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# Street green space and electricity demand: evidence from metered consumption data

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## ABSTRACT

Growing climate change impacts call for increased efforts to adapt and to reduce its adverse consequences on society. Adaptation responses can themselves be a source of climate risk, generating negative environmental externalities while entailing budgetary costs for both governments and private citizens. A key example is the private use of air-conditioning for indoor air temperature regulation in the face of rising urban heat. In this paper, we empirically evaluate the impact of street green spaces (SGS) on residential electricity demand through their urban temperature regulation effect. We exploit a monthly panel of household metered electricity demand data from 129,524 households located in 2,181 municipalities distributed across Italy, in the period between 2020 and 2022. We find evidence of a significant non-linear mediating role of SGS on the impact of temperature on household electricity demand. The most salient effect is a reduction in electricity consumption when hot temperatures occur - lowering monthly average electricity consumption by up to 11-25% (for monthly maximum temperatures of 30 and 35° C, respectively). The observed moderating effects of SGS are heterogeneous across municipalities, as they depend on contextual factors such as the degree of urbanization, baseline heat and SGS levels, and average income level. To dissipate across-municipality sorting concerns, we conduct propensity score weighting on a range of potentially confounding observables, and find our results remain consistent. We estimate that a policy increasing the average Green View Index (GVI) level across all municipalities to a value comparable to the median of the current distribution would reduce the growth in residential electricity consumption driven by climate change by more than two thirds (under Representative Concentration Pathway 8.5 climate conditions around 2050). This corresponds to a gross national-level private saving in energy bills of €150 million yearly in 2050. This is a noticeable benefit that represents about 7.3% of our estimated costs to implement such policy, and informs on a potentially substantial social and economic benefit of urban green spaces. Our results provide new quantitative evidence of the role of street green spaces for both energy demand reduction, and therefore climate change mitigation, and in terms of outdoor temperature reduction, supporting climate change adaptation.

## Keywords

Street green space; energy demand; public-private adaptation; urban heat islands; nature-based solutions; climate change impacts

## JEL classifications:

D12, O13, Q41, Q5

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## 1 Introduction

2 Growing climate change impacts call for increased effort on adaptation plans capable of achieving multiple benefits  
3 (IPCC, 2023). Adaptation responses can themselves be a source of climate risk, generating negative environmental  
4 externalities while entailing budgetary costs for both governments and private citizens. A key example is urban heat  
5 adaptation, and specifically air conditioning (AC), including mechanical ventilation systems based on heat-pumps.  
6 These technologies are considered effective forms of private adaptation, capable of regulating indoor temperature and  
7 reducing the impact of heat on mortality (Barreca et al., 2016; Sera et al., 2020) and other health-related outcomes  
8 (Park et al., 2020). However, AC significantly increases households' expenditure (De Cian et al., 2025; Randazzo, De  
9 Cian and Mistry, 2020). It is also considered a form of maladaptation (Magnan et al., 2016; Vigié et al., 2020) due  
10 to its high energy intensity (De Cian et al., 2025; Falchetta et al., 2024), its adverse impacts on local urban outdoor  
11 temperatures (Jin et al., 2020; Salamanca et al., 2014), and its contribution to global greenhouse gas emissions  
12 (Byers et al., 2024). Finally, access to private means of heat adaptation is unequally distributed across citizens due to  
13 economic barriers and inequalities in adaptive capacity (Kianmehr A and Li, 2023; Romitti et al., 2022).

14  
15 Urban green infrastructures represent another set of potentially effective adaptation strategies to tackle extreme  
16 heat (Li et al., 2024). Among those, street green spaces (SGS) are vegetation-covered areas located along roads  
17 within urban boundaries and in the proximity of buildings (Russo and Cirella, 2018). SGS provide a broad range  
18 of ecosystem services in terms of human health (Jungman et al., 2023; Jabbar, Yusoff and Shafie, 2021; Liu et al.,  
19 2024; Tan, 2022; van den Berg et al., 2015a) and well-being (Kwon et al., 2021; Olszewska-Guizzo et al., 2022).  
20 They contribute to flood control (Kim, Lee and Sung, 2016; Staccione et al., 2024), carbon sequestration (Fryd,  
21 Pauleit and Bühler, 2012; Sun, Xie and Zhao, 2019), and urban biodiversity (Belaire et al., 2022; Uchida et al., 2021;  
22 Wooster et al., 2022). SGS are mostly public in nature and they provide a stream of benefits to the general population  
23 that are non-excludable and non-rivalrous (Tompkins and Eakin, 2012). On the other hand, nature-based adaptation  
24 is not without risks and trade-offs, as it also implies monetary costs, such as the need for recurrent maintenance (Tate  
25 et al., 2024), and it might entail unintended risks, such as the increase in local disease-spreading vectors (Mercat  
26 et al., 2025).

27  
28 This paper evaluates the effectiveness of the availability of SGS as a public adaptation option for regulating  
29 outdoor and indoor local temperatures and hence indirectly reducing the need for using energy-consuming cooling  
30 appliances in households. It primarily contributes to advancing the understanding of the relationship between  
31 SGS, the local microclimate within cities, and the consequent role of SGS for energy consumption in buildings.  
32 While both topics have been investigated in the literature, existing studies rely on bottom-up, engineering-based  
33 approaches applied to specific cities or neighborhoods. Large-scale, empirically grounded assessments of the role of  
34 SGS in shaping electricity demand remain missing, in part due to the lack of high-resolution, large-area electricity  
35 consumption data and to limitations in the availability of harmonized, spatio-temporal SGS datasets. A recent  
36 exception is Han et al. (2024), who exploit an exogenous shock to urban green space in Toronto to identify its causal  
37 effect on electricity consumption.

38  
39 Here we provide an empirical contribution linking SGS and the energy use dimension, with a specific focus  
40 on the role of hot temperatures at a national scale. We quantify the benefits of SGS by appraising its temperature  
41 regulation effect - measured through the street-based Green View Index (GVI) - and its relevance for household  
42 electricity demand. To achieve this goal, we build a monthly panel of household metered electricity demand data  
43 from  $n = 129,524$  households located in 2,181 municipalities distributed across Italy over the 2020-2022 period  
44 augmented with monthly weather characteristics and GVI data and use a household-level fixed effects regression  
45 model to estimate how households' electricity-temperature response function is mediated by the extent of SGS. To  
46 explore the underlying temperature regulation mechanism through which SGS can affect temperature-related energy

47 use in buildings, we develop an auxiliary regression model linking SGS and local temperature at the spatial resolution  
48 of 100 meters within a subset of large municipalities where urban microclimate data are available. We then use the  
49 estimated relations to assess the private benefits of a public policy targeted at increasing SGS. We characterize SGS  
50 provision as a public good generating positive externalities for households, which we quantify in terms of private  
51 electricity expenditure and welfare. As a guide for the empirical analysis, we develop a simple theoretical model in  
52 which a social planner chooses the socially optimal amount of green spaces and private households adapt to weather  
53 conditions through an intensive adjustment in the use of electricity. When maximizing their utility, private house-  
54 holds' choices are influenced by the experienced temperature and therefore by the extent of surrounding green spaces.

