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Original research paper

Who is more dependent on gas consumption? Income, gender, age, and urbanity impacts

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ABSTRACT

A Dutch household is two times more dependent on gas than an average European Union household. The Dutch Climate Agreement targets phasing out households' gas consumption before 2030. However, it is unclear who will be affected by this policy. Controlling for various building and climate factors, this study analyses the associations between socioeconomic characteristics of households, Gas-use, i.e. annual gas consumption per capita, and Gas-dependency, i.e. the share of gas from total household energy consumption, in the residential zones of the Netherlands in 2018. As a result, three types of socioeconomic groups are identified: (1) more gas-use and more gas-dependency, including low-incomes, high-incomes, the population age 65 or more; (2) more gas-use and less gas-dependency, including the population age 14 or younger; (3) less gas-use and less gas-dependency, including large households, the population age 15–24, immigrants, females, urban households, and tenants. It shows that Gas-use and Gas-dependency spatial patterns do not necessarily overlap, and the simultaneous study of the two variables is essential. It offers a series of policies for gas-intensive groups: progressive energy tax (high incomes), safety net against energy poverty (low incomes), Third Places and local communities (senior citizens), demand response management (population younger than 14 years old).

1. Introduction: gas dependency of households in the Netherlands and its neglected socioeconomic geography

Household gas consumption in the Netherlands is double of European Union average (Fig. 1). Gas accounts for almost 71% of household energy consumption in the Netherlands compared to 32% in EU-27 member states in 2017 (Eurostat, 2018). The dependency of Dutch households on natural gas can be traced back to 1959 when the discovery of a large-size gas field in the Northern parts of the country, the so-called "Groningen" or "Slochteren" gas field, set implementation of nationwide gas infrastructure and gradual connection of all Dutch households to the gas grid in motion. The highly liberalised and competitive energy market of the Netherlands created a situation in which energy companies compete to reduce tariffs and expand their market share. Subsequently, Dutch households' per capita GHG emission was 37% higher than the EU-28 average in 2016 (European Energy Agency, 2018). Acknowledging Dutch households' dependency on natural gas, the Dutch National Climate Agreement urges for phasing out gas consumption in the residential sector before 2030 (Ministry of Economic Affairs and Climate Policy, 2019).

Phasing out gas could deprive households of a cheap energy source and force many of them to use electricity as a more expensive source of energy. Gas accounts for 86%, 66% and 89% of the energy used for space heating, cooking and water heating in the Netherlands (Eurostat, 2020). In 2018, according to EPOV's report on energy poverty in the Netherlands, 10.7% of Dutch households spent a high share of their income on energy expenditures (EU Energy Poverty Observatory, 2020a). Phasing out gas can significantly increase this portion, given that the difference between gas and electricity prices will persist for the coming decade. According to EU Energy Poverty Observatory (EPOV) data on energy prices, the households' gas price in the EU has decreased since 2015. In contrast, households' electricity price has been almost stagnated (EU Energy Poverty Observatory, 2020b). Low-income households and ethnic minorities appear to be dependent on cheap and traditional fuel types (Nguyen et al., 2019). Energy-poor and low-income households are less likely to install solar panels and generate energy (Chapman & Okushima, 2019). Therefore, they are likely to remain dependent on purchasing energy sources more expensive than gas. The concerns over the possible increase in energy poverty lead to a crucial question: Who are the most gas-dependent households of the Netherlands – in terms of income, gender, age, family and ethnicity – and where do they live? The standpoint of this study is that identification of gas-dependent households and locations is the first step

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Abbreviations

$\widehat{\beta}(\mu, \vartheta)$	the unbiased estimate of the coefficient β in the GWR models
$\beta_0(\mu_i, \nu_i)$	the intercept of the GWR models specific to the zone *i*
β_0	the intercept of the OLS models
$\beta_k(\mu_i, \nu_i)$	the coefficient of independent variable *k* estimated specific to the zone *i*in the GWR models
β_k	the *k*th independent variable's coefficient in OLS models
ε_i	the random error term at the location *i* in the OLS models
Θ	adaptive bandwidth size in the GWR model
μ_i	longitude of the zone *i*
ν_i	latitude of the zone *i*
d_{ij}	geodesic distance between zone *i* and *j*
$W(\mu, \vartheta)$	spatial weight matrix quantifying the importance of the adjacent zones of the zone *i*
W_{ij}	is the weight assigned to the zone *j*in the estimation of the GWR
x_{ik}	the value of the independent variable *k* at the location *i* in the OLS and GWR models
y_i	the estimated value of Gas-use or Gas-dependency at the zone *i* in OLS and GWR model
0-14 y/o	the population aged 14 years or younger
15-24 y/o	the population aged between 15 and 24 years
65+ y/o	the population aged 65 years or more
AICc	Akaike Information Criterion
CBP	Dutch Central Bureau for Economic Policy Analysis
CBS	The Netherlands Bureau of Statistics
CDD	cooling degree days
DWH	domestic water heating
EPOV	EU Energy Poverty Observatory
Female	the percentage of females minus percentage of males in a residential zone
Gas-dependency	the share of gas from total Joules of gas and electricity consumption
Gas-use	annual gas consumption per capita (in Joules)
GWR	geographically weighted regression
HDD	heating degree days
KNMI	the Royal Netherlands Meteorological Institute
LNG	Liquefied natural gas
LPG	Liquefied petroleum gas
LST-day	Average land surface temperature at 10:30 a.m. and 1:30 p.m.
LST-night	Average land surface temperature at 10:30 p.m. and 1:30 a.m.
MACs	marginal abatement costs
NDVI	Normalized Difference Vegetation Index
OLS	ordinary least square regression
TM	mean monthly temperature
TN	minimum daily temperature
TOU	time-of-use
TX	maximum daily temperature
VIF	variance of inflation

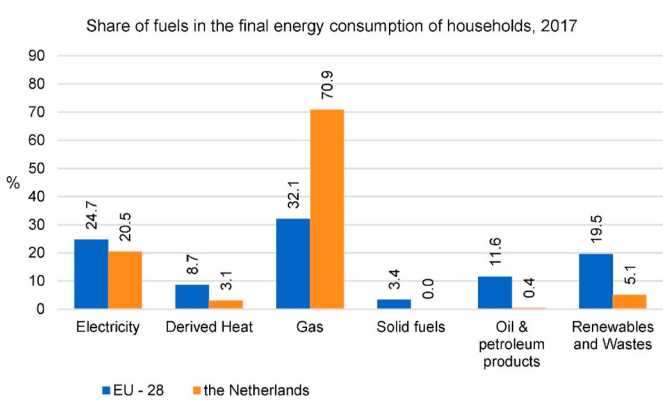

Fig. 1. Share of fuels in households' final energy consumption in the Netherlands and member states of EU27 for space heating, space cooling, water heating, cooking, appliances, and lighting – author's illustration based on Eurostat data (Eurostat, 2020).

for achieving an inclusive energy transition.

