Title
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Journal
Science Advances, 10(14)

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Publication Date
2024-04-05

DOI
10.1126/sciadv.adh5543

ENVIRONMENTAL STUDIES

Drivers of natural gas use in U.S. residential buildings

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Natural gas is the primary fuel used in U.S. residences, yet little is known about its consumption patterns and drivers. We use daily county-level gas consumption data to assess the spatial patterns of the relationships and the sensitivities of gas consumption to outdoor air temperature across U.S. households. We fitted linear-plus-plateau functions to daily gas consumption data in 1000 counties, and derived two key coefficients: the heating temperature threshold (T_{crit}) and the gas consumption rate change per 1°C temperature drop (Slope). We identified the main predictors of T_{crit} and Slope (like income, employment rate, and building type) using interpretable machine learning models built on census data. Finally, we estimated a potential 2.47 million $MtCO_2$ annual emission reduction in U.S. residences by gas savings due to household insulation improvements and hypothetical behavioral change toward reduced consumption by adopting a 1°C lower T_{crit} than the current value.

INTRODUCTION

The United States is currently the top global producer and consumer of natural gas (*1*). U.S. households account for 15% of total U.S. gas consumption (*2*), gas being the dominant heating fuel (*3*) and representing 42% of the energy consumed by residential households (*4*). Households use gas primarily for heating and hot water, as well as for cooking and other miscellaneous uses. Previous studies in Europe (*5*) showed that the daily gas consumption of residential and commercial buildings was negatively correlated with daily outdoor air temperatures, reflecting higher heating requirements in the cold season, typically when the temperature drops below a critical level. Although this inverse relationship has been observed consistently across eight major European countries, it showed different sensitivities related to building insulation. In the context of energy savings policies and climate change mitigation, it is thus important to quantify the relationship between temperature and natural gas use and understand how it relates to human behavior and income, gas access and price, and insulation.

Prior research has highlighted certain facets of residential natural gas consumption in the United States, yet there is a notable knowledge gap that warrants our attention. The Residential Energy Consumption Survey (RECS) (*6*) has provided insights into various aspects of energy consumption, including natural gas. It is a recurring survey conducted by the U.S. Energy Information Administration. The 15th iteration of 2020 RECS estimated consumption based on responses from 18,496 households across the United States, a relatively small sample size that may not capture specific populations or geographic regions. RECS samples homes that are occupied as primary residences and excludes households that are difficult or costly to survey. This study (*7*) used RECS data to model end-use characteristics like space heating, cooling, and water heating of residential energy with a regression approach. They found potential errors in RECS data, which raises issues of reliability. Another study (*8*) analyzed temperature-consumption correlations in a region limited to the Central and Eastern United States.

Energy consumption has an important socioeconomic angle, and understanding its predictors is crucial for addressing various energy-related challenges and opportunities. A study (*9*) recently shed light on the vital concept of energy poverty. It is defined as an inability to get access to energy due to issues with affordability, quality, or other reasons. Their study introduced the topic of inflection temperature (the temperature at which households start cooling) and then discussed policy implications for eradicating energy poverty. They conducted the study using residential electricity consumption data from 6000 households in the U.S. state of Arizona and did not address the use of natural gas. Again, we observe a limitation of spatial coverage, also highlighted by another study on energy poverty (*10*), which only focuses on Buffalo, NY. This shows the strong necessity for research that covers the entire United States.

Natural gas has the potential to act as a "transitional" fuel (*11*) and an intermediary step toward the path for a sustainable and decarbonized future energy. It offers a pragmatic approach to addressing the urgent need for reducing the carbon intensity of the residential sector. Natural gas has lower carbon emissions (44% less) than other fossil fuels like coal (*12*) and burns clean, which makes it a relatively "greener" fuel. By leveraging the advantages of natural gas, local communities can make substantial progress in the reduction of their carbon footprint, especially in nations with abundant natural gas reserves (like the United States). This is crucial in achieving the United Nations Sustainable Development Goals (*13*), particularly Goal 12, which emphasizes the importance of sustainable consumption and production patterns. However, we should note that natural gas is not the solution for a greener economy and could be controversial in some aspects. Notably, some studies (*14*, *15*) have analyzed the methane emissions linked to the leakages in the natural gas production and transport sector. Even advanced natural gas production techniques like hydraulic fracturing or fracking can have negative effects on the environment (*16*). It is therefore essential to also focus on strengthening the natural gas network, enhancing its efficiency, until we can seamlessly transition to greener energy alternatives.

Hence, with this study, we aim to provide a thorough and detailed analysis of natural gas consumption patterns in the United States at the county level. We extend our analysis to a broader

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geographical area to deliver a comprehensive understanding of regional variations in natural gas consumption. To do so, we use a dataset of daily pipeline gas flows for gas delivered to residential households and some small commercial entities (large building complexes that may be equipped by small gas generators) across 1000 U.S. counties, with the aim of answering the following questions: (i) What are the spatiotemporal patterns of natural gas consumption by households across the United States? (ii) What are the predictors underpinning the dependence of gas consumption on temperature across counties? and (iii) How can predictors be leveraged to reduce gas consumption in buildings across the United States? Here, we fit linear-plus-plateau functions to county-specific data to summarize local nonlinear relationships between daily gas usage and temperature based on two key parameters: the heating temperature threshold, also called critical temperature below which heating begins (T_{crit}), and the rate of increase in gas consumption when the temperature below the T_{crit} threshold drops by 1°C (Slope) during the cold season. Here, T_{crit} is a fundamental characteristic in understanding how gas consumption increases when temperature drops. The Slope, on the other hand, explains how sensitive gas consumption is to temperature changes during the cold season. These two parameters encapsulate the essential consumption-temperature relationship, which is central to our research questions. Subsequently, we built interpretable machine learning models to assess regional differences in these parameters considering related and socioeconomic factors from sources like the U.S. census. This approach allows us to propose two gas-saving scenarios for the United States, assuming changes in T_{crit} and Slope to represent behavioral changes (as a solution with direct effect on natural gas demand) or extensive building renovation (as a long-term solution). The International Energy Agency mentioned the importance of behavioral interventions and their potential impact on energy efficiency policies (*17*). Behavioral interventions are policies that apply insights from human behavior studies to encourage socially desirable actions. This paper (*18*) discussed practical interventions to reduce carbon emissions from the residential sector, with proposed consumption reduction and retrofitting homes. Overall, our study addresses all aspects of interest, including socioeconomic considerations explaining gas consumption and their effect on CO_2 emissions.