55  
56 Our paper contributes to advancing the understanding of the relationship between SGS and local microclimates  
57 within cities. Street trees are a key solution for mitigating urban heat islands, primarily by providing shade and  
58 enhancing evapotranspiration (Aram et al., 2019; Du et al., 2017; Massaro et al., 2023; Meili et al., 2021, 2025;  
59 Turner, Middel and Vanos, 2023; Wong et al., 2021; Yin et al., 2023; Zhang et al., 2014). The concept of *cooling*  
60 *efficiency* is widely used to describe the slope of the relationship between urban green space and air temperature (Li  
61 et al., 2024). A growing body of empirical contributions has quantified this parameter using different metrics and  
62 modeling approaches (Chan et al., 2024; Yang et al., 2022; Zhan et al., 2024), showing that cooling efficiency varies  
63 substantially across geographical, infrastructural, and climatic contexts and is better represented as a non-linear  
64 function rather than a constant (Liu et al., 2022; Ouyang et al., 2020). For example, based on a large sample of  
65 European cities, Marando et al. (2022) estimate that a minimum tree-cover fraction of approximately 16% is required  
66 to achieve a 1°C reduction in urban temperatures. Complementing this, Zawadzka, Harris and Corstanje (2021)  
67 demonstrate the importance of using high spatial resolution data, as well as accounting for additional landscape  
68 features such as water bodies, to accurately detect the cooling effect of urban green space. The magnitude of  
69 the cooling benefit from SGS has also been shown to decline with distance from the tree canopy, underscoring  
70 the importance of trees' proximity to buildings for maximizing temperature-reduction benefits (Park et al., 2021).  
71 Overall, a comprehensive review by Wong et al. (2021) concludes that urban green infrastructure is an effective  
72 strategy for mitigating urban heat, but that its cooling potential is highly context-dependent, varying with the spatial  
73 scale of analysis, the extent of greenery, and plant selection and placement. We find that areas of cities with higher  
74 GVI warm less in relation to the average warming experienced throughout the city. Moreover, we find evidence of  
75 non-linearity in the effect of GVI on local temperature.

76  
77 Our second contribution relates to the understanding of the consequent role of SGS for energy consumption  
78 in buildings. Existing work on the benefits of SGS is dominated by context-specific case studies, both in the  
79 Mediterranean region (Aboelata, 2021; Karachaliou, Santamouris and Pangelou, 2016; Napoli et al., 2022; Olivieri  
80 et al., 2013; Vurro et al., 2024; Zinzi and Agnoli, 2012) and in other climatic settings (Kim, Yi and Lee, 2019; Moss  
81 et al., 2019; Quaranta, Dorati and Pistoche, 2021; Zhang et al., 2014). For instance, in Athens, Olivieri et al. (2013)  
82 estimate that installing a green roof can reduce the annual cooling load of the host building by about 19%, while in  
83 Cairo, Zinzi and Agnoli (2012) find that green roofs implemented on 12-meter high buildings can lower cooling  
84 energy use by 3.2–4% on a typical summer day. In Beijing, Zhang et al. (2014) quantify the cooling effect and  
85 associated environmental benefits of SGS and estimate that air-conditioning demand is reduced by roughly 0.3 TWh  
86 (terawatt-hour)/yr. A simulation study for Miami (USA) by McPherson, Herrington and Heisler (1988) shows  
87 that dense SGS can decrease annual cooling electricity expenditures by \$249 (61%) and reduce local peak cooling  
88 loads by 31–49%. Methodologically, Zhu et al. (2022) emphasize the importance of relying on air temperature  
89 metrics, rather than land surface temperature, when assessing the potential of urban greenery to curb building  
90 energy consumption. Synthesizing evidence across case studies, Seyam (2019) concludes that greenery systems  
91 generally contribute to building energy savings, but cannot fully substitute air-conditioning systems for maintaining  
92 indoor thermal comfort; instead, their performance depends critically on appropriate management conditions,  
93 including adequate watering, to fully realize trees' cooling capacity (Gao, Feng and Santamouris, 2024). This  
94 evidence suggests that SGS should be viewed as a form of public adaptation that can lower, but not entirely replace,  
95 private adaptation efforts such as mechanical cooling, thus giving rise to public–private synergies in adaptation

96 (Tompkins and Eakin, 2012). We find that SGS levels - as measured by GVI - significantly and non-linearly affect  
 97 how temperatures influence household electricity demand. SGS limits the increase in electricity consumption as  
 98 temperatures rise, with the effect being stronger when temperatures reach the hottest levels ( $\geq 30^\circ$  C of monthly  
 99 average of daily maximum temperatures). The identified moderating effects of SGS are heterogeneous across  
 100 municipalities, as they depend on contextual factors such as the degree of urbanization, baseline heat and SGS levels,  
 101 and average income level. A policy aimed at bringing the municipality-level average GVI to at least 21 - a value  
 102 at around the median of the current distribution across the municipalities covered by our analysis - would reduce  
 103 by more than two thirds the temperature-induced residential electricity consumption growth driven by climate change.

104  
 105 Since green spaces also require maintenance, our third contribution is to provide a back-of-the-envelope cal-  
 106 culation of the public budgetary implications of nature-based solutions such as SGS in relation to the private  
 107 savings they can generate. A systematic review of the literature on the costs of nature-based solutions, including  
 108 green spaces (Panduro et al., 2021), found that the establishment cost of green spaces has a mean value of of  
 109 €60/m<sup>2</sup>, but with a wide range between €323/m<sup>2</sup> and €1.7/m<sup>2</sup>, though costs in general are not well-documented.  
 110 Maintenance costs have a mean value of €1.8/m<sup>2</sup>, but again are characterized by a big spread, between €12.5/m<sup>2</sup>  
 111 and €0.05/m<sup>2</sup>. Costs vary across space, over time, and with the extent of future warming. For six cities in Austria,  
 112 annual average costs for new investments in green spaces as well as their maintenance and operation until 2030  
 113 have been quantified to lie in the range between €108 and €166 million (Loibl et al., 2015). EU-wide assessments  
 114 based on geospatial implementation of the meta-models (Quaranta, Dorati and Pistocchi, 2021) have quantified  
 115 the costs of green roofs and their benefits, in terms of reduced energy demand and CO<sub>2</sub> emissions. Specifically,  
 116 the cost of turning 26,450 squared kilometers of impervious urban areas in Europe into green surfaces is estimated  
 117 at €60/year per urban resident with a total Net Present Value (NPV) of costs over €1,323 billion. In our paper,  
 118 we use open public budget data on the yearly costs of maintenance of public green spaces and enhancement of the  
 119 natural environment for Italian municipalities to estimate investments required to support policies that expand green  
 120 areas. We then relate these cost estimates to the estimated private benefits in terms of reduced electricity expenditure.  
 121 National-level private savings in terms of energy bills represent about 7.3% of the costs to implement and maintain  
 122 the policy. The already significant private benefits of SGS underline the important role of urban green spaces as a  
 123 form of public adaptation that can reduce the risk of private maladaptation from unregulated active cooling energy use.

124  
 125 The remainder of the paper is organized as follows: Section 2 introduces a theoretical framework for describing  
 126 the role of SGS for residential energy use from the perspectives of both the social planner and the private household;  
 127 Sections 3 and 4 illustrate the sources of data and econometric approach used for empirically evaluating the relations  
 128 described in theoretical framework; Section 5 presents the results of the empirical analysis; Section 6 discusses  
 129 heterogeneity and robustness checks, while Section 7 derives a set of policy and climate change impacts simulations  
 130 and their economic implications. To conclude, Section 8 discusses the relevance of the empirical and simulation  
 131 results and lays out implications for policy and future research.

## 132 2 Theoretical framework

133 To guide our empirical analysis, we develop a simple model in which a social planner decides on the intensity  
 134 of provision of SGS,  $G$ , as a public good while private households maximize their individual utility subject to a  
 135 standard budget constraint taking the provision of the public good  $G$  as exogenous.