This research aims to study the socioeconomic geography of households' gas dependency in residential zones of the Netherlands in 2018. The manuscript is structured in eight main parts. First, a knowledge gap in the literature on gas consumption of households is presented, and the approach and objective of this study are explained. Subsequently, the method and data of the study are presented. The results are reported and discussed, and conclusions and policy implications are presented.

2. Literature review and knowledge gap

The previous studies on household gas consumption can be categorised into three types. The first type of studies solely focused on household gas consumption, regardless of its share of the total energy demand. Namazkhan et al. (2019) found that gas use for space heating in winters was significantly affected by individual characteristics and building quality. Li et al. (2021) showed that an increase in temperature and tariffs was associated with lower levels of household gas consumption and identified four temporal patterns of consumption: single point spike, double-point flat-peak, micro-peak and linear. Harold et al. (2018) studied the impacts of demand-side management on gas consumption. They concluded that demand stimuli had a more significant impact on high-income households rather than low-income households. Zhu, Zhang, Tao, and Yu (2015) found that gas prices had a larger impact on urban than rural households. Namazkhan et al. (2020) concluded that psychological factors significantly impacted the level of gas consumption, among them biospheric, egoistic, hedonic and altruistic values. van denBrom, Meijer, and Visscher (2017) found a significant gap in the actual and expected gas consumption of buildings with different energy labels. The authors disclosed that low-income households consume more gas than expected. Li et al. (2016) simulated the impact of time-of-use (TOU) gas pricing and concluded that TOU measures could control the peak demand load. Krauss (2016) showed that an increase in natural gas tariffs could push more households under the poverty line. Liu et al. (2018) concluded that price and income affected household gas consumption and forecasted a sharp increase in consumption by 2025 in China. Franco (2016) modelled the demand for natural gas based on socioeconomic indicators, urbanity, economic development, and weather. Panapakidis and Dagoumas (2017) developed a hybrid model using genetic algorithms and neural networks to forecast gas use at the metropolitan scale in Greece. Jiang et al. (2021) concluded that deregulation of gas prices would decrease China's carbon marginal abatement costs (MACs).

The second type of studies offered parallel analyses of different fuels, among them gas. However, these studies did not offer an insight into the gas share of households' energy consumption. Najmi, G, and Keramati (2014) analysed the impact of various factors on household gas and electric consumption, including socioeconomic characteristics, the energy efficiency of buildings and appliances, and the size of dwellings. A study on the Randstad region in the Netherlands compared the determinants of gas and electricity consumption, among them socioeconomic and urban form factors (Mashhoodi & van Timmeren, 2018). Morris, Allinson, Harrison, and Lomas (2015) developed two separated models for households' gas and electricity consumption, analysing the impacts of income, climate, and dwelling size. Zhang et al. (2021) studied the impact of economic growth on gas and electricity consumption. Wu et al. (2019) illustrated the energy profile of Chinese rural households by separated analyses of different energy sources, among them coal, electricity, LPG, wood. Ravindra et al. (2019) studied the trends in household energy consumption in India, considering different energy sources: firewood, biogas, LPG, and electricity. Adua (2020) analysed the annual gas and electricity consumption of households in the United States. Acharya and Adhikari (2021) studied Nepal's electricity, coal/briquette, LPG, and Kerosene consumption.

The third type of previous studies offered a perspective on the energy structure of households, i.e. share of different fuels of overall consumption. The studies, however, focused on the country- or regional scale and did not offer a spatial perspective at the neighbourhood scale. Wang et al. (2021) analysed the share of different fuel types, including LNG, electricity, coke, in Chinese provinces between 2005 and 2017. Zhou and Gu (2020) studied households' direct and indirect CO_2 emissions by coal, oil, natural gas, heat, and electricity consumption. Liu et al. (2021) analysed household energy structure and consumption of different fuels for transport, housing, food and clothing. Shi et al. (2019) decomposed households' energy structure to study spatial and temporal variations of carbon emissions at the regional scale. Niu et al. (2019) analysed the energy structure of rural households and offered policy implications for improving energy efficiency. Jiang et al. (2020) studied the determinants of gas consumption at the national and regional scales: GDP, urbanisation, energy intensity, energy structure, and economic structure.

There is a knowledge gap in the previous studies on households' dependency on gas consumption: the lack of comprehensive study at the neighbourhood scale taking the impact of socioeconomic, climate and urbanisation determinants into consideration and disclosing the spatial variation of such impacts across a large-scale territory, e.g. a country. The first two types of previous studies either analysed the combined consumption of fuels or conducted parallel analyses of different fuels, among them gas. These types of studies offered no insight into the dependency of households on gas. The third type of studies analysed the energy structure at the country- or regional scale. Given their large scale, these studies did not offer a detailed perspective on the socioeconomic characteristics and the exogenous impacts such as urban morphology, climate, urban heat islands. This study is an endeavour to bridge this gap. The following section illustrates the objective and approach of this study.

3. Objective and approach of this study

This study aims to bridge the knowledge gap in the previous studies. To do so, it defines two indicators for gas consumption at the neighbourhood scale:

a. Gas-use: annual gas consumption per capita (in Joules);
b. Gas-dependency: the share of gas from total Joules of gas and electricity consumption.

The study puts two research questions forward: first, what socioeconomic characteristics affect Gas-use and Gas-dependency at the neighbourhood scale, controlled for climate factors? Second, are socioeconomic groups' Gas-use and -dependency similar across all neighbourhoods of the Netherlands, or do they vary from one neighbourhood to another?

In order to find answers to these questions, ten socioeconomic characteristics of the residential zones of the Netherlands in 2018 are quantified and studied:

1. Household size, as it is related to the economies of scale in the use of energy, as well as number of children and the purposes of energy use (Middlemiss & Gillard, 2015; Anderson et al., 2012);
2. The presence of low-income inhabitants, associated with the lack of investment in building maintenance (Langevin et al., 2013), use of appliances with low energy efficiency (Xu & Chen, 2019), and difficulties with affording energy bills which may affect the pattern of consumption (Cayla et al., 2011);
3. Presence of high-income households, associated with living in relatively larger dwellings (Estiri, 2014), relatively higher levels of investment in building maintenance (Trotta, 2018), seeking for higher levels of comfort rather than reduction of energy expenditures (Cayla et al., 2011);
4. The population younger than 14 years old, associated with high energy consumption for space heating (Braun, 2010) and water heating (Fuentes et al., 2018), and the ratio of gas and electricity consumption of a household (Brounen et al., 2012);
5. The presence of population aged between 15 and 25 years old, associated with higher-than-average time use for leisure (Roeters, 2018), and lower-than-average time use for house care (Roeters, 2018), and high levels of electricity consumption (Bartusch et al., 2012);
6. The presence of population older than 65 years old, due to the difference between thermal comfort of elderlies and other age groups (Schellen et al., 2010) and extensive hours spent on personal care (Roeters, 2018);
7. The percentage of females, associated with different energy-saving behaviours and energy-efficiency investments (Trotta, 2018), perception of thermal comfort (Petrova et al., 2013), and type of employment in the labour market (The World Bank Group, 2020);
8. Immigrants, associated with low-quality dwellings (Hartog & Zorlu, 2009) and low income compared to the Dutch average (CBP, 2019);
9. Urbanity, associated with lifestyle (Heinonen et al., 2013) and the levels of energy consumption (Mashhoodi, Stead, & van Timmeren, 2020);
10. Tenants, associated with dwellings' quality and frequency of maintenance (Filippidou et al., 2016; Vringer et al., 2016).