RESULTS

Spatiotemporal patterns of gas consumption in the United States

The relationship between daily household and commercial buildings gas consumption and ambient temperature was analyzed using a harmonized database established from natural gas pipeline nominations and flows from Wood Mackenzie's "Natural Gas Analyst" (*19*), and ambient air temperature data from Copernicus ERA5 gridded data (*20*). Gas consumption by residential and commercial buildings was separated from that of the large power plants, large industries, and storage using only data from so-called "Citygate" (*21*) pipeline delivery points in (*19*) (Fig. 1C). The resulting dataset provided details for 1000 individual counties, and per-household consumption was then calculated using U.S. census data (*22*). Per-household gas consumption is shown in Fig. 1A for the entire country and in Fig. 1B for five regions (*23*). The East Coast, West Coast, and Midwest display higher gas consumption per household than other regions. Because we aimed to derive relationships between daily consumption per household and temperature during normal conditions, we removed the data from 2020 when consumption was affected by COVID lockdowns, although we observed no substantial change during the peak lockdown from 15 March 2020 to 24 April 2020 (*24*). Therefore, using only data from 2018 and 2019, we characterized the local relationship between daily natural gas consumption and daily average air temperature in each county.

Gas consumption typically peaks during winter due to low temperatures, and household heating is required (Fig. 1). In most counties, we find that the relationship between daily per-household gas consumption and the ambient temperature is well described by a linear-plus-plateau function, as shown in Fig. 1D for Middlesex County, MA. For this county, consumption decreases linearly with temperature below a threshold of approximately 15°C, defined as critical temperature (T_{crit}). Above this threshold, gas consumption does not change substantially with temperature, reflecting a plateau corresponding to the base consumption for cooking and hot water usage. A similar pattern is observed for nearly all counties in the United States, consistent with the results from previous research at the national scale in European countries (*5*). By fitting a linear-plus-plateau function to the data from each county, we obtain the spatial distribution of T_{crit} and the linear regression coefficient for temperatures below T_{crit} to define the Slope parameter. Slope represents the rate of increase in gas consumption when the temperature drops by 1°C. Strong and significant correlations between gas consumption and air temperature were mainly found in counties in the Midwest and East Coast regions (Fig. 2A). The median T_{crit} value across the United States is 16.5°C, with T_{crit} values increasing from north to south (Fig. 2B). For a handful of counties in Minnesota and Wisconsin, the T_{crit} values are below zero. The linear relationship between gas consumption and temperatures below T_{crit} is significant in most counties, with Slope values spanning a large range from −1500 to 170 metric million British thermal units (MMBtu)/100 households per degree Celsius (Fig. 2, C to F). For a majority of the counties, the slope values are negative. The small number of positive values is viewed as outliers, due to a lower quality of fit in those cases. Counties in the Midwest, East Coast, and West Coast regions exhibit more negative slopes, that is, a steeper increase in consumption per unit drop in temperature (fig. S1). The quality of fit (R^2) was also assessed over the 1000 U.S. counties (see Materials and Methods). In 70% of the counties, the R^2 values were higher than 0.5 (Fig. 2D). Although the distribution of T_{crit} is close to normal, the distributions of R^2 and Slope across counties are left-skewed (Fig. 2, D to F).

Drivers of regional differences in household gas use

Next, we examined the potential predictors that influence the spatial distribution of R^2, T_{crit}, and Slope across counties by using explainable machine learning models (see Materials and Methods). We considered 19 different predictors listed in table S1, grouped into three families: (i) building characteristics such as the age of construction, the fraction of residential versus commercial and administrative buildings, and the number of housing units per building, derived from a combination of the American Community Survey (ACS) and Zillow's ZTRAX databases of housing units (*22*, *25*); (ii) socioeconomic predictors such as population, employment rate, and income, collected from U.S. census data (*22*); and (iii) energy-related predictors such as the type of fuel used for heating, derived from the ACS (*22*). Two machine learning models, Random Forest (RF) and CatBoost, were trained to explain the spatial patterns of R^2, T_{crit}, and

