Transport Accessibility on Location Choice of FDI in Central Jakarta: Application of Geographically Weighted Regression*
2018	Erasmus University Rotterdam, IHS Institute	Masters graduation thesis of Maureen Waikinda entitled *The Influence of Road Network Centrality on the Attraction of Foreign Direct Investment in Africa*

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19#05

The Spatial Dimension of Household Energy Consumption

Bardia Mashhoodi

The vast majority of previous studies on household energy consumption (HEC) has presumed that the influencing factors of HEC are similar in each and every location regardless of the location-specific circumstances. In other words, they assume that some generalizable facts explain the level of HEC and energy poverty across all areas of a city, country, region, and/or continent. At the national scale, the Third National Energy Efficiency Action Plan for the Netherlands, regarding the reduction of household energy consumption has introduced a variety of policy measures and incentives for reduction of HEC among them energy tax, reduction on VAT rate on labour cost of renovation of dwellings, energy saving agreement for rental sector, etc. Furthermore, the policy document emphasise that the geographic scope of all policy measures is "the Netherlands".
In this respect, Third National Energy Efficiency Action Plan for the Netherlands, introduce an identical set of measures and instrument for all areas of the Netherlands regardless of their location-specific circumstances. The objective of this thesis is to examine the validity of this presumption through five different studies four of which published as a scientific journal, and one of which is accepted for publication. To do so, the impact of a variety of the determinants of HEC of the Dutch neighbourhoods are studied and compared. The result of the studies shows that the impact of such determinants is spatially homogenous (i.e. similar across all neighbourhoods in question) or spatially heterogeneous (varies from one neighbourhood to another).

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