In addition to the socioeconomic variables, seven types of control variables are included in the analysis:

1. Building age, as a proxy for energy efficiency of the dwellings (Brunner et al., 2012; Fahmy et al., 2011);
2. Building surface to volume ratio, affecting thermal transfer between indoor and outdoor space (Bernabé et al., 2015; Steemers & Yun, 2010);
3. Number of heating and cooling degree days, associated with energy consumption for space heating, space cooling and water heating (Wiedenhofer et al., 2013; Reinders et al., 2003);
4. Humidity, given its effect on the felt temperature (Alfano et al., 2011; Chow et al., 2010);
5. Wind speed, associated with ventilation and thermal loss of dwellings (Sanaieian et al., 2014; van Moeseke et al., 2005);
6. The presence of vegetated land cover, associated with the felt temperature (Taleghani, 2018; Letu et al., 2010);
7. Land surface temperature, associated with energy consumption for space heating- and cooling (Santamouris et al., 2001; Hassid et al., 2000) and variations of such associations across socioeconomic groups (Mashhoodi, 2020).

In the next part, the study's method and data are described.

4. Method

The statistical method of this study is geographically weighted regression (GWR). There are three reasons for the application of GWR. The first reason is that the data available to the public on energy consumption and socioeconomic indicators are aggregated at the scale of residential zones due to privacy limits. Therefore, it is essential to adopt a statistical model accounting for spatial autocorrelations. An aspatial model, e.g. ordinary least squares regression (OLS), ignores the spatial autocorrelation and results in spatially clustered residuals and biased results. Second, the GWR model has two advantages over other spatial models, i.e. spatial lag and spatial error. The GWR model offers coefficients specific to each residential zone, illustrating location-specific impacts, highly beneficial for policymakers. Additionally, there is no argument supporting that gas consumption in one zone affect that of its adjacent zone (the assumption for spatial lag models), or there is an unobserved factor that is spatially clustered (the assumption of spatial error models).

The methodology of this consists of two steps. First, an ordinary least square model (OLS) is adopted. The model aims to measure the variance of inflation (VIF) of the independent variables and assess the potential multicollinearity between them. Equation (1) shows the specification of the OLS:

$$y_i = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i \tag{1}$$

y_i represents the estimated value of Gas-use or Gas-dependency at the zone i, β_0 and β_k respectively show the intercept and the kth independent variable's coefficient. β_k represents the increase in Megajoules of Gas-use, or the percentage of Gas-dependency, in return for one unit increase in the value of independent variable k. x_{ik} is the value of the independent variable k at the location i and ε_i is the random error term. Subsequently, in order to assess the spatial variation of impacts, a geographically weighted regression model (GWR) is developed:

$$y_i = \beta_0(\mu_i, \nu_i) + \sum_k \beta_k(\mu_i, \nu_i) x_{ik} + \varepsilon_i \tag{2}$$

where (μ_i, ν_i) denotes the longitude and latitude of the zone i. $\beta_k(\mu_i, \nu_i)$ and $\beta_0(\mu_i, \nu_i)$ are the coefficient and intercept of independent variable k estimated specific to the zone i. $\beta_k(\mu_i, \nu_i)$ estimates the increase in Megajoules of Gas-use, or the percentage of Gas-dependency in the zone i, when the value of independent variable k increases for one unit. Location-specific coefficients are calculated as follow:

$$\widehat{\beta}(\mu, \vartheta) = \left(X^T W(\mu, \vartheta) X\right)^{-1} X^T W(\mu, \vartheta) y \tag{3}$$

where $\widehat{\beta}(\mu, \vartheta)$ represents the unbiased estimate of the coefficient, β, and $W(\mu, \vartheta)$ is the spatial weight matrix, quantifying the importance of the adjacent zones of the zone i. $W(\mu, \vartheta)$ is an adaptive bisquare spatial weight matrix, formulated as follows:

$$W_{ij} = \begin{cases} \left(1 - \dfrac{d_{ij}^{2}}{\theta}\right)^2, \ if\ d_{ij} < \theta \\ 0, \ otherwise \end{cases} \tag{4}$$

W_{ij} is the weight assigned to the zone $j$in the estimation of the GWR model specific to the zone i. d_{ij} is geodesic distance between zone i and j. θ represents the adaptive bandwidth size of the spatial weight matrix: the number of closest zones included in the calculation of W_{ij}. The optimal value of θ is set at the value that minimises the GWR model's corrected Akaike Information Criterion (AICc).

5. Data and case study

5.1. Dependent variable and case study

This study's spatial elements are the residential zone, the so-called wijken in Dutch, of the Netherlands in 2018. The zones are administrative boundaries defined by The Netherlands Bureau of Statistics (CBS), for which socioeconomic and energy consumption data are available. The zones equipped with district heating and those with an abnormally high or low Gas-use or Gas-dependency (absolute standardised values greater than 2.5) are excluded from the study. The study includes 2707 zones. Fig. 2 shows the dependent variables: Gas use per capita (MJ), and Gas dependency (%), i.e. the gas share from the total annual megajoules of gas and electricity consumption (author's mapping based on CBS, 2018).

5.2. Independent variables: the socioeconomic characteristics of Dutch households

This study uses ten independent variables. *Household size* represents the average size of families in the zones. *Low-income* and *High-income* show the percentage of inhabitants among the lowest 40% or the highest 20% levels of income. Three variables represent the percentage of inhabitants in different age groups: *Population age 14 or younger*, *Population age 15–24*, *Population age 65 or older*. One variable reflects the gender mix of the neighbourhoods: *Female*, i.e. the percentage of females subtracted by the percentage of males in a neighbourhood. *Immigrants* (%) is the total percentage of the residents designated as Western or Non-Western immigrants. Western immigrants have at least one parent from the EU, US, Canada, Japan, Australia, New Zealand or Indonesia. Non-Western immigrants are immigrants from other countries of origin. *Urbanity* is quantified by population density - the number of registered residents per square kilometre. *Tenants* (%) is the percentage of the dwellings which their owner does not occupy. The socioeconomic data source is CBS statistics of the residential zones in 2018 (CBS, 2018). Table 1 shows the descriptive statistics of the independent variables.

5.3. Control variables: buildings' quality and geometry, microclimate, and land cover

This study uses nine control variables to control the effects of buildings' quality and geometry, microclimate, and land cover on Gas-use and -dependency. Two variables reflect the status of the housing and dwellings in the zones: *Building age* – the median age of the buildings which are entirely or partially residential, weighted by the gross floor area of the buildings; *Surface to volume ratio* – the ratio of the total area of buildings' walls and roofs facing open space to the overall volume of the buildings in blocks. *Building age* data is provided by the Dutch GIS database of buildings, the so-called 3D BAG database (Esri Netherlands, 2016). The database is also used to compute the *Surface to volume ratio* at the scale of residential zones.