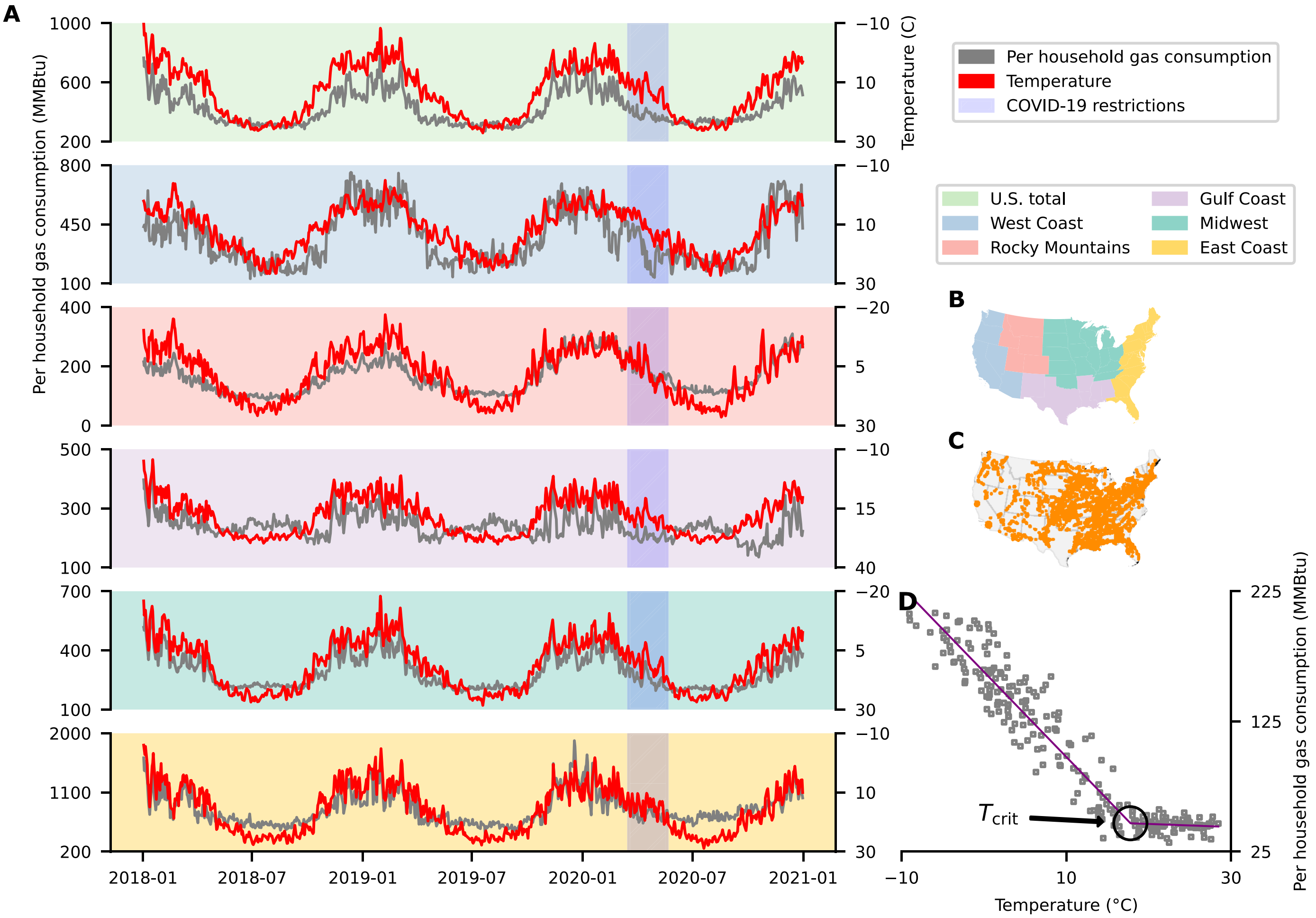

Fig. 1. Spatial and temporal fluctuations in the daily per-household gas consumption and temperature in the United States. (**A**) Time series plot for the entire United States and different regions showing the gas consumption and temperature values, where the hatched area is the main period of mobility restrictions during COVID. The left *y* axis shows gas consumption, and the right *y* axis shows temperature. (**B**) Map showing the U.S. regions considered. (**C**) Distribution of the Citygate pipeline gas delivery locations in the United States. The size of the dots on the map indicates the consumption value. Sample sizes of different counties in the regions are as follows: West Coast (6.3%), Rocky Mountains (6.2%), Gulf Coast (16.2%), Midwest (46.3%), and East Coast (25%). (**D**) Piecewise function with one breakpoint fitted based on the gas consumption and temperature data from Middlesex County, MA (2018). This plot presents data derived from processed data sources.

Slope from a parsimonious subset of predictors. The modeling objective was formulated as a multiclass classification task where each of the three predicted variables (R^2, T_{crit}, and Slope) was subdivided into four discrete classes (see Materials and Methods). Although the performances of RF and CatBoost models only differed by 1 to 5%, the model with the highest accuracy score was selected to explain R^2 (CatBoost), T_{crit} (RF), and Slope (RF) (see table S2). Results of machine learning models predicting the three target parameters as continuous outcomes were consistent with the relevant classifications (table S3). The selected models were used to identify the most influential predictors explaining the spatial variability in the three predicted parameters. To do so, we calculated the Shapley index values (SHAP) (*26*) to assess the sensitivity of the dependent variables R^2, T_{crit}, and Slope to the predictors and ranked all predictors according to their importance. Shapley indices use a game theory strategy to extract the contribution of each predictor on the final prediction.

The results show that building properties (green bars in Fig. 3A) are the most important group of predictors for predicting the spatial patterns of R^2; more precisely, the fraction of single-family residential buildings, the fraction of residential buildings reporting indoor heating, and the fraction of housing units built between 1950 and 1999 in each county are the most important predictors. The second group of important predictors for R^2 is socioeconomic factors (blue bars), particularly the fraction of the population working in the largest employing industry in each county, the fraction of the employed population, and the median income. The spatial distribution of T_{crit} is influenced by a mix of building-related and social predictors (Fig. 3B), mainly the fraction of "old" houses built between 1950 and 1999, the fraction of the employed population, and the average household size in each county. A high fraction of houses built between 1950 and 1999 and a low median home value contributed to higher T_{crit} values (see fig. S2 for the sign of the SHAP indices for predictors). This result is consistent with the expectation that older buildings are characterized by less effective insulation than recent buildings, resulting in more gas consumption and an increase in T_{crit}. Finally, we found that the share of gas

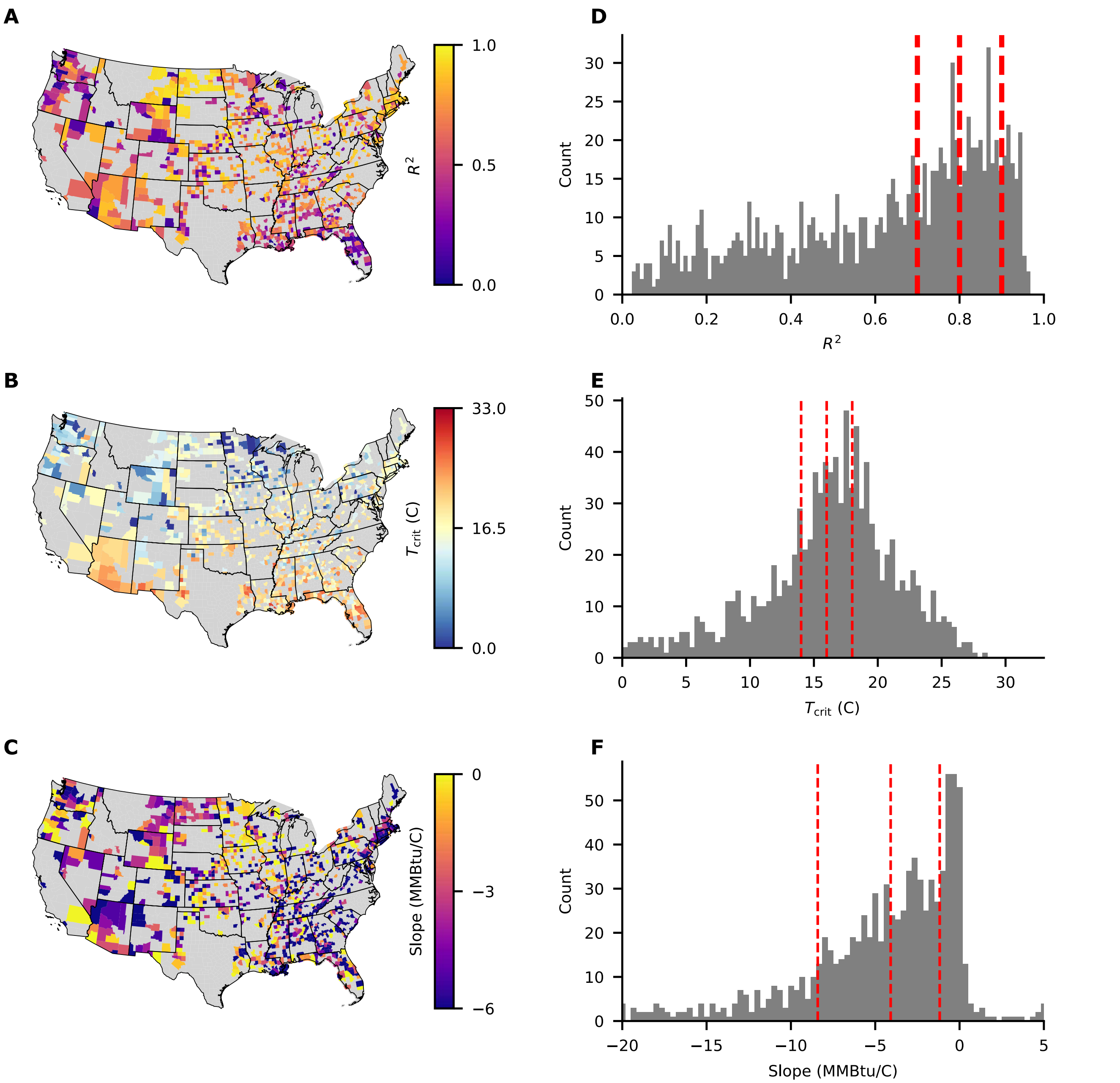

Fig. 2. Spatial distribution of the parameters derived from linear-plus-plateau functions fitted based on the daily per-household gas consumption and air temperature data. (**A** to **C**) Spatial distributions of R^2, T_{crit}, and Slope, respectively. (**D** to **F**) Distributions of R^2, T_{crit}, and Slope, with the four classes (low, medium, high, and very high, which are used in the formulation of machine learning classification problem) defined for explainable machine learning models as delimited by the vertical red lines.

used in buildings relative to total fossil fuel use, i.e., the sum of gas and oil excluding biomass, is the most influential predictor of the spatial patterns of Slope (Fig. 3C). Other factors explaining the spatial distribution of Slope values are the median income, the type of property (fraction of renters and multifamily residential buildings), and the average number of household units per building (Fig. 3C). We found that high income and employment levels tend to be associated with lower Slopes (fig. S2). However, the age of buildings, based on the fractions built between 1950 and 1999 or before 1949, ranked as moderately influential predictors for the Slope (Fig. 3C), whereas this influence was more important for T_{crit} and R^2.