136  
 137 **The social planner.** For each year  $t$ , let  $G_{a,t}$  be the density of SGS in each administrative area,  $a$ . The provision  
 138 of the public good  $G$  is a function of the social planner's decision to implement policies ( $POL$ ) and invest ( $INV$ )  
 139 in the expansion and maintenance of SGS, for instance through the plantation of trees along roads or through the  
 140 conversion of land use to create new urban parks. At the same time,  $G$  is exogenously affected by inter-yearly  
 141 variations in temperature, rainfall, and other weather events ( $c$ ), such as the frequency and intensity of outdoor  
 142 chronic and acute heat:

$$G_{a,t} = f(POL_{a,t}, INV_{a,t}, c_{a,t}) \quad (1)$$

143 The public good  $G$  hence generates a stream of positive externality value accruing to an array of private  
 144 individuals. Each household  $i$  in a given administrative area  $a$  adjusts the use of electricity,  $q_E$ . We assume that the  
 145 intensity of such energy use is a function of income  $y$ , relative prices ( $p_e, p_x$ , see private household model below), the  
 146 meteorological climatic conditions experienced by each household,  $c$ ; a set of household-specific factors  $B$  affecting  
 147 the behavioral reaction to  $H$  in relation to  $c$ ; and  $Z$ , which captures characteristics (different from  $G$ ) that determine  
 148 the vulnerability to heat, such as the average characteristics of the building stock and the local demographic structure:

$$q_{E,i \in a,t} = f(p_{E,a,t}, p_{x,a,t}, y_{i \in a,t}, G_{a,t}, c_{a,t}, B_{i \in a,t}, Z_{a,t}) \quad (2)$$

149 The objective of the public decision-maker taking decisions related to  $G$  is to maximize discounted social welfare  
 150 such that the costs function of expanding and maintaining  $G$  ( $COST^G$ ) is balanced against its total public and private  
 151 benefits. We assume these benefits mainly consist of two components. First, the net reduction in private electricity  
 152 use  $\Delta q_{E,i \in a,t}$  (private positive externality value). Second, the additional set of benefits due to ecosystem services  
 153 provision ( $\Delta q_{ECO,i \in a,t}$ ):

$$BENEFIT^G = f\left(\sum_i \Delta q_{E,i \in a,t}, \sum_i \Delta q_{ECO,i \in a,t}\right) \quad (3)$$

154 In each municipality, assuming a planning horizon of 20 years, the social planner solves the following intertem-  
 155 poral maximization problem:

$$\max W = \sum_{t=0}^{20} \beta^t NB_{a,t}^G = \sum_{t=0}^{20} \beta^t BENEFIT_{a,t}^G - \beta^t \sum_{t=0}^{20} COST_{a,t}^G \quad (4)$$

156 subject to the intertemporal budget constraint:

$$\sum_{t=1}^{20} \frac{COST_{a,t}^G}{(1+r)^{t-1}} \leq \sum_{t=1}^{20} \frac{PB_{a,t}}{(1+r)^{t-1}} \quad (5)$$

157 where:

$NB_t^G$  : net benefits from  $G$  in period  $t$

$PB_{a,t}$  : public budget available at each time period  $t$

$\beta$  : Discount factor

$r$  : Discount rate

158 The first-order conditions identify the optimal level of  $G$ , inclusive of private externality benefit:

$$\frac{\partial \mathcal{L}}{\partial NB^G} : \beta^{t-1} W'(NB^G) - \frac{\lambda}{(1+r)^{t-1}} = 0, \quad \text{for } t = 1, 2, \dots, T, \quad (6)$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} : \sum_{t=1}^T \frac{NB^G}{(1+r)^{t-1}} - \sum_{t=1}^T \frac{PB_{a,t}}{(1+r)^{t-1}} = 0 \quad (7)$$

159 The availability of the public good green spaces,  $G$ , influences the conditional electricity demand of an optimiz-  
 160 ing household in a given municipality  $a$  and in a given year  $t$  (for clarity we here omit the individual, regional, and  
 161 time subscripts).

162  
 163 **The private household.** Each household  $i$  (we now omit the subscripts for notational clarity) derives utility,  $u$ ,  
 164 from the consumption of a generic good,  $x$  — which we treat as the numeraire, with  $p_x = 1$  —, and electricity,  $q_E$ :

$$u = u(q_E, x) \quad (8)$$

165 where  $u_{q_E} > 0$  and  $u_x > 0$ .

166  
 167 Electricity consumption is a function of the locally experienced meteorological conditions,  $c$ , which in turn are  
 168 influenced by the availability of green spaces,  $G$ :

$$q_E = q_E(c(G), G)$$

169 where  $q_{E_c} = \frac{\partial q_E}{\partial c}$  can be either positive or negative depending on the level of  $c$  relative to a set-point of  
 170 thermal comfort,  $\bar{c}$ . We assume that  $G$  has also a direct impact on  $q_E$ , e.g. through its influence on lifestyle and  
 171 behavioral choices, for instance the tendency to spend more time outdoors if a household lives in a more green-dense  
 172 neighborhood. The effect on green spaces on electricity occurs through two mechanisms:

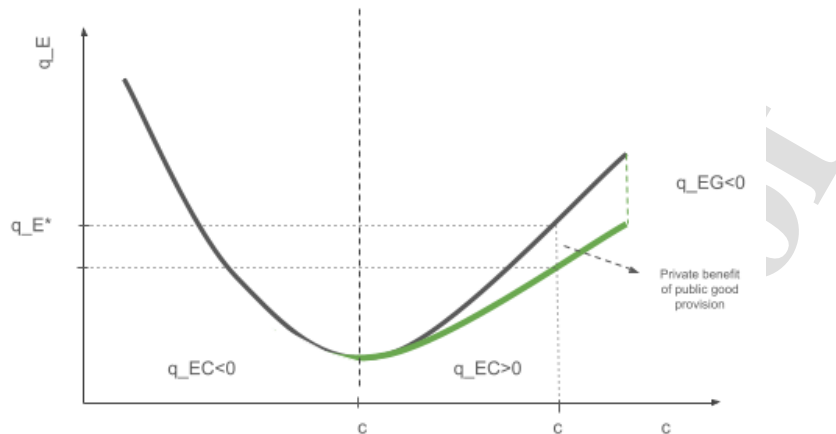
$$q_{E_G} = \frac{\partial q_E}{\partial G} = \underbrace{\frac{\partial q_E}{\partial G}}_{\text{Direct effect}} + \underbrace{\frac{\partial q_E}{\partial c} \cdot \frac{\partial c}{\partial G}}_{\text{Indirect effect}}$$

173 We apply a comparative static analysis to the constrained optimization problem of the household and use the  
 174 implicit function theorem to derive the impact of the exogenous variable  $G$  on the household optimal demand of  
 175 electricity,  $q_E^*(p_E, y; G, c, B, Z)$ . We differentiate the three FOCs for  $q_E$ ,  $x$ , and  $\lambda$  (see Appendix ) with respect to  $G$ ,  
 176 and apply Cramer's rule to obtain the effect of  $G$  on the optimal demand  $\frac{\partial q_E^*}{\partial G}$ . Since from the second-order sufficient  
 177 conditions for constrained maximization, the sign of the Jacobian matrix is positive, since we assume that green  
 178 spaces reduce temperature,  $\frac{\partial c}{\partial G} < 0$  and we have that  $p_x^2 u_{q_E q_E} < 0$  and  $u_{x q_E} \geq 0$ , then the sign of  $\frac{\partial q_E^*}{\partial G}$  is determined  
 179 by the sign of  $\frac{\partial q_E^*}{\partial c}$ :

180  
 181 If  $\frac{\partial q_E^*}{\partial c} < 0$ , then  $\frac{\partial q_E^*}{\partial G} > 0$

182  
 183 If  $\frac{\partial q_E^*}{\partial c} > 0$ , then  $\frac{\partial q_E^*}{\partial G} < 0$

184  
 185 Figure 1 represents the comparative static effect of  $G$  on electricity demand for different levels of  $c$ . The green  
 186 line depicts electricity demand following an increase in green spaces, and the area between the black and green  
 187 curves represents the energy savings from SGS's temperature regulation effect. Our empirical analysis aims at  
 188 empirically estimating the sign and the magnitude of  $\frac{\partial q_E^*}{\partial G}$ . Our auxiliary regression shows empirically that  $\frac{\partial c}{\partial G}$  is  
 189 negative (see Results section).  
 190



**Figure 1.** Schematic framework of the assumed SGS effect on electricity consumption. The area between the black and the green lines represents the household energy saving induced by SGS's temperature regulation effect.