Based on the recorded observation at the 28 meteorological stations of the Royal Netherlands Meteorological Institute, KNMI (KNMI, 2018), four climate-related independent variables are calculated and involved in the statistical models. The variables' calculation followed the KNMI scientific team's guideline titled "Interpolation Methods for the Climate Atlas, KNMI technical rapport" (Sluiter, 2012). An ordinary kriging interpolation with exponential variogram is used to calculate *Humidity (%)* at 1.5 m. To calculate *Wind-speed* at the height of 10 m, the two-layer model of the planetary boundary layer interpolation is used (Stepek & Wijnant, 2011). The aerodynamic roughness length values at the scale of residential zones are calculated using the European land cover database, CORINE (European Energy Agency, 2018), and estimated aerodynamic values for different land covers (Silva et al., 2007).

Two of the climate-related variables quantify air temperature at the residential zones. First is the cooling degree days, *CDD* - the total number

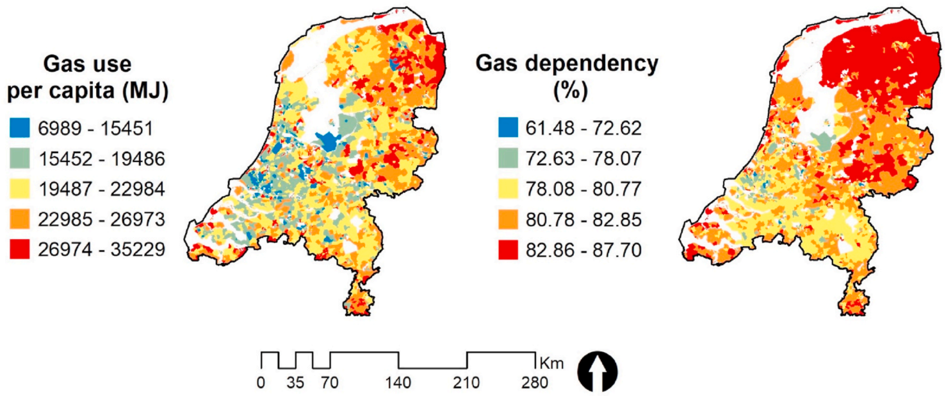

Fig. 2. Study areas and the dependent variables of this study: Gas use – i.e. annual gas use per capita (MJ), and Gas dependency – i.e. share of gas from total annual energy use (%).

Table 1
Descriptive statistics of the independent variables.

Variable	Mean	Minimum	Maximum	SD
Household size	2.28	1.20	3.50	0.30
Low-income (%)	39.55	19	65	5.04
High-income (%)	20.17	3	55	6.38
Population age 14 or younger	15.61	1	35	3.43
Population age 15-24	11.93	2	44	2.90
Population age 65 or older	20.09	2	74	5.80
Female	−0.53	−46	17	3.79
Immigrants (%)	16.29	1	92	12.99
Urbanity	2167.19	10	28,139	3453.66
Tenants	32.85	2	100	16.60

of degree days in which air temperature exceeded a specific threshold temperature and space cooling was inevitable. Second is heating degree days, *HDD* - the total degree days in which temperature fell below a certain threshold, and space heating was necessary. In order to calculate *CDD* and *HDD*, three values at each KNMI metrological station are retrieved: the maximum daily temperature (TX), minimum daily temperature (TN) and mean monthly temperature (TM). Subsequently, following KNMI technical guideline (Sluiter, 2012) by universal kriging interpolation of the observations at the meteorological stations with an external drift of logarithmic distance to the shore, the three values at each of the residential zones are retrieved. Subsequently, based on the study by Spinoni and Barbosa on the degree-days in Europe (Spinoni and Barbosa, 2015), The base temperature (Tb) for *CDD* and *HDD* are respectively set at 22 °C and 15 °C, and *CDD* and *HDD* are calculated as follows (equations (5)–(8)):

$$CDD_i = \begin{cases} 0, \quad if\ T_b \geq T_X \\ \dfrac{T_X - T_b}{4}, \quad if\ T_M \leq T_b < T_X \\ \dfrac{T_X - T_b}{2} - \dfrac{T_b - T_N}{4}, \quad if\ T_N \leq T_b < T_M \\ T_M - T_b, \quad if\ T_b \leq T_N \end{cases} \tag{5}$$

$$CDD = \sum_{i=1}^{182} CDD_i \tag{6}$$

$$HDD_i = \begin{cases} T_b - T_M, \quad if\ T_b \geq T_X \\ \dfrac{T_b - T_N}{2} - \dfrac{T_X - T_b}{4}, \quad if\ T_M \leq T_b < T_X \\ \dfrac{T_b - T_N}{4}, \quad if\ T_N \leq T_b < T_M \\ 0, \quad if\ T_b \leq T_N \end{cases} \tag{7}$$

$$HDD = \sum_{i=1}^{183} HDD_i \tag{8}$$

where CDD_i is the cooling degree at a day between April 1st and September 30th, and HDD_i is the heating degrees of a day between October 1st and March 31st.

Three satellite-driven variables show the properties of the land surface. Average monthly *NDVI*, Normalized Difference Vegetation Index, in 2018 shows the overall "greenness" of the residential zones. *NDVI* values are retrieved from the monthly satellite data of MODIS/Terra Vegetation Indices Monthly L3 Global 1 km SIN Grid V006 (Earthdata, 2019a, 2019b). To retrieve land surface temperature (LST) at days and nights in the summer of 2018, four sources of satellite images with four different local overpassing times are used (Earthdata, 2019a, 2019b): MODIS Terra day (10:30 a.m.), MODIS Aqua day (1:30 p.m.), MODIS Terra night (10:30 p.m.), and MODIS Aqua night (1:30 a.m.). The first two sources are used to retrieve daily LST, hereinafter called *LST-day*, the two latter sources are used to calculate nightly LST, hereinafter called *LST-night* (Table 2). Table 3 summarises the descriptive statistics of the independent variable.

Table 2
Satellite images used for retrieving LST day and LST night.

Satellite image	Overpassing local time (source)	Time period
LST day	10:30 a.m.	**T01**: 26/06/2018 - 03/07/2018
	(MODIS/Terra, MOD11A2)	**T02**: 04/07/2018 - 11/07/2018
		T03: 12/07/2018 - 19/07/2018
	1:30 p.m.	**T04**: 20/07/2018 - 27/07/2018
	(MODIS/Aqua, MYD11A2)	**T05**: 28/07/2018 - 04/08/2018
		T06: 05/08/2018 - 12/08/2018
LST night	10:30 p.m.	**T07**: 29/08/2018 - 05/09/2018
	(MODIS/Terra, MOD11A2)	**T08**: 06/09/2018 - 13/09/2018
		T09: 14/09/2018 - 21/09/2018
	1:30 a.m. (MODIS/Aqua, MYD11A2)	

Table 3
Descriptive statistics of the control variables.