The relative importance of the three categories of predictors, that is, the share of gas as a heating fuel (energy), building properties (building), and socioeconomic predictors (social), varies across the U.S. regions (Fig. 4). On the East Coast, both T_{crit} and Slope were mainly controlled by the share of gas in the heating fuel mix, and by building characteristics. Parts of New England and Mid-Atlantic along the East Coast are primarily influenced by the share of gas as a heating fuel. We see a dominance of predictors linked to the

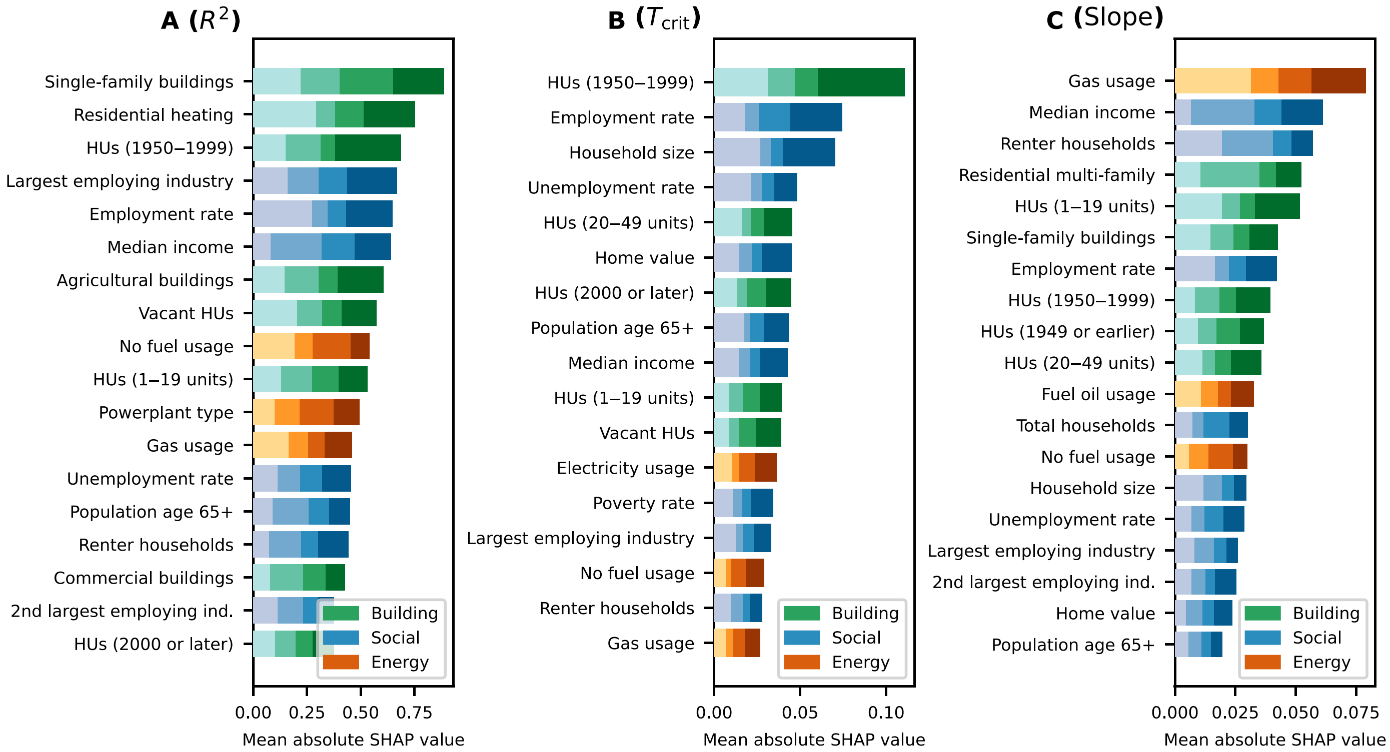

Fig. 3. Mean absolute values of the Shapley indices (SHAP). This figure shows the importance of different predictors in the machine learning models used in prediction of R^2 (**A**), T_{crit} (**B**), and Slope (**C**). The Shapley indices are ranked by decreasing order of importance from top to bottom, as selected by the machine learning models. Positive or negative signs of the Shapley indices are shown in fig. S2. The shades of the bars (increasing saturation) denote the four discrete classes of the predicted variables (low, medium, high, and very high). The name of each predictor is detailed in table S1. In the figure, HU indicates housing units. These predictors are grouped into three families: type of fuel or energy used in buildings (orange), building characteristics (green), and other socioeconomic predictors (blue).

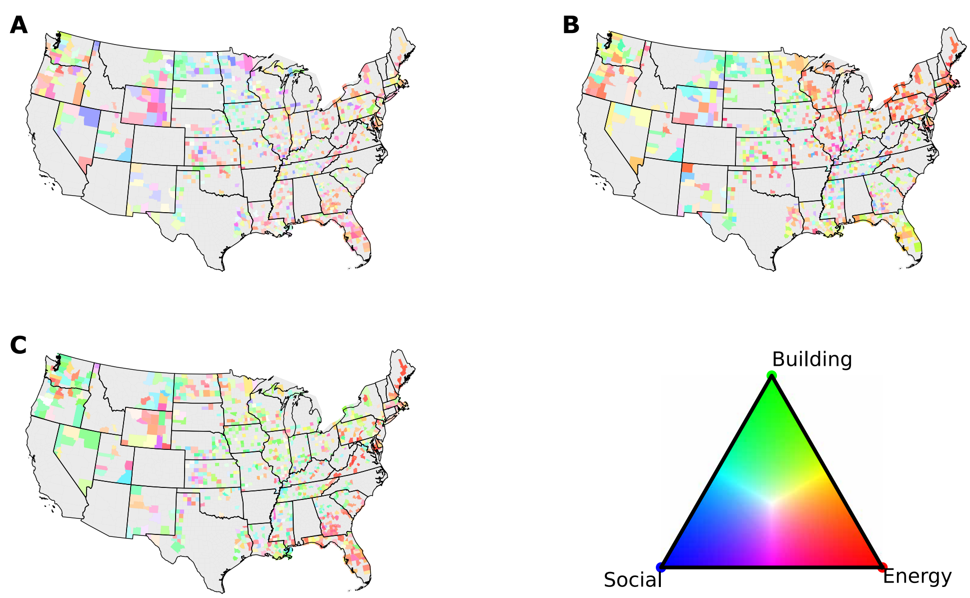

Fig. 4. Map showing the dominance of the three families of predictors. This map illustrates mean absolute values of Shapley indices for the three predicted parameters of per-household gas consumption fitted as a function of temperature: R^2 (**A**), T_{crit} (**B**), and Slope (**C**).