### 3 Data

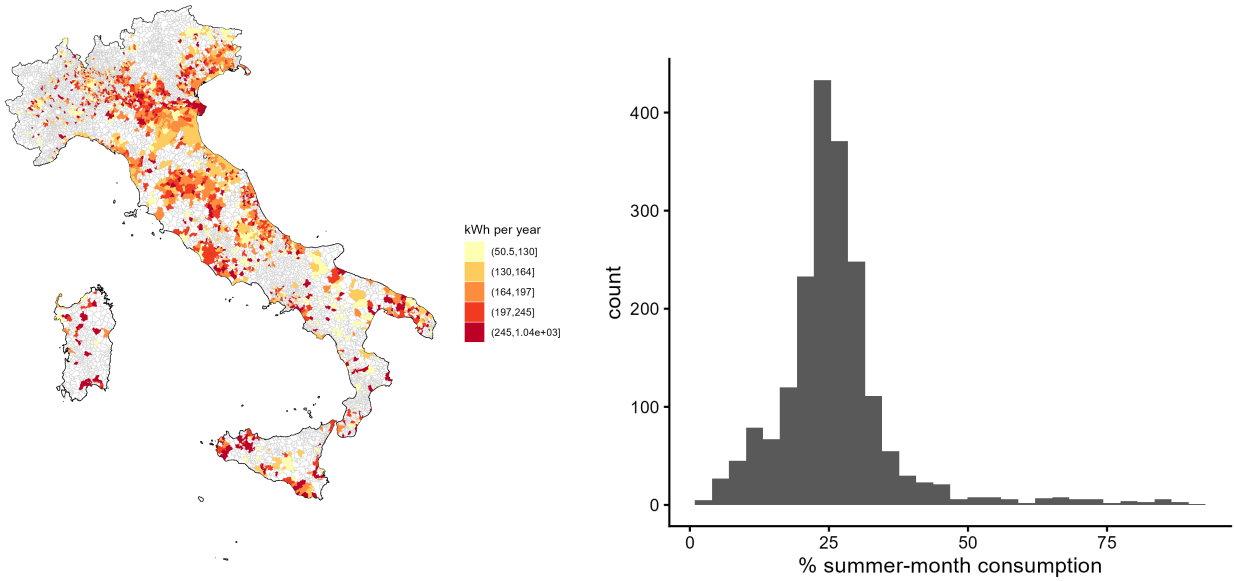
191

192 To empirically evaluate our theoretical framework, we assemble two datasets. First, we combine data on monthly  
 193 metered household electricity use, with municipality-level climate and SGS indicators. This dataset is used in our  
 194 main analysis relating green spaces and temperature to electricity demand. This is the core dataset, covering  $n =$   
 195 129,524 households located in 2,181 municipalities distributed across Italy over the period between 2020 and 2022.  
 196 Second, as an ancillary dataset, we combine high spatial resolution (100 meters) data on temperature and SGS for a  
 197 subsample of 10 large Italian cities selected on the basis of data availability from the UrbClim urban microclimate  
 198 model runs from the PROVIDE project (Lamboll, Rogelj and Schleussner, 2022). We use this dataset to perform an  
 199 auxiliary set of regressions to estimate the underlying direct relation between SGS and local temperature. We exploit  
 200 the greater spatial granularity and the variation that exists even within a given city to examine the local association  
 201 between temperature and SGS.

202

203 **Metered household electricity consumption data.** We assemble household electricity consumption data  
 204 available at Point Of Delivery (POD) for the 2020-2022 period. Our sample comprises residential electricity  
 205 contracts, implying that a POD identifies a household. The data are provided by a private utility operating throughout  
 206 Italy. The dataset consists of a monthly panel of POD-level data on electricity consumption and expenditure (average  
 207 bills, unit prices of electricity, and marginal expenditure per unit of energy) with geographic information available  
 208 at the municipality spatial resolution. It covers 129,524 PODs distributed across 2,181 municipalities of Italy, as  
 209 mapped in Figure 2 and Figure A-1, and has a monthly temporal resolution (Figure A-2). The right panel of Figure 2  
 210 shows that the majority of households allocate more than 25% of their annual electricity expenditure to the summer  
 211 period June-August.

Average monthly electricity consumption per POD, by municipality



**Figure 2.** Average monthly electricity consumption per POD across the municipalities covered by the household metered electricity dataset over whole year (left) and share of summer months (June-August) electricity consumption over the total yearly electricity consumption (right).

212 **Municipality-level characteristics.** Since the metered electricity consumption data do not include household  
 213 characteristics, we augment this dataset with some socio-economic attributes at the municipality level to conduct  
 214 heterogeneity analysis and propensity score weighting (see Section 6). We calculate a time-invariant measure of  
 215 total resident population in the municipality, *pop*, based on the GHS-POP gridded population 2019 revision from  
 216 the EC-JRC (Florczyk et al., 2019); based on total population and the land area of the municipality, we obtain the  
 217 average population density, *popdens*. Henceforth, we categorize municipalities into urban (population density 500),  
 218 semi-urban (density between 250 and 500), and sparse (density <250). We retrieve the average annual income at  
 219 the municipality level, *avgincome*, based on the ISTAT yearly, municipality level average taxable income (ISTAT,  
 220 2024) for the 2020-2022 period. We also construct a set of indicators of the shares of the building stock in each  
 221 municipality that were built in a set of year groups based on the GHS-AGE R2025A data product from the European  
 222 Commission JRC (2025). Finally, we augment each observation with the latitude and elevation of the municipality's  
 223 centroid coordinates pair, obtained from Amazon Web Services (AWS) Terrain Tiles AWS (2025).

224  
 225 **Meteorological data.** The main meteorological variables used to perform the main analysis on metered elec-  
 226 tricity consumption include the monthly average of daily maximum temperatures, *Tmax*, and - in an additional  
 227 specification - the Cooling Degree Hours (CDH) per month, *CDH*. While *Tmax* captures acute exposure to heat,  
 228 *CDH* is calculated as the count of hours in a given month when the hourly average temperature is above a threshold  
 229 level of 25° C and it captures the chronic or cumulative exposure to heat. These variables are computed from hourly  
 230 temperature data from ERA-5 Land climate reanalysis data (Copernicus Climate Change Service, 2019) available  
 231 at the native spatial resolution of about 9km for the period covered by our metered electricity consumption data  
 232 (2020-2022). The two heat metrics are extracted within the administrative boundaries of each municipality, weighted  
 233 over space by population density to attribute more weight to temperatures in the proximity of densely populated  
 234 areas. Figure 3 illustrates a map of the spatial variability of the calculated climate metrics across municipalities for  
 235 their yearly maximum value across months, while Figure A-3 presents similar maps for the twelve months of the  
 236 year. As a remark, in the fall and winter months in Italy, temperature drops significantly, which explains a median  
 237 value of 0 for monthly CDH, as seen from Table 1 below.