Variable	Mean	Minimum	Maximum	SD
Building age	45.18	3	375	19.11
Surface to volume ratio	0.26	0.10	0.40	0.04
Humidity (%)	78.11	74.22	84.08	1.77
Wind speed (km/hr)	36.25	21.96	70.96	7.08
CDD	1622.18	1615.38	1625.58	2.07
HDD	96.73	27.30	147.82	28.76
NDVI	0.58	0.17	0.76	0.10
LST day	29.52	23.31	35.05	1.86
LST night	13.59	10.50	17.16	1.33

6. Results

6.1. Diagnosis of the OLS and GWR models

At the first step of the analysis, two OLS models are developed. The Variance Inflation Factor (VIF) of the independent variables in the two OLS models shows that VIF of all independent variables falls below the commonly accepted threshold of VIF, indicating the impact of the independent and control variables are fairly independent. The estimated coefficients of eight out of ten independent variables in the OLS model of Gas-use are significant at the *p-value* < 0.05 level. In the Gas-dependency model, those of nine independent variables are significant (*p-value*<0.05).

At the second step of the analysis, two GWR models, with Gas-use and Gas-dependency as dependent variables, are developed. The models' adaptive bandwidths are respectively set at 251 and 263 nearest zones – the bandwidths which minimise the AICc value of the models. The GWR models outperform the OLS models in three aspects – indicating that the associations between independent and dependent variables are spatially variant. First, the measurements of goodness-of-fit, Adjusted R-square, improve by 15% and 19%. Second, the AICc measurements of the GWR models are significantly lower than those of the respective OLS models – indicating more "informative" estimations in the former models. Third, the Morans' I measurements of the GWR models' residuals are closer to zero than those of the OLS models, indicating that the former models' residuals are more randomly distributed (Table 4).

The F-statistics of the GWR and OLS models' residuals show that the formers are significantly smaller, indicating that the GWR models explain more variation of the dependent variables (Table 5).

6.2. The spatial variation of socioeconomic impacts on gas-use and gas-dependency

Fig. 3 illustrates significant impacts of socioeconomic groups on Gas-use and Gas-dependency. The red colour indicates the zones where the presence of a socioeconomic group is associated with higher levels of Gas-use. The blue colour indicates the associations with lower levels of

Table 5
Comparison between residuals of the OLS and GWR models of Gas-use and Gas-dependency.

GWR ANOVA Table	SS	DF	MS	F
Gas-use model				
Global Residuals	996.309	2687.000		
GWR Improvement	491.058	558.248	0.880	
GWR Residuals	505.251	2128.752	0.237	3.706
Gas-dependency model				
Global Residuals	1404.438	2687.000		
GWR Improvement	681.950	535.059	1.275	
GWR Residuals	722.488	2151.941	0.336	3.796

Table 4
Diagnosis and estimates of the OLS and GWR models of Gas-use and Gas-dependency.

Variable	OLS					GWR			
	gas-use model		gas-dependency model			gas-use model		gas-dependency model	
	β	t	β	t	VIF	β mean	β SD	β mean	β SD
Independent variables									
Household size	−0.06	−1.94	−0.38	−11.14	6.09	−0.04	0.23	−0.28	0.22
Low-income (%)	0.32	12.46	0.36	11.69	4.81	0.30	0.17	0.32	0.23
High-income (%)	0.27	11.49	0.05	1.64	4.04	0.32	0.13	0.12	0.13
Population age 14 or younger (%)	−0.27	−11.75	0.07	2.48	3.79	−0.23	0.16	0.07	0.12
Population age 15–24 (%)	−0.18	−10.25	−0.12	−5.55	2.29	−0.13	0.11	−0.06	0.17
Population age 65 or older (%)	0.12	5.45	0.10	3.54	3.81	0.17	0.14	0.16	0.16
Female (%)	−0.06	−3.65	−0.05	−2.64	1.96	−0.10	0.12	−0.07	0.11
Immigrants (%)	−0.02	−0.99	−0.14	−5.41	3.56	−0.13	0.17	−0.14	0.22
Urbanity	−0.17	−7.86	−0.07	−2.66	3.61	−0.18	0.25	−0.22	0.29
Tenants (%)	−0.40	−14.24	−0.40	−12.08	5.72	−0.28	0.21	−0.28	0.24
Control variable									
Building age	0.32	22.07	0.38	22.02	1.55	0.31	0.12	0.35	0.19
Surface to volume ratio	−0.02	−1.42	−0.04	−2.28	1.72	−0.02	0.09	0.00	0.12
Humidity (%)	0.05	1.46	0.04	0.95	7.32	0.02	0.71	0.10	0.62
Wind speed (km/hr)	0.00	−0.02	0.00	0.19	2.92	0.07	0.15	0.04	0.14
HDD	0.02	0.98	0.08	4.17	1.97	−0.13	0.40	0.02	0.47
CDD	0.15	4.30	−0.09	−2.19	8.96	0.23	0.73	0.02	0.69
NDVI	0.03	1.23	0.20	6.99	4.34	0.02	0.13	0.09	0.15
LST day	−0.06	−3.33	−0.06	−2.88	2.54	−0.08	0.14	−0.03	0.17
LST night	−0.20	−8.32	−0.09	−3.23	4.29	−0.03	0.17	0.04	0.19
R-square	0.631		0.48			0.813		0.733	
Adjusted R-square	0.629		0.477			0.762		0.664	
AICc	5018.7		5948.1			4228.3		5142.8	
Residual Moran's I	0.1254		0.1309			−0.0107		−0.0076	
Adaptive bandwidth	NA		NA			251		263	

β: standardised regression coefficient.
SD: standard deviation.
OLS coefficients significant at *p-value* $<$ 0,05 are marked underlined.