"energy" category in this region that has a high density of gas pipeline infrastructures (Fig. 1C). In the Midwest, encompassing states like Iowa, Minnesota, Nebraska, North Dakota, Ohio, and Washington, the spatial pattern of T_{crit} was predominantly influenced by building properties and to a lesser extent by socioeconomic or energy predictors (Fig. 4B). The emphasis on building characteristics in the Midwest suggests that factors like insulation related to the age of the house are critical in assessing the gas consumption temperature threshold. Nevertheless, the share of gas as a heating fuel remains relevant in the states harboring the Great Lakes. The building properties were the dominant predictors of the Slope (Fig. 4C) in the Midwest. The presence of well-insulated buildings plays a crucial role for gas consumption in this region. In certain parts of both the Midwest and Rocky Mountain regions, socioeconomic predictors interact with building-related predictors. In the Midwest, this is mainly in association with the temperature-consumption correlation (R^2), while in the Rocky Mountains, the influence is on T_{crit} and Slope. We included four predictors: county mean annual temperature, cooling degree days, heating degree days, and county temperature range (maximum minus minimum temperature) to check the influence of climate indicators on gas consumption. Degree days indicate the extent to which outdoor temperatures deviate from a standard temperature, typically 65°F (18.3°C) in the United States, indicating the need for cooling or heating (*27*). These predictors were in addition to the list of 19 previously chosen predictors. The climate predictors show the strongest influence for all three cases (R^2, $T_{\mathrm{crit},}$ and Slope) in the SHAP importance plot (fig. S3). It is difficult to ascertain whether this is a "direct" effect of temperature (as the parameters were derived from a temperature-consumption fit) or whether it is because temperature could be a better proxy of insulation than building features. Therefore, we excluded the climate predictors from the study.

Potential gas savings inferred from gas consumption models

In this section, we assessed how much gas could potentially be saved in the U.S. residential sector through the adoption of measures to reduce the demand for gas in households based on the fitted linear-plus-plateau functions and explainable machine learning models. Two idealized gas-saving scenarios were proposed: a behavioral change scenario and a massive building renovation scenario. In the first scenario, we supposed a hypothetical change in household behavior to reduce T_{crit} and Slope within plausible ranges. This scenario corresponds to a response of households to a potential surge in gas prices, as observed in Europe in 2022, or to a voluntary shift toward reduced individual consumption. In this scenario, we assumed that the entire U.S. population adopts a lower critical heating start temperature (T_{crit}) and reduces their consumption of gas per degree of air temperature cooling (Slope). In each county, the lower T_{crit} was defined as being 1°C less than the current value (*28*), and the lower Slope was defined within a plausible range by fitting only the lower 25th percentile of daily gas consumption in each temperature bin below T_{crit} (Materials and Methods). It is worth noting that the data used in this section only pertains to normal working days, and does not include holidays, special days, or weekends. In the second scenario, we explored the potential effects of a hypothetical extensive renovation of buildings. To do so, we exploited the partial sensitivities of our machine learning models that relate the gas consumption-temperature functions to building age, and everywhere in the best model, we replaced the predictors related to "old" buildings (houses built before 1999) with 100% of "recent" buildings (houses built after 2000). When this renovation scenario was applied to all the counties, the residential sector's regional and national gas consumption was reduced because both T_{crit} and Slope were lowered.

The impact of the behavioral change scenario is illustrated in Fig. 5A for Middlesex County in Massachusetts. In this county, a 1°C decrease in T_{crit} and a 2% decrease in Slope reduced the cold season gas consumption by 14.4%. Extending this scenario to all the 1000 counties included here, we find that the average Slope decreased by 10.9% and that the mean annual gas consumption was reduced by 26.1%. In this behavioral change scenario, the resulting map of relative gas consumption changes (Fig. 5B) shows that the savings range from 20% to 40% in most counties. We found that only 1.2% of counties have savings greater than 70%, which is quite high and may be due to variability in the data or local outliers. About 78% of the potential national gas savings are found in the Midwest and East Coast regions of the United States, where the climate is cold in winter, and the extensive gas pipeline network makes gas the dominant heating fuel. At a regional level, this scenario provided the highest relative reductions of gas consumption over the West Coast and the Gulf Coast, 33.8% and 28.1% less than current consumption levels, respectively. The Midwest, East Coast, and Rocky Mountain regions had lower relative saving potentials, within the range of 22 to 23%.

The impact of the renovation scenario (fig. S4) also decreased the values of T_{crit} and Slope. Specifically, a hypothetical retrofitting of all buildings to "recent" standards, that is, changing their characteristics to an age posterior to 2000, resulted in a drop in the critical temperature by 2°C in 14% of counties. The impact of renovation on gas savings through T_{crit} was found to be particularly substantial in the Midwest and East Coast regions (fig. S4A). A few counties, however, showed an increase in T_{crit} (6.7% of all counties) and Slope (2.7%), but these counties could be considered outliers, given their low correlation between gas consumption and temperature. The lower T_{crit} values derived from the renovation scenario were used to recalculate the gas consumption-temperature relationship for each county and deduce the pertaining gas savings. We found that the renovation scenario would result in a gas savings of 24.8% on a national scale, which is similar to the behavioral change scenario. The range of gas savings can vary depending on the extent of renovations carried out. Completing between a quarter and half of the renovations can result in gas savings ranging from 14.2% to 49.3% of the total potential savings achievable through a complete renovation. The largest contributions to national savings were mostly found in the Midwest and East Coast regions. Nevertheless, building renovations led to the highest relative gas savings in the West Coast and Gulf Coast regions, by 34.4% and 29.3%, respectively. The Rocky Mountains, Midwest, and East Coast showed slightly lower relative savings of about 23%.