238

239 In parallel, for conducting the auxiliary regressions to demonstrate the effect of SGS on local heat metrics, we  
240 leverage high-granularity climate data derived from the PROVIDE Climate Risk Dashboard (Lejeune et al., 2024),  
241 which delivers 100-meter spatial resolution heat metrics (sum of monthly Cooling Degree Hours and monthly average  
242 of daily maximum temperatures) for a pool of cities calculated based on the urban-scale climate model UrbClim  
243 (De Ridder, Lauwaet and Maiheu, 2015). The simulations of UrbClim explicitly account for the cooling role of  
244 vegetation through the use of high-resolution land cover data, shading algorithms, and energy balance modeling. For  
245 the case of Italy, data for the following ten cities, which are also part of the GVI and metered electricity consumption  
246 datasets and are rather homogeneously distributed across the territory of Italy, are currently available: Turin, Genoa,  
247 Milan, Bologna, Padua, Rome, Palermo, Trieste, Naples, and Bari.

248

249 The use of spatially granular climate data in the auxiliary analysis is motivated by the lack of within-city variation  
250 in the municipality-level weather variables derived from ERA5-Land which are used in the main regression analysis.  
251 These coarser variables are insufficient for investigating the assumed SGS–temperature mechanism. Spatially  
252 granular climate data from PROVIDE are available only for 2008–2017, and we treat this interval as a historical  
253 climatological baseline. For each grid cell within the ten cities, we compute the mean monthly values over this  
254 ten-year span to obtain representative seasonal conditions, a standard practice in climate science (Hersbach et al.,  
255 2020). Although this period precedes the weather–consumption window examined in the main analysis (2020–2022),  
256 the mismatch does not undermine the identification of the underlying physical mechanism—temperature reduction  
257 through vegetation cover. While this mechanism can be influenced by long-term factors such as urban development  
258 or building characteristics, these features change slowly. In the relatively stable urban settings of Italy, substantial  
259 shifts over a single decade are unlikely.

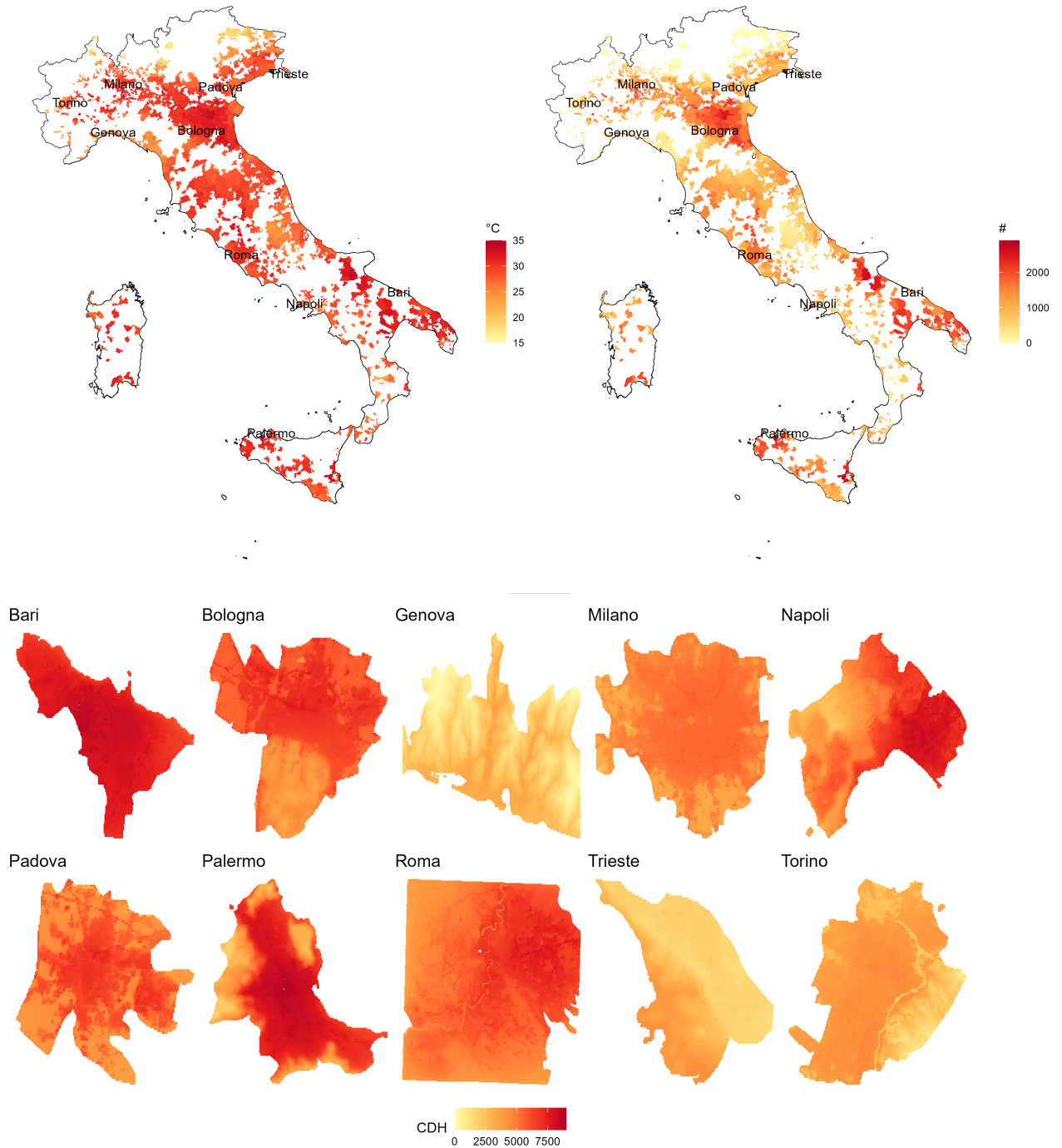
260

261 As an additional comparative exercise, we evaluate the consistency between the yearly sum of CDH derived  
262 from ERA-5 Land (using the average across years for the period 2020–2022) and the spatially granular UrbClim  
263 PROVIDE dataset, providing yearly sum of CDH based on simulation year 2020 (i.e. the representative climate,  
264 and not the specific weather year). For the ten cities where the granular PROVIDE data is available, Figure A-8  
265 shows that - while generally consistent - coarser municipality-level data from ERA5 Land tends to systematically  
266 underestimate the yearly heat metrics, compared to granular climate model output data at the within-city level. This  
267 is likely owing to the coarse spatial resolution of the ERA5 reanalysis data, which does not explicitly resolve for the  
268 urban heat island (UHI) effect (Adinolfi et al., 2023).