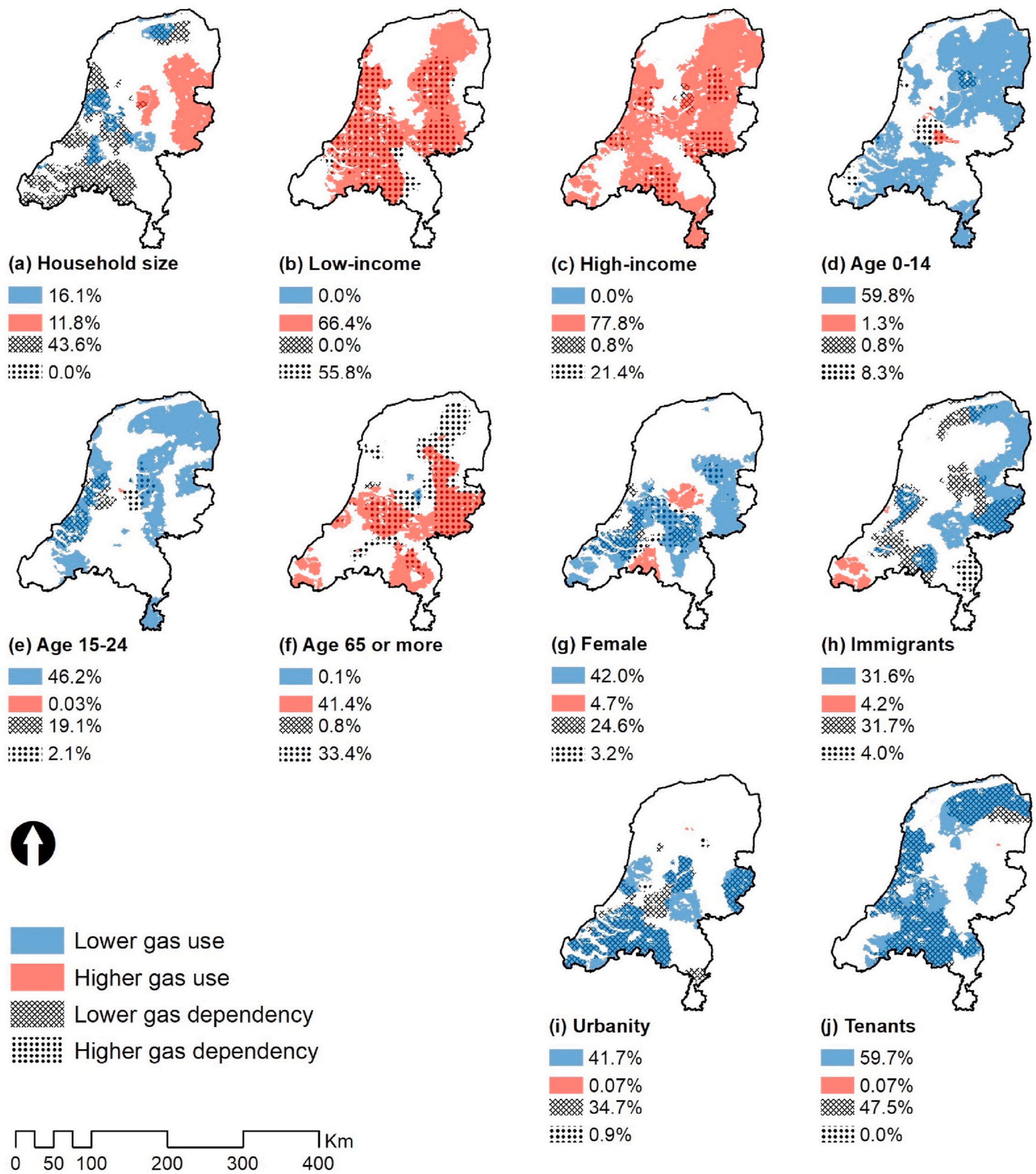

Fig. 3. Significant impacts of socioeconomic characteristics on Gas-use and Gas-dependency.

Gas-use. The dotted hatch shows a zone where the presence of socioeconomic group is associated with higher Gas-dependency. The line hatch indicates associations with lower levels of Gas-dependency. Two types of spatial relations between Gas-use and Gas-dependency can be identified. First, in the case of six socioeconomic groups, the level of Gas-use affects gas dependency. The Gas-use of the low-income (Firgure3b) and high-income households (Fig. 3c) is more than average in most of the country's zones. This boosts the Gas-dependency of low-income in a significant portion of zones. To a lesser degree, a similar pattern is observed in the case of high incomes. Oppositely, the population aged 15–24 years old (Fig. 3e), females (Fig. 3g), urban households (Fig. 3i) and tenants (Fig. 3j) intend to consume less gas than average, decreasing their gas-dependency. Second, in the case of four socioeconomic groups, Gas-use and Gas-dependency have relatively independent spatial patterns. This indicates that higher levels of Gas-dependency are due to relatively low consumption of electricity rather than high consumption of gas. The dependency on gas among large households (Fig. 3a), the population aged 14 or younger (Fig. 3d), and immigrants (Fig. 3h) is pretty independent of their level of gas use. To a lesser degree, in many zones, the population aged 65 or more (Fig. 3f) is highly dependent on gas without consuming an abnormally high amount of it.

6.3. *The three types of socioeconomic characteristics*

Fig. 4 shows three types of socioeconomic characteristics according to their overall impact on Gas-use and Gas-dependency. The types are bivariate: if the zones with the significant positive impact of socioeconomic characteristics on Gas-use or Gas-dependency outnumber those with significant negative impact, the factor is categorised as “More Gas use” or “More Gas dependency”. Oppositely, if zones with significant negative impact outnumber those with a significant positive impact, the factor is categorised in the categories of “Less Gas use” or “Less Gas dependency”. The three types of socioeconomic characteristics are as follows (Fig. 4):

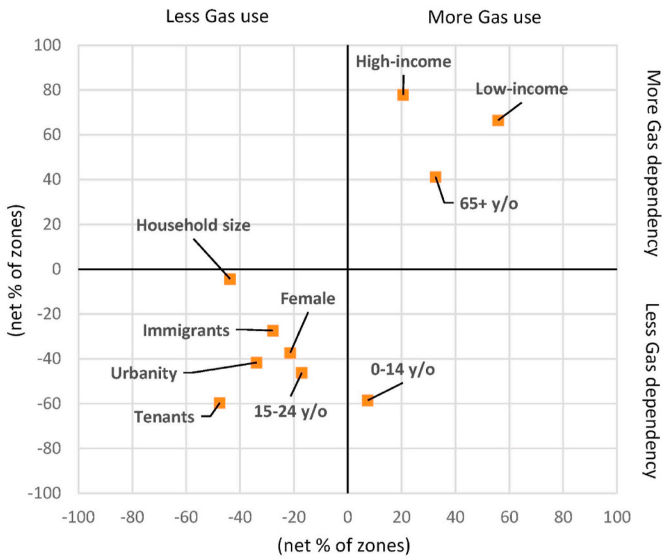

Fig. 4. The three types of socioeconomic characteristics, based on their impact on Gas-use and Gas-dependency.

- more Gas-use and more Gas-dependency: *Low-income*, *High-income*, *The population age 65 or more*;
- more Gas-use and less Gas-dependency: *The population age 14 or younger;*
- less Gas-use and less Gas-dependency: *Household size*, *the population age 15–24*, *Female*, *Immigrants, Urbanity*, *Tenants.*

In the next section, the possible societal and behavioural explanations for each category are presented and discussed.

7. Discussion

This study's core result is that the spatial patterns of Gas-use and Gas-dependency are not necessarily overlapping. In the case of some of the socioeconomic characteristics, the results show that a factor may increase the level of Gas-dependency without significantly affecting the level of Gas-use. In such cases, the increase in Gas-dependency is because of low electricity consumption. In extreme cases, it is observed that the level of Gas-use is dropped in a zone while the level of Gas-dependency increased, or vice versa. This study argues that such observations underline the importance of simultaneous studying of the two variables. In the following paragraphs, acknowledging the independent spatial behaviours of Gas-use and -dependency, the three types of socioeconomic characteristics and their potential association with Gas-use and -dependency are discussed.