DISCUSSION

Gas consumption patterns in the United States

Our results demonstrate that in most U.S. counties, household gas consumption decreases as a function of ambient air temperature when the temperature is lower than a county-specific critical temperature threshold and reaches a plateau of minimum consumption when the temperature is above this threshold. We found that

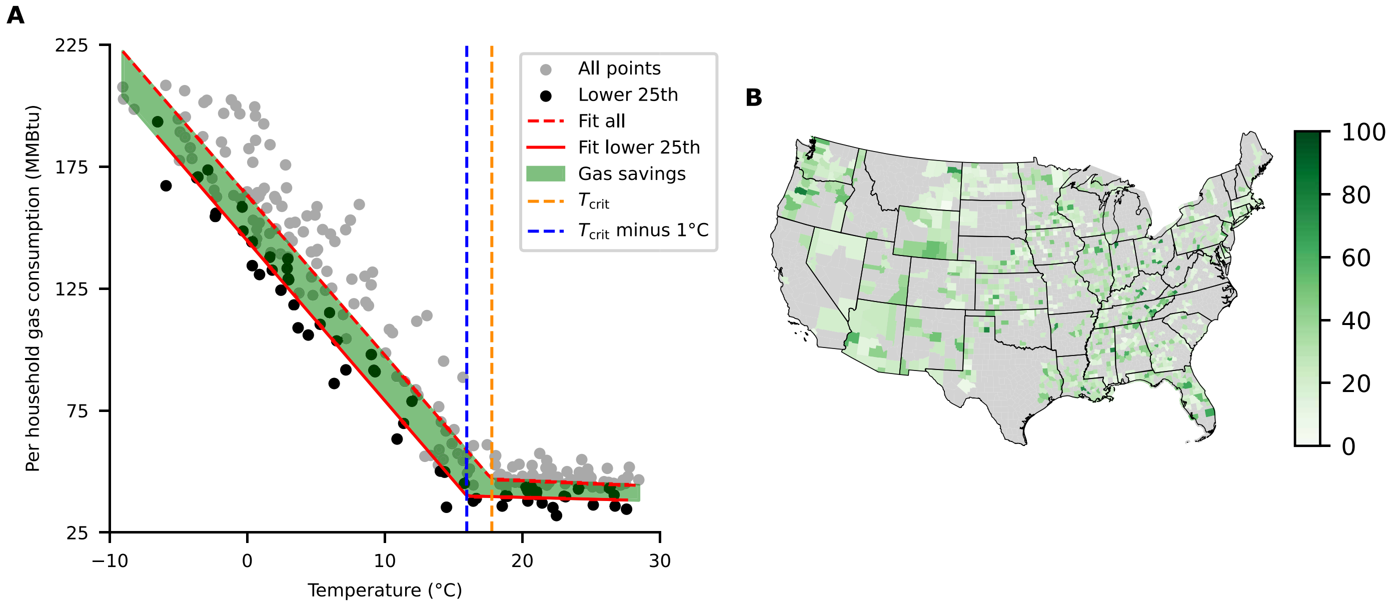

Fig. 5. Illustration of the gas consumption savings in the behavioral change scenario assuming a high rate of compliance. (**A**) Example of gas consumption savings in Middlesex County, MA, when adopting a 1°C lower critical temperature and a lower slope resulting from fitting only the lower 25th percentile of current consumption data (the black points). The potential gas savings are indicated by the green-shaded area. (**B**) Map showing the relative savings in percentage below the current consumption levels in each county of the United States according to this scenario.

pipeline operators in 396 counties reported highly irregular gas consumption, which led us to remove these data (see Materials and Methods). This filtering procedure still provided us with a sufficient number of counties (i.e., 1000 counties) suitable for analysis with machine learning models and covering all regions of the United States. Furthermore, in a few counties (11 of 1000; see fig. S5), we detected a substantial increase in gas consumption when the temperature exceeded T_{crit}. Most of those counties are characterized by hot summers during which electricity is largely used for air conditioning. Our gas consumption data from "Citygate" pipelines excluded power generation from large power plants but included power generation for cooling by small power plants located in cities, such as in business districts, hospitals, commercial malls, and buildings with multiple household units. The presence of such small gas-powered plants, which could not be distinguished from households and other building types in the pipeline gas consumption dataset, likely explains the increased gas consumption above T_{crit}. In another small group of counties (128 of 1000), we found a weak relationship between gas consumption and temperature. These counties are characterized by a high proportion of buildings that do not rely on natural gas for heating.

Predictors with expected effects on gas consumption

We showed that counties with a high proportion of "old" houses built in the period of 1950–1999 have a steeper Slope and higher heating setpoints (T_{crit}). On the basis of this result, we developed two scenarios for estimating gas savings: reduced household consumption behavior and the renovation of "old" buildings to "recent" standards (age posterior to 2000). Using these scenarios, annual reductions in gas use can be translated into reductions in residential CO_2 emissions (*29*). We estimate that reduced consumption and building renovations would reduce CO_2 emissions by 1.22 million $MtCO_2$ and 1.24 million $MtCO_2$ per year, respectively (table S4). At the regional scale, improving building energy efficiency through renovation would yield slightly increased gas savings for every region in the United States. In each scenario, about 79% of the potential national CO_2 reductions were found in the Midwest and East Coast regions. The Rocky Mountain region, which has fewer houses connected to gas pipelines, displays a comparatively lower reduction of only 2%. Combining the effects of both behavior change and renovation scenarios, we found potential gas savings amounting to 44.79 million MMBtu/100 households, which is about 46% of the total gas consumption in the country for 2018. In terms of potential CO_2 emissions, it translates to a mitigation potential of 2.47 million $MtCO_2$ per year. The behavior change has a direct effect on reduction in gas consumption while building renovations provide long-term energy and emissions savings. Together, both scenarios create a powerful strategy for substantial reductions in gas consumption. Note that although both scenarios are modeled separately, there could be interactions between them, causing the calculated value of potential gas savings to appear slightly lower than indicated here.

We propose the Midwest region as a good candidate for an initial renovation pilot project aimed at reducing CO_2 emissions. In the Midwest, gas consumption as a function of temperature is well defined (high R^2 in Fig. 2A), and T_{crit} is dominantly explained by building-related predictors (Fig. 4B), thus making renovation relevant for reducing gas consumption and CO_2 emissions (table S4). On the other hand, on the East Coast, where the share of gas as a heating fuel is the most influential predictor of the Slope, compared to building properties (Fig. 4C), measures to encourage reduced consumption could be the best option for reducing gas-related emissions. In relation to the climate warming scenarios from the Coupled Model Intercomparison Project Phase 6 (*30*), it is suggested that in urban areas, a 1°C warming could lead to a 10.5% reduction in building natural gas consumption, primarily for space heating purposes (*31*). Building energy efficiency policies could take this into account to create more effective and sustainable solutions.

Predictors with unexpected effects on gas consumption

A key point of discussion is that household gas consumption is sensitive to income level, as shown in Fig. 3, B and C. Wealthy counties with high employment rates display a T_{crit} about 0.6°C lower than the national average and a lower Slope value as well (fig. S2). Despite living in larger and single-family houses, more affluent households with a median income greater than \$70,488 in 2018 and 2019 (*32*) consumed 57% less gas per household for heating than poorer households (wealthier counties have twice the median home value than the rest, so we presume the higher home value may be correlated to the higher floor area/size of homes). The comparatively high T_{crit} in counties with high unemployment rates can be tentatively explained by poor house insulation and by higher gas consumption due to the longer presence of unemployed people in private houses. This finding suggests that counties with low-income and high-unemployment rates should be prioritized in efforts to reduce gas consumption per household in the United States. Naturally, these counties also have a higher proportion of households below the poverty rate as defined in (*33*). We also found that the base rate of gas consumption when the temperature exceeds T_{crit} is 9.4% higher in counties with high rates of unemployment than in other counties. This all points toward the need for targeted energy efficiency programs for counties with low-income households and high unemployment rates. It is vital to tackle this energy poverty issue. A study about U.K. households (*34*) suggested that energy efficiency policies yielded considerable gas savings, but they did not produce consistent results for households experiencing multiple deprivations, highlighting the need to consider the diverse impacts of policies. Policymakers can use our results to prioritize areas to implement incentives for building renovations. To complement the financial incentives, targeted policies could also invest in public awareness campaigns to educate residents about the benefits of energy efficiency and promote available assistance programs. In addition, intervening energy audit services to assess a household's energy usage and recommend improvements will be beneficial. All such measures would aid in energy poverty alleviation.