269

Mean monthly maximum temperature, Summer months, 2020-2022

Mean monthly Cooling Degree Hours, Summer months, 2020-2022



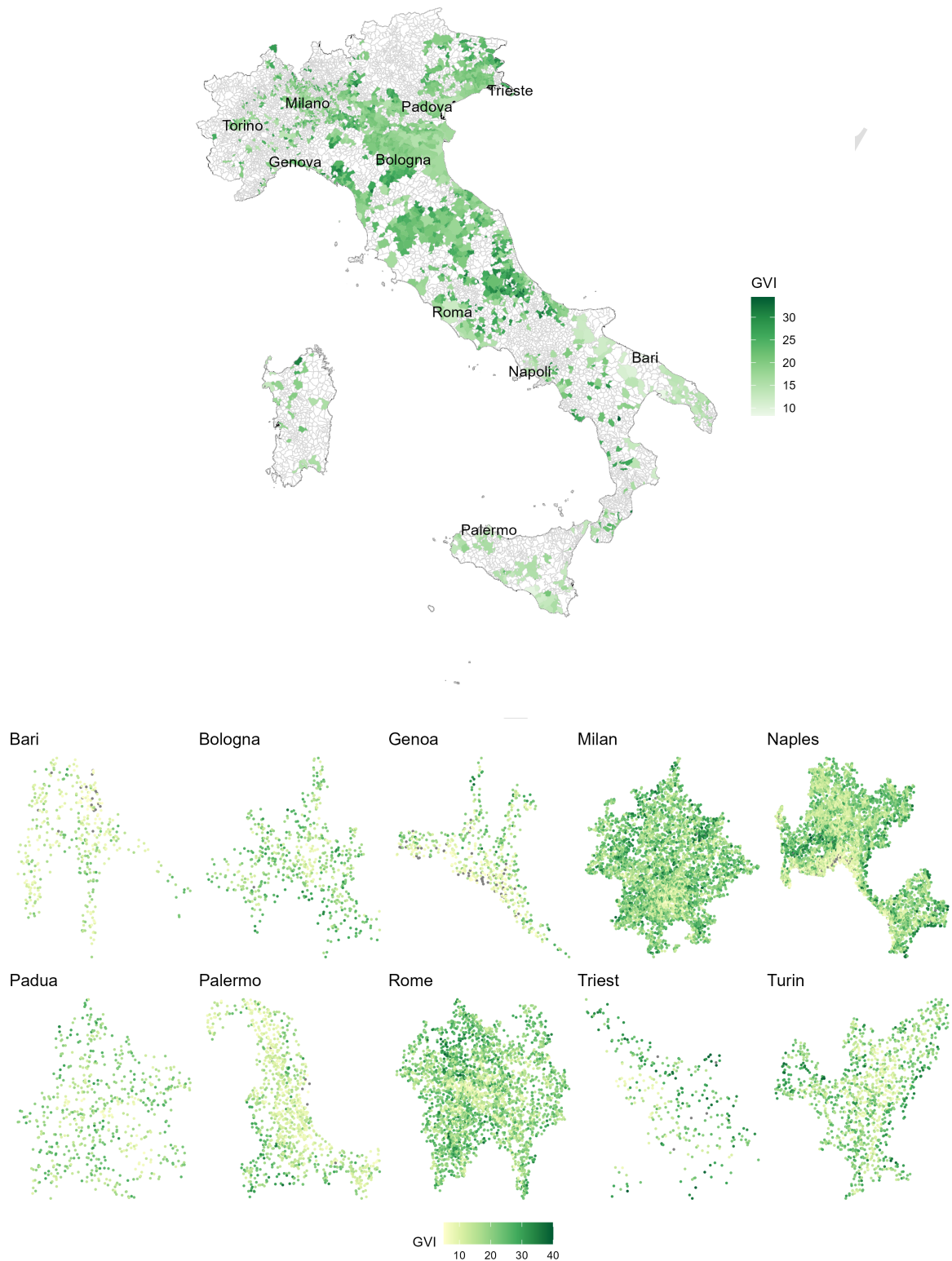
**Figure 3.** Maps of municipality-level heat metrics - average monthly level across the Summer months (June-August). Top-left: Monthly mean maximum temperature (Data source: ERA-5 Land); Top-right map: Monthly mean Cooling Degree Hours (Data source: ERA-5 Land); Bottom panel: Spatial distribution of Cooling Degree Hours (CDH) heat metric in ten large Italian municipalities (Data source: PROVIDE Climate Risk Dashboard). Note: the location of the ten large Italian municipalities where high-resolution urban microclimate data is available is reported in the upper panel maps.

270 **Street green space data.** We adopt the methodology developed in [Falchetta and Hammad \(2025\)](#)<sup>1</sup> to estimate  
271 the GVI in a set of randomly picked sampling coordinates along streets in each year and within each municipality.  
272 Based on such samples, we derive the average GVI for each municipality covered in our electricity consumption  
273 dataset. To contextualize the interpretation of GVI values, Figure A-9 illustrates representative street-based imagery  
274 examples and their associated GVI value. Figure 4A illustrates a map of the average GVI value in each Italian  
275 municipality for which electricity data are available (with a yearly analysis of the distribution and time trend, and a  
276 regional heterogeneity assessment presented in Figure A-7). Figure 4B illustrates within-city heterogeneity for the  
277 ten cities used in the second database to examine the relationship with the more granular meteorological data. Finally,  
278 the Supplementary Appendix file contains a table providing a range of municipality-level statistics (including the  
279 estimated average GVI value) for all municipalities covered by our analysis.

280  
281 **Sampling-point specific urban covariates.** For conducting the auxiliary regressions evaluating the direct  
282 effect of green spaces on local temperatures within each of the ten municipalities where granular climate data is  
283 available, we also extract a set of sampling point-specific (i.e. in the same randomly sampled point locations where  
284 GVI estimates are obtained within each city) covariates. These variables describe additional local urban features  
285 and their inclusion in the empirical model aims at controlling for confounding factors and isolating the individual  
286 contribution of SGS. Such factors include: local average buildings height and population density from the EC-JRC  
287 GHS-BUILT-H 2023 and GHS-POP 2023 data products ([Florczyk et al., 2019](#)), having a spatial resolution of  
288 100 meters; the local presence of water bodies, with data obtained from the Copernicus Land Monitoring Service  
289 ([Copernicus, 2018](#)) with a spatial resolution of 100 meters; and local elevation obtained from the AWS Terrain Tiles  
290 ([AWS, 2025](#)), with a 30-meter spatial resolution.

---

<sup>1</sup>[Falchetta and Hammad \(2025\)](#) train a machine learning algorithm to estimate the GVI (a street-based indicator of vegetation density, ranging within a theoretical range of 0 to 100%; see [Seiferling et al. \(2017\)](#) for details) at any coordinate point in urban areas of the world based on high-resolution multispectral satellite data and additional granular data.



**Figure 4.** Maps of the spatial distribution of the GVI (average value over 2020-2022 period). Top panel: Map of municipality-level mean GVI in areas covered by the metered electricity consumption dataset; Bottom panel: within-city GVI heterogeneity in ten large Italian municipalities used in the auxiliary regression. Data source: [Falchetta and Hammad \(2025\)](#). Note: the location of the ten large Italian municipalities visualized in the lower panel is reported in the upper panel map.

### 291 3.1 Descriptive statistics

292 Average monthly maximum temperature across the whole year ranges within an interquartile range of 12.8–27°C,  
 293 whereas the summer average monthly maximum temperature during June, July, and August ranges between 27 and  
 294 31.4°C, with an average value of 29.1°C (see Table 1 and Figure A-4 for a heatmap of the frequency of observations  
 295 by  $T_{max}$  and GVI exposure levels). The average value of GVI across the Italian municipalities considered varies  
 296 between 8 and 37, with a standard deviation of 3. Figure A-6 presents a histogram of the distribution of GVI in 2022,  
 297 showing the presence of tails on both sides of the distribution. Significant spatial variation in the GVI level across  
 298 municipalities and regions is observed, as seen from Figure 4 and summarized with boxplots in Figure A-7, with  
 299 higher average density in Central Italy and in areas near the Alps. Regarding the temporal variation in GVI, Figure  
 300 A-5 shows municipality level maps of the absolute and percentage change for the 2020-2022 period covered by our  
 301 analysis, highlighting a moderate and spatially widespread decrease in GVI over the study period. Average annual  
 302 electricity consumption ranges within an interquartile range of 101-223 kWh/household/month, whereas summer  
 303 electricity during June, July, and August, ranges between 97-219 kWh/household/month. At the municipality level,  
 304 hotspots of municipalities with electricity peaks appear in several regions of both the North and South of Italy,  
 305 with a pattern that, especially in summer, reflects more the local altitude than the latitude. Note that for regression  
 306 analysis, we drop observations (POD  $\times$  month  $\times$  year) with consumption of less than 50 kWh/POD/month to remove  
 307 PODs-month combinations in periods of the year when such homes are not regularly inhabited<sup>2</sup>. Finally, electricity  
 308 expenditure metrics at the POD-level are summarized for each region in Table A-16.

309  
 310 In addition to the dataset used in the main electricity consumption analysis, Table A-1 reports summary statistics  
 311 for the auxiliary analysis based on within-city sampling points data to assess the impact of SGS on urban temperature,  
 312 controlling for relevant covariates.