7.1. More gas-use, more gas-dependency

The first type of socioeconomic characteristics consists of three socioeconomic characteristics: *Low-income*, *High-income*, *Population age 65 or more*. The results show that at both ends of the income spectrum in the Netherlands, Gas-use and Gas-dependency increase. Low-income households' high level of Gas-use is presumably due to the lower energy efficiency of dwellings and appliances used for space heating, water heating, and cooking. A study by Langevin et al. (2013) identified the lack of building maintenance as one of the main determinants of low-income household energy consumption. In a study on energy efficiency and justice for low-income U.S. households, Xu and Chen showed that Low-income households possessed fewer energy-efficient appliances than other income groups (Xu & Chen, 2019). Trotta showed that households with higher income levels were more likely to invest in energy-efficient retrofits (Trotta, 2018). The high level of Gas-dependency amongst low-income households is presumably due to the possession of fewer electric appliances than other income groups. A study by Jeong et al. (2011) showed that low-income households had a low tendency to buy appliances such as electric beds for space heating.

The high Gas-use and Gas-dependency in high-income households are presumably due to accommodation in relatively larger dwellings, which increases energy consumption for space heating. This can lead to higher Gas-use as, according to Eurostat data on the share of fuels in households final energy consumption, gas accounts for more than 82% of the total energy used for space heating in the Netherlands (Eurostat, 2020). Steemers and Yun (2010) found a significant association between households' income, size of their dwellings and number of windows. Estiri (2014) showed that the increase in rooms and dwelling size explained the associations between income and energy consumption in the U.S. residential sector.

The observed increase in Gas-use and Gas-dependency of the population aged 65 or older is presumably related to comfort in higher temperatures and, consequently, higher use of gas for space heating. By an experiment on thermal comfort of a group of young adults versus a group of elderlies in a moderate temperature, Schellen et al. concluded that the latter group preferred higher temperatures (Schellen et al., 2010). A study on the impact of demographic trends on energy consumption in the European Union since the 1960s by York showed that the increase in the percentage of inhabitants aged 65 years or older had a significant impact on energy consumption (York, 2007). By studying 300,000 Dutch households, Brounen et al. showed that elderlies' presence increases gas consumption. However, it had a negative or no relation with electricity consumption (Brounen et al., 2012). Alberini et al. found that elderlies in the U.S. intended to use significantly higher amounts of gas. However, their electricity level was lower than average or did not show a deviation from the average (Alberini et al., 2011).

7.2. More gas-use, less gas-dependency

High Gas-use of the population younger than 14 years old is presumably due to an increas in energy consumption for space- and water heating in households with children. As gas accounts for 86% and 89% of space and water-heating in the Netherlands, the presence of children younger than 14 years old is associated with high Gas-use. A review on the domestic water heating (DWH) and consumer profiles by Fuentes et al. found that most of the studies on DWH had concluded that children's presence is a strong, positive predictor of higher levels of DWH (Fuentes et al., 2018). In a study on German household space heating types, Braun showed that German households with children used more gas for space heating than average (Braun, 2010).

The low level of Gas-dependency indicates that the impact of residents younger than 14 years old on increasing electricity consumption outsizes its impact on gas consumption. A study by Brounen et al. on 300,000 Dutch households showed that the impact of the children's presence on Joules of electricity consumption was greater than that on gas consumption (Brounen et al., 2012). A review by Jones et al. on socioeconomic factors affecting electricity consumption showed that various previous studies concluded that children's presence increased electricity consumption (Jones et al., 2015). The studies have also pointed out that the impact of a series of factors, presumably associated with households with children, could increase electricity consumption, e.g. floor area (Wiesmann et al., 2011) and the number of bedrooms (McLoughlin et al., 2012).

7.3. Less gas-use, less gas-dependency

The observed impact of household size on reducing Gas-use and Gas-dependency is presumably related to the phenomenon that O'neill and Chen described as "economies of scale" of household energy consumption (O'Neill & Chen, 2002). In a comparative study on household energy consumption in Australia, Brazil, Denmark, India and Japan, Lenzen et al. showed that larger household sizes were associated with lower energy consumption in four of the five countries (Lenzen et al., 2006). Such "economies of scale" in the larger households presumably explains the lower levels of Gas-use and -dependency in large Dutch households. According to Eurostat, space heating account for a substantial portion of Dutch households energy use, 63% (Eurostat, 2018), and gas account for 82% of energy sources for space heating (Eurostat, 2020).

The low Gas-use of the population aged between 15 and 24 is presumably related to their lifestyle and relatively low spent-at-home time, reducing their energy consumption for space heating and cooking. A survey by the Netherlands Institute for Social Research showed that in 2016 the men aged between 12 and 19 spent more time for leisure than any other age group younger than 65 (Roeters, 2018). In the women's case, the hours outnumbered those of families aged 20 to 64 with children. The hours spent on household and care is the lowest between the age group 12–19 years old by a significant margin (Roeters, 2018). The low Gas-dependency of the population aged between 15 and 24 is presumably related to their higher-than-average electricity consumption, possibly due to extensive use of digital appliances. A review by Jones et al. on socioeconomic determinants of electricity consumption in Europe showed that teenagers' presence was associated with higher electricity consumption in all case studies (Jones et al., 2015). Bartiaux et al. showed that per capita electricity consumption of children aged 13 to 19 was higher than average in Denmark, regardless of housing type (Bartiaux et al., 2005). By a survey on households in central Sweden, Bartusch et al. showed that electricity consumption per square meter reached its highest level in families with teenagers (Bartusch et al., 2012).

Females' low Gas-use and Gas-dependency are presumably related to the concentration of the gender group in urban areas, which due to the urban heat island effect (Santamouris et al., 2001) and compactness of the buildings (Ratti et al., 2005) contributes to the reduction of energy use for space heating. According to Dutch Central Bureau for Statistics (CBS), in "very highly urbanised", "highly urbanised", or "moderately urbanised" zones, females outnumber males by 1.36%, 1.66%, 0.83%. In contrast, the gender groups are almost in balance in the "barely urbanised" – i.e. rural areas, where females outnumber males by only 0.06%. In "not urbanised" zones – i.e. agricultural, industrial or natural areas, males outnumber females by 2.38% (author's computation based on Centraal Bureau voor de Statistiek, 2018). This uneven distribution of gender groups across the urban and rural areas is presumably related to gender inequality in industry and agriculture economic sectors. According to the Gender Data Portal of The World Bank, in 2019, only 6% and 1.2% of women worked in industry and agriculture sectors – the job opportunities abundant in "barely urbanised" and "not urbanised" areas. The respective numbers in the case of the men, however, were 25% and 3%. Conversely, women were more likely to work in the service sector than men, 92.6% compared to 72.9% (The World Bank Group, 2020), the jobs more present in urbanised areas.

In the case of the *Immigrants*, lower levels of Gas-use and -dependency are presumably related to their concentration in highly urbanised zones and low level of income. In the 1960s and 1970s, immigrants from Turkey, Morroco, Antilles and Suriname mainly dwelled in the Randstad region, the most urbanised region in the Netherlands (Musterd & Van Kempen, 2009). More than six decades later, Non-Western are still overrepresented in the most urbanised and dense neighbourhoods of the major cities like Amsterdam and Rotterdam (Sleutjes et al., 2018, 2019). A similar spatial distribution is also observed in Western immigrants, who have mainly immigrated after the Eastward expansion of the EU in 2004 and 2007 (OECD, 2012). A study on Polish and Bulgarian immigrant by the Social and Cultural Planning Office of the Netherlands showed that the latter group also tend to dwell in the country's major cities (Gijsberts and Lubbers, 2013). On average, immigrants' have a lower income level than native households, presumably contributing to seeking lower thermal comfort levels. A study by the Dutch Central Bureau for Economic Policy Analysis on income difference between migrant and native groups in the Netherlands (CBP, 2019) showed that the average income of Moroccans, Turkish, Surinamese, Antilleans is between 23% and 35% lower than that of Dutch households.