Moreover, it is worth considering that America is aging (i.e., the average age of the U.S. population is increasing), which will affect gas consumption in the future. Elderly people over 55 years old will represent about 35% of the U.S. population by 2060 (*35*). In this context, we found that counties with a higher number of elderly people display a stronger correlation between gas consumption and temperature (fig. S2) and a lower value of T_{crit}, possibly indicative of better-insulated houses. Furthermore, elderly people also have a higher per-household energy consumption than the rest of the population (*36*). Therefore, policies targeted toward further improvement of household energy efficiency in counties with aging populations could be valuable to achieve substantial gas savings per household.

Despite some shortcomings, the 2020 RECS provides valuable independent estimates and analysis of gas consumption for different variables such as type of housing unit, income, etc. RECS made a study on gas consumption based on the age of the building and income levels (*37*). The buildings with a year of construction between 1950 and 1999 represented 58.9% of the total gas residential gas consumption in the United States. On the other hand, older buildings constructed before 1950 represented 24.1% of the total consumption. This result supports our findings on building renovation. On the income levels, RECS estimated that poor households (median income < \$70,488) represented 45.5% of the total gas consumption, which is not the same as our finding (we found that poor households consumed 57% of the total gas consumption). It should be noted that RECS data are subjected to higher sampling error as their sample size is rather small (18,496 households across the United States). Moreover, the spatial scale for comparing RECS (households) and our study (counties) is not the same.

In summary, our analysis shows the expected negative relationship between gas consumption by U.S. households and outdoor temperature. However, along with climatic variables, we identify several key social predictors of gas use, such as median household income, employment levels, population age, and features of the housing stock, such as home age, size, and value that substantially influence patterns of gas use. According to our simulation, lowering thermostat setpoints by 1°C could reduce the current level of U.S. gas consumption by up to 25% and by as much as 40% in some counties. Renovation of the building stock and consumption behavioral changes could further reduce gas use, especially for counties in the Midwest and East Coast regions. Our calculations indicate a potential reduction in residential CO_2 emissions, amounting to 2.47 million $MtCO_2$ annually if behavioral changes in gas consumption and building modernization are implemented. Future research could explore long-term behavioral trends in gas consumption in association with the integration of renewable energy sources into the energy grid. By addressing these, explainable machine learning models such as those presented in this work pave the way for effective policies and practices aimed at promoting sustainable energy transitions for a zero-carbon energy future.

MATERIALS AND METHODS

Natural gas data

Daily natural gas consumption data were obtained from Wood Mackenzie's "Natural Gas Analyst," a comprehensive database of gas nominations and flows (*19*). Our dataset includes data from different gas delivery points across the United States called a "Citygate." A Citygate can be defined as a point or a measuring station where the gas is collected from the natural gas pipeline company and delivered to the end consumers like residential and small commercial entities (*21*). The gas data comprise two entities: net scheduled capacity and no-notice capacity. The net scheduled capacity is the volume requested by an end-user 1 day before consumption. The no-notice capacity is the amount of gas delivered as needed without scheduling the gas quantity in advance to meet a sudden surge in gas demand. The total gas transported to the distributing company or Citygate from the pipeline company is computed by aggregating the net scheduled capacity and no-notice capacity. The unit used for gas volume is metric million British thermal unit. Data reported at Citygate delivery points can cover multiple locations in a given county. Location-based hourly Citygate gas data were aggregated to county-level daily values. For temperature-consumption fittings, only pre-COVID period data were used as we assumed that the influence of the pandemic had overridden the effects of climate predictors. The Citygate delivery points covered 1000 counties (of 3143), as not all counties in the United States have gas pipeline access.

Gas consumption
We calculated per-household gas consumption values using demographic data from the American Community Survey (ACS 2019) (*38*). Normalization of the consumption values was necessary as different counties have different population levels, resulting in high gas consumption variability. Consumption values were normalized by the total number of households (ACS variable B11016_001E) using gas as a heating fuel in each county. The units of consumption are MMBtu/100 households. The no-notice capacity values in the data were not reported daily but with a lag of 2 to 4 days, and tended to fluctuate considerably. To maintain the homogeneity of the data, we retained only counties with a low proportion of the no-notice capacity (<49%) in the final aggregated consumption values. Data reported on weekends and U.S. holidays were removed.

Temperature
We obtained daily gridded air temperature data at 2 m above ground at a 25-km spatial resolution from ERA5 (*39*) on the same dates as the gas use data. The gridded data were clipped using county vector polygons, and spatially distributed temperature values across each county were averaged to obtain a time series of daily average county temperatures. Counties smaller than the ERA5 grid were resampled to a spatial resolution of 2 km using a linear interpolation technique (*40*). Temperature data were obtained for all the counties with the gas consumption data.

Housing structure properties and socioeconomic indicators
A list of 39 housing structure properties and socioeconomic indicators was assembled to be used as predictors for natural gas consumption (see table S1). The predictors were selected assuming they would play a role in household gas consumption and can be classified into three categories: (i) building structure, (ii) social, and (iii) energy and miscellaneous. Building structure–related predictors describe attributes such as the size and year of construction of a housing unit, as well as its use type (commercial, agricultural, residential, etc.). Social predictors cover income, poverty rate, employment rate, population size, etc. Energy-based predictors address the types of fuel used by households to heat housing units (natural gas, electricity, fuel oil or kerosene, and coal). We also added some miscellaneous predictors that focus on the number of mega-cities and the number of pipelines present in a county to the third category. The data sources include the ACS and the Zillow Group's ZTRAX data (*25*). The ACS provides data at the county level, and Zillow's ZTRAX provides data at the housing unit level, which was aggregated to the county level. All predictors were normalized based on the number of households in each county using gas as heating fuel.

Relationship between gas consumption and temperature
We fitted a linear-plus-plateau piecewise function (with one breakpoint) to the gas consumption and temperature data. The function identifies the breakpoint location based on a global optimization that minimizes the sum of squares errors. Piecewise regression models were built separately for each county for 2018 and 2019. From the fit, we derive the quality of the fit (R^2), the critical temperature (the breakpoint, T_{crit}), and the slope of the line below T_{crit} (the first segment of the piecewise fit). These results for both years were averaged to obtain the final values for each county. We found that the piecewise function (with one breakpoint) was the best fit for the data as it had the lowest Akaike information criterion (AIC) (*41*) out of the other models we tested (simple linear regression and generalized additive models). AIC explains how complex it is to use a particular model. Lower AIC values indicate better-fitting and more parsimonious models.