---

<sup>2</sup>We deem this a reasonable threshold which can be reached by always-on appliances such as refrigerators and appliances in standby mode, considering that according to national statistics the average household consumes around 145 kWh/household/month in Italy (ARERA, 2025). Note that we assess the implications of excluding POD-month observations with consumption below 50 kWh/household/month, on the grounds that such a threshold likely reflects the usage profile of an unoccupied or rarely used dwelling (e.g., a vacation home), given that the combined consumption of a refrigerator/freezer and standby appliances alone can reach this level. Such filtering procedure decreases the sample size by 12.7%, from  $n = 3,563,158$  to  $n = 3,109,091$ . Table A-9 compares the results that are obtained when re-estimating the main quadratic specification for (i) the full sample (without filtering) and (ii) the filtered sample (the same used in the main specifications presented in the Results section). These demonstrate that the sign and the statistical significance remain consistent in the full sample and on the filtered sample, while coefficient magnitudes differ despite the only moderate reduction in observations count.

**Table 1.** Summary statistics of the household metered electricity consumption data and covariates.

	Min	Q1	Median	Mean	Q3	Max	SD
Year	2020	2020	2021	2021.1	2022	2022	0.8
Month	1	4	7	6.6	10	12	3.5
Electricity use (kWh/POD/month)	50	100.6	150	180.6	222.5	14189.6	130
Monthly $T_{max}$	-10	12.8	18.6	19.6	27	35.2	8.1
Monthly $T_{mean}$	-12.9	8.6	14	15.1	21.9	29.9	7.5
Monthly $T_{min}$	-16.4	4.7	9.6	10.9	17.1	26.4	6.9
Monthly Cooling Degree Hours (CDH)	0	0	0	418.3	519.7	3761.4	722.3
Green View Index (GVI)	8	16.9	17.9	18.9	20.6	36.9	3
Tot. population	77.7	12823	33912.4	124968.8	358482.8	2607104.2	149590.1
Pop. density (pop/km <sup>2</sup> )	2.3	226.4	344.5	984.8	2611.9	8107.2	1074
Avg. income (€)	10511.3	21914.9	23496.8	23655.6	27238.6	48385.6	3006.1
% no buildings	0.0	0.3	0.6	0.5	0.7	1.0	0.2
% buildings < 1980	0.0	0.2	0.2	0.3	0.5	0.9	0.1
% buildings 1980-1990	0.0	0.0	0.0	0.0	0.1	0.1	0.0
% buildings 1990-2000	0.0	0.0	0.0	0.1	0.1	0.2	0.0
% buildings 2000-2010	0.0	0.0	0.1	0.0	0.1	0.2	0.0
% buildings 2010-2020	0.0	0.0	0.0	0.0	0.0	0.1	0.0
Elevation	-37.0	15.0	61.0	87.8	79.0	2736.0	144.1

**Note:** Electricity use and climate metrics are measured at a monthly level; GVI is measured at a yearly level; Tot. population, pop. density, avg. income and building age features are time-invariant in the three-year panel.

## 313 4 Empirical framework

### 314 4.1 Main analysis: street green space and household electricity demand

315 We rely on the household metered electricity consumption dataset with municipality-level treatment variables to  
 316 implement the following interactions-based, quadratic temperature specification, which allows us to capture the  
 317 POD-level and municipality-level fixed effects, as well as additional time-invariant and time-trend components:

$$\begin{aligned}
 \log(q_{E,i,m,t}) = & \beta_1 H_{a(i),m,t} + \beta_2 H_{a(i),m,t}^2 + \beta_3 SGS_{a(i),t} + \beta_4 H_{a(i),m,t} \cdot SGS_{a(i),t} + \beta_5 H_{a(i),m,t}^2 \cdot SGS_{a(i),t} + \\
 & \zeta_i + \theta_a + \mu_m \times \lambda_a + \rho_t + \varepsilon_{i,a,m,t}
 \end{aligned} \quad (9)$$

318 where, for each household  $i$ , municipality  $a$ , month  $m$ , and year  $t$ ,  $q_E$  is the metered electricity consumption,  $H$  is  
 319 the spatial average value at the municipality level of - depending on the specification - the monthly average of daily  
 320 maximum temperature or the monthly cooling degree hours calculated with a threshold comfort temperature of 25°C;  
 321  $SGS$  is the average street green space in municipality  $a$  at year  $t$  as measured by the GVI index. The identification  
 322 strategy exploits POD ( $\zeta$ ), municipality ( $\theta$ ), year ( $\mu$ ), month ( $\lambda$ ) and region by year dummies ( $\rho$ , allowing to capture  
 323 unobserved time-variant variation that is specific to each region in each given year, such as regional policies or  
 324 localized weather events) fixed-effects to absorb household, seasonal, yearly, as well as location-invariant unobserved  
 325 factors such as building type and quality, geographical and environmental factors and conditions, appliance stock,  
 326 behavior, electricity price, as well as COVID and gas price crisis exogenous shocks, and hence isolate our quantity  
 327 of interest, namely the role of municipality-level  $SGS$  on the POD-level temperature-electricity demand relation.  
 328 The error term,  $\varepsilon$ , is clustered at the municipality and POD level, and captures the residual unobserved variation in  
 329 the outcome.

330

## 331 4.2 Mechanism analysis: street green space and local temperature regulation

332 Our main specification outlines the role of SGS in moderating the temperature-electricity consumption relation. A  
 333 key mechanism underlying this phenomenon is likely the cooling effect of SGS, particularly during hot periods,  
 334 when it can serve as an alternative to other electricity-consuming cooling methods. However, our main specification  
 335 does not enable us to clarify the underlying mechanism of such interplay, i.e. the direct temperature regulating  
 336 effect of SGS. To explore this result, we exploit within-municipality spatial variation in SGS coverage and local  
 337 temperature levels, which we can retrieve for a subset of municipalities (see Data section for details). We estimate  
 338 the following spatially granular regression model:

$$T_{c,a,t} = \delta_1 T_{a,t} + \delta_2 SGS_c \times T_{a,t} + \zeta_c + \mu_t + \varepsilon_{c,a,t} \quad (10)$$

339 where, for each sampling cell  $c$ , municipality  $a$  and month  $t$ ,  $T$  is the average monthly maximum temperature for  
 340 the climatological period 2008-2017,  $SGS$  is the local density of street green space (average value across years),  $\zeta$   
 341 are cell-level fixed effects and  $\mu$  are monthly fixed effects. The error term,  $\varepsilon$ , is clustered at the cell and month level,  
 342 and it captures the residual unobserved variation in the outcome. The coefficient  $\delta_2$  captures the cooling effect of  
 343 SGS coverage.

344  
 345 The regression setup is hence a month-cell panel with 12 observations for each cell and where, for each cell  $c$ ,  
 346 meteorological variables capture the local historical average value at each month of the year. Using the average  
 347 monthly max temperatures reduces the dimensionality of the panel, being virtually equivalent to estimating a  
 348 two-way fixed-effects regression (TWFE) with data demeaned by month-of-year. The choice is therefore one of  
 349 implementation rather than identification. The regression specification thus captures the within-city spatial (cross-  
 350 sectional) and average seasonal variation. The covariates included in the auxiliary regressions (specifically, the  $GVI$   
 351 and the population density variables, while the elevation and water bodies variables are assumed to be time-invariant)  
 352 refer to years 2017-2023 and 2020, respectively. Both variables are sufficiently time-stable to confidently rule  
 353 out that they might have significantly and systematically deviated from the temporally near climatological period  
 354 (2008-2017).

355  
 356 In the auxiliary specification, SGS coverage is a time-variant variable ( $GVI$  data has yearly, but no monthly  
 357 variation), and hence its main effect is absorbed by cell-level fixed effects. As temperatures recorded at the city level  
 358 can be considered exogenous in this setting, under the assumption that temperature discrepancies within the city are  
 359 not a driver to the presence of green spaces in specific cells, the coefficient captures how a common temperature  
 360 shock is perceived in different areas of a city depending on the presence of SGS, net of unobserved time-invariant  
 361 spatial heterogeneity and seasonality.

362  
 363 As a robustness test, we augment this specification by including a quadratic term of  $SGS$  or, in alternative, a  
 364 quantile-based categorical bins specification based on the distribution of the continuous  $SGS$  variable, to test for the  
 365 non-linearities in the effect of  $GVI$  on temperature. Finally, we also test the robustness of our results to the explicit  
 366 inclusion of a vector of time-invariant cell-level covariates (including population density, water bodies presence, and  
 367 elevation), instead of controlling for cell-level fixed effects. The elevation and water bodies variables are assumed to  
 368 be time-invariant over the period covered by the time-variant variables.

## 370 5 Results

### 371 5.1 The role of street green space for residential electricity consumption

372 We estimate Equation 9 to appraise the role of SGS in residential electricity demand through its mediating effect  
 373 on temperature, as hypothesized in Figure 1. Table 2 illustrates the results of different regression specifications,  
 374 with the preferred one being the quadratic in temperature specification with POD, municipality, year, month and

375 region-by-year fixed effects and municipality and POD-level clustered standard errors, reported in column (5). The  
 376 key coefficients of interest are the interactions between heat metrics (maximum temperature in our main specification,  
 377 and cooling degree hours and temperature quantile bins as alternative variables, Table A-7) and GVI levels (i.e. the  
 378 multiplication of the two treatments of interests). Table A-3 reports specifications which only include temperature to  
 379 compare the results without the inclusion of the GVI mediator variable.

**Table 2.** POD-level fixed-effects regression results on household metered electricity consumption

	(1)	(2)	(3)	(4)	(5)
<i>Variables</i>					
$T_{max}$	0.0091*** (0.0020)	0.0096*** (0.0020)	0.0126*** (0.0032)	0.0125*** (0.0032)	-0.0753*** (0.0142)
$GVI$	0.0304*** (0.0029)	0.0151*** (0.0016)	0.0144*** (0.0015)	0.0131*** (0.0017)	-0.0146*** (0.0051)
$T_{max} \times GVI$	-0.0007*** (0.0001)	-0.0008*** (0.0001)	-0.0007*** ( $9.42 \times 10^{-5}$ )	-0.0007*** ( $9.41 \times 10^{-5}$ )	0.0022*** (0.0006)
$T_{max}$ square					0.0020*** (0.0003)
$T_{max}$ square $\times$ $GVI$					$-6.61 \times 10^{-5}$ *** ( $1.58 \times 10^{-5}$ )
<i>Mean outcome (kWh/POD/month)</i>					
Total avg. marginal effect of $GVI$	0.0162	0.0003	0.0004	0.0004	-0.0012
<i>Fixed-effects</i>					
Municipality	Yes	Yes	Yes	Yes	Yes
POD	Yes	Yes	Yes	Yes	Yes
Year		Yes	Yes	Yes	Yes
Month			Yes	Yes	Yes
Region-year dummies				Yes	Yes
<i>Fit statistics</i>					
Observations	3,106,695	3,106,695	3,106,695	3,106,695	3,106,695
R <sup>2</sup>	0.75649	0.75686	0.77694	0.77697	0.77813
Within R <sup>2</sup>	0.02727	0.01948	0.00368	0.00363	0.00878

*Notes:* Dependent variable: logarithm of monthly metered electricity consumption (kWh)

Clustered (Municipality & POD) standard-errors in parentheses

Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1

380 All regression specifications suggest the existence of a regulating function of SGS on the temperature-electricity  
 381 demand relation. SGS partly reduces heat-related electricity consumption: the results of the quadratic treatments  
 382 regression specification (5) show that temperature and electricity demand have a U-shaped quadratic relation, with  
 383 SGS affecting such quadratic relation - and a stronger effect on the hot temperature side of it (right-hand side of the  
 384 curve). Interestingly, the  $GVI$  main coefficient is negative and statistically significant, highlighting that households  
 385 living in more SGS-dense municipalities tend to display lower electricity consumption levels due to unobserved  
 386 factors (such as behavior or housing energy efficiency). In the linear specifications (as we move from column (1) to  
 387 (4) gradually adding POD, municipality, time, and time-trend fixed-effects to absorb variation from unobservable  
 388 confounders), the average monthly maximum temperature has a negative effect on electricity demand when the  
 389 entire year is considered, reflecting the Italian climate, which tends to lead to overall higher electricity consumption  
 390 in wintertime for heating and lighting.

391  
 392 Figure 5 illustrates this effect by showing, in the top row, the average model predictions of residential electricity  
 393 demand at different levels of heat exposure, differentiated by GVI level. The lines clearly demonstrate both the  
 394 U-shaped electricity demand response to temperature, with strong increases during cold temperature periods of the  
 395 year, a minimum value at moderate temperatures, and a further spike once temperature grow further. Moreover, the

396 differentiated predictions across GVI levels show the cooling role of SGS and its relevance for mitigating the increase  
397 of electricity consumption during periods of the year when hot temperatures are experienced. This is particularly  
398 visible in the lower panel of the figure. For instance, we estimate that a representative household when the monthly  
399 average maximum temperature stands at 30° C would consume 170 kWh/month if the average municipality GVI  
400 level is 20 (a value at the 35th percentile of the municipalities GVI levels distribution), while such consumption  
401 would be reduced to 163 kWh/month (-4.2%) if GVI stood at 25 (a value at the 80th percentile of the municipalities  
402 GVI levels distribution). On the other hand, we find evidence of a much more moderate positive association between  
403 electricity consumption and GVI during cold periods of the year, consistently with (Alberini et al., 2019).

404

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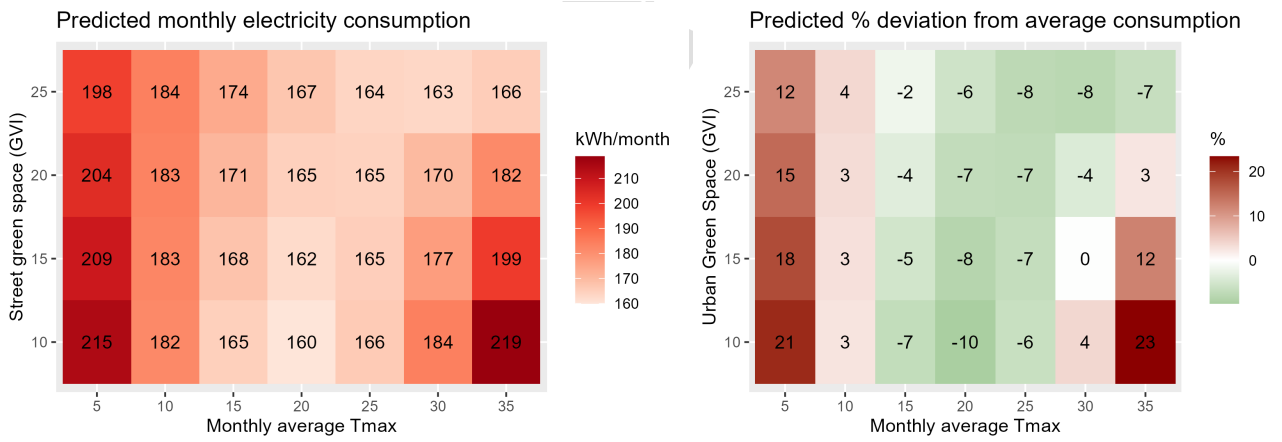