The decreasing impact of urbanity on Gas-use and -dependency is presumably related to the smaller size and volume of dwellings and the lifestyle in highly populated areas. In their seminal study on the impact of urban form on energy consumption, Ewing and Rong established links between population density, on the one hand, and compactness and types of dwellings, on the other hand. The authors concluded that this impact linked population density to households' energy consumption (Ewing & Rong, 2008). Presumably, the heat transfer between compact dwellings in the urbanised areas results in a decrease in the amount of energy consumed for space heating, gas accounts for 82% of which (Eurostat, 2020). Another reason for low Gas-use and -dependency in the highly urbanised areas is presumably the urban lifestyle and different patterns of time use between urban and rural areas. Comparing the urban and rural lifestyle in Finland, Heinonen et al. showed that the time used for food and domestic activities in rural areas outnumbered those in urbanised areas (Heinonen et al., 2013). Such different time use presumably reduces gas consumption for space heating and cooking in urban areas.

Low Gas-use and -dependency of tenants is presumably related to the large-size non-profit rental sector in the Netherlands. The dwellings of the sector belong to housing corporations, providing accommodation for low-income households. According to Filippidou et al., 31% of dwellings in the Netherlands are non-profit rental houses. By analysing 1.5 million dwellings in this sector, the authors showed that these dwellings received regular and significant renovations. For instance, between 2010 and 2013, more than 36% of dwellings with a single glass, 33% of dwellings with gas boilers, 11% of dwellings without wall insulation, and 18% of dwellings without roof insulation were retrofitted (Filippidou et al., 2016). In contrast, owner-occupied dwellings are not necessarily regularly renovated. The reason for regular renovation in the non-profit rental sector could be housing corporations' obligation to adapt the energy-efficiency regulation. In contrast, the new rules are not necessarily enforced for privately-owned houses (Vringer et al., 2016).

8. Conclusions and policy implications

The results show that three socioeconomic groups consume a substantial amount of gas and are highly dependent on gas consumption: high-income households, low-income households, and those older than 65 years old. Additionally, the population younger than 14 years old consume a high level of gas. Nevertheless, the share of gas of their overall consumption is relatively small, indicating a high level of dependency on both electricity and gas. The following paragraphs introduce and discuss a set of possible policy measures specific to each group.

In the case of the high-income, gas-dependent households, policies need to introduce a new scheme for a progressive energy tax, or carbon tax, based on two criteria: a minimum of gas consumption per capita and a maximum share of energy expenditure of household income. Such a price adjustment is a necessity, given the relatively low gas price in the Netherlands. In 2018, the year of this study, the real GDP in the Netherlands was 149% of the average of EU-27 countries (Eurostat, 2021a). In the same year, the gas price in the Netherlands was only 125% of the EU-27 average (Eurostat, 2021b). In other words, consuming gas for a consumer in the Netherlands is 17% cheaper than an average EU consumer. This urge for extra gas pricing for the high-income, gas-intensive Dutch households.

In the case of low-income, gas-dependent households, two types of policies need to be adapted. The first set of policies need to provide a safety net for the households in danger of energy poverty. The first step is to introduce an inclusive, multicriteria definition of households in energy poverty. Currently, the Dutch government only acknowledges the most severe form of energy poverty, the so-called vulnerable consumers, i.e. those who lost their access to energy because of not affording their energy bills (EU Energy Poverty Observatory, 2020b). Energy poverty is more than such an extreme level of vulnerability. According to EU Energy Poverty Observatory, in 2018, 2.2% of Dutch households had a problem with adequately warming their dwellings and 10.7% faced difficulties with affording energy bills (ibid). The policies need to expand their safety net for the households who spend a substantial share of their income on energy expenditure or cannot afford adequate indoor temperature and warm water. The second set of policies could offer financial aids to low-income households in the form of reduced VAT or tax rebates for purchasing energy-efficient appliances.

The high level of gas use and gas dependency among the population older than 65 is presumably due to the overrepresentation of single-person households among the age groups and the long hours spent at home. Policies need to target the time-use of the senior citizens and mitigate their number of home-alone hours by fostering the formation of the so-called Third Places. Third Places, a term coined by the sociologist Ray Oldenburg, is a place in addition to one's home (first place) or workplace (second place) where he or she regularly, voluntarily and happily attend social gatherings (Oldenburg, 1999). A Third Place might be a cafe, restaurant, chess club, barbershop, gym, etc. (Rosenbaum et al., 2009). Over and above their impact on the mental well-being of senior citizens, Third Places can significantly reduce the energy demand of the age group for space heating. In collaboration with local communities and municipal authorities, policies need to encourage bottom-up initiatives to establish Third Places.

Households with children younger than 14 years old consume a relatively high amount of gas, while the share of gas from their total energy demand is relatively small. This finding indicates that such households are already highly dependent on electricity consumption, too. Therefore, it can be expected that subsequent to phasing out gas use in the residential sector, the electricity consumption of such households would soar. This can impose a substantial load on the electricity grid and cause blackouts. Policies need to introduce active "demand response management" tools to divert this electricity demand from peak hours. To do so, the use of smart appliances need to be encouraged and subsidised.

Phasing out gas in the residential sector is more than a technical issue. Policymakers need to consider the socioeconomic consequences of such transition and be equipped with various policy measures to protect vulnerable consumers. The *gilets jaunes* movement in France showed that the socioeconomic dimension of energy transition needs to be an integrated part of policies on climate and energy. In his seminal book "Energy: A human history", Richard Rhodes illustrates how energy transition has shaped societies in different historical periods (Rhodes, 2018). The social dimension of the energy transition is an unignorable historical fact.

The results and methodology of this study pave the way for further geographic studies on gas dependency. By application of GWR, this study improved the estimates of gas dependency offered by aspatial models. It, additionally, identified the gas-intensive and -dependent zones of the Netherlands. These findings assist policymakers to develop location-specific strategies, an approach put forward by the Dutch National Climate Agreement (Ministry of Economic Affairs and Climate Policy, 2019). Further studies can improve such geographic understanding by application of more advanced models. They can adapt semi-parametric geographically weighted regression models to investigate gas dependency at different spatial scales (similar to Jin et al., 2019; Dąbrowski, Stead, & Mashhoodi, 2019). By applying geographically and temporally weighted regression models, further studies can analyse panel data and the trajectory of the gas dependency across space and time (similar to Ma et al., 2018; Guo et al., 2017).

Author statement

Bardia Mashhoodi: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Software; Validation; Visualization; Writing - original draft; Writing - review & editing.

Declaration of competing interest

The author has no conflict of interest to declare.

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