Formulation of machine learning models
We built a dataset to train a machine learning model using the 39 variables from ACS and Zillow as predictors to predict (i) the quality of the fit (R^2), (ii) the temperature heating threshold (T_{crit}), and (iii) the estimated slopes representing the rate of decrease in the gas consumption at temperatures below T_{crit}. These three variables were classified into four classes based on three different thresholds. For R^2, we chose thresholds of 0.7, 0.8, and 0.9 and obtained four classes: low (0 to 0.7), medium (0.7–0.8), high (0.8 to 0.9), and very high (0.9 to 1) quality of fit (Fig. 2). For T_{crit}, the thresholds were chosen as 14°, 16°, and 18°C. For Slope, the thresholds were the 25th percentile, 50th percentile, and 75th percentile values. Two ensemble tree-based machine learning models, RF and CatBoost (*42*), were trained and evaluated to classify the three above-mentioned variables (see Supplementary Methods). A recursive feature elimination technique was applied to remove half of the least important predictors. Model evaluation was performed using standard metrics: accuracy, precision, recall, and F1 score. The best model was selected for each variable according to the highest accuracy scores. We made sure the data used in training the machine learning models were devoid of any missing information.

Interpretable machine learning model
The differences between machine learning predictions and average predictions were explained by the SHAP (SHapley Additive exPlanations) framework (*26*). SHAP is a state-of-the-art approach that can be used to find the main predictors of machine learning model output. It uses a game theory approach, assigning an importance value to each predictor observation to enable local and global interpretability. With this framework, each difference between individual and average predictions is decomposed into a sum of the contributions of the different predictors. The most influential predictors can then be identified from their individual contributions. The formula to calculate SHAP values is as follows:

$$\boldsymbol{\phi}_{\boldsymbol{i}}(\boldsymbol{f},\boldsymbol{x}) = \sum_{\boldsymbol{z}\subseteq\boldsymbol{x}} \frac{|\boldsymbol{z}|!(\boldsymbol{M}-|\boldsymbol{z}|-1)!}{\boldsymbol{M}!}[\boldsymbol{f}_{\boldsymbol{x}}(\boldsymbol{z})-\boldsymbol{f}_{\boldsymbol{x}}(\boldsymbol{z}\setminus\boldsymbol{i})]$$

where $\boldsymbol{\phi}_{\boldsymbol{i}}$ is the Shapley value for the predictor $\boldsymbol{i}$, $\boldsymbol{f}$ is the machine learning model, $\boldsymbol{x}$ is the input datapoint, $\boldsymbol{M}$ is the total number of predictors, and $\boldsymbol{z}$ is the subset of predictors. A high positive SHAP value for a predictor indicates that the predictor has a significant impact on producing the outcome. In our experiments, a high SHAP value is associated with the following outcomes:

1. In the R^2 case, a high SHAP value suggests that the predictor is likely to yield high R^2 values.
2. In the T_{crit} case, a high SHAP value suggests that the predictor has a significant influence on increasing T_{crit} values, ultimately contributing to higher gas consumption.
3. In the Slope case, a high SHAP value suggests that the predictor plays a significant role in generating low Slope values, which implies that temperature has a minimal influence on gas consumption.

Refer to Fig. 3 for the importance of predictors based on their mean absolute SHAP values and to fig. S2 to understand how the nature of predictor affects the SHAP value.

Gas consumption reduction potential (behavior change scenario)

One method of reducing household gas consumption is by changing residents' consumption habits to consume less gas. Here, a mathematical simulation of the amount of gas that could be saved was investigated by considering a scenario that each household adapts to a 1°C reduction in the starting heating temperature of the residence (T_{crit} reduced by 1°C). To do so, we constructed a plausible reduction scenario by modifying two variables derived from the piecewise function. We assumed a lower critical heating start temperature that was 1°C less than the actual and computed a lower slope below critical temperature by using the data below a low threshold percentile of gas consumption data. The threshold was set to be the 25th percentile (*28*). The experiments were applied for each county for both 2018 and 2019.

Effect of building renovations or changing building age proportions (renovation scenario)

Another method used to reduce gas consumption is improving the insulation of buildings to increase indoor heat retention and decrease the use of gas heating. The age or year of construction of a building is typically linked to gas consumption efficiency, with older structures generally being less efficient than recent ones due to poor insulation. Hence, we use the year of construction as one of the predictors in the machine learning model. We split the predictor into three different time period intervals: housing units built in 1949 or earlier, from 1950 to 1999, and in 2000 or later. A housing unit can be a single-family home, a unit within a multifamily building, a unit within a condominium or cooperative home, a shared-family house, or an apartment that serves as a separate living quarter (*43*). In the experiment, we assumed complete renovation of all the "old" buildings in all the counties. Therefore, the proportion of housing units built in 2000 or later was set to 100% and the rest was set to 0%. The obtained modified dataset was used to make new predictions with the previously trained machine learning model. The final predictions based on the modified and original data were compared to see how the renovation affected the output.

CO_2 emission calculation

The per-household natural gas consumption values are used to compute the carbon dioxide emissions using the Greenhouse Gas Equivalencies Calculator (*29*) provided by the U.S. Environmental Protection Agency.

Supplementary Materials

This PDF file includes:
Supplementary Text
Figs. S1 to S10
Tables S1 to S5

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Acknowledgments
Funding: R.T.M has been supported by a grant of the French National Research Agency (ANR) 'Plan de Relance CEA-ATOS'. **Author contributions:** Designed the study: R.T.M. and P.C. Performed the analysis: R.T.M. and P.C. Analyzed and prepared data (from the Zillow database): J.E.S. Helped with machine learning models: D.M. and C.Z. Writing—original draft: R.T.M. and P.C. Writing—review and editing: All authors. **Competing interests:** The authors declare that they have no competing interests. **Data and materials availability:** Natural gas data were licensed from Wood Mackenzie's "Natural Gas Analyst" and we do not have the right to redistribute it. Paid licensing information can be found at https://woodmac.com/industry/gas-and-lng/natural-gas-analyst/. Please note that while the data are accessible to any reader through the provided licensing channel, there may be costs associated with accessing it. Temperature data (open-access) were provided by Copernicus Climate Change Service (C3S) (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=form). Building data (open-access) were provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at https://zillow.com/data/. The results and opinions are those of the author(s) and do not reflect the position of the Zillow Group. Socioeconomic data (open-access) were provided by American Community Survey (ACS) Data (https://census.gov/programs-surveys/acs/data.html). All other data needed to evaluate the conclusions in the paper are present in the paper and/or the Supplementary Materials.

Submitted 17 March 2023
Accepted 28 February 2024
Published 3 April 2024
10.1126/sciadv.adh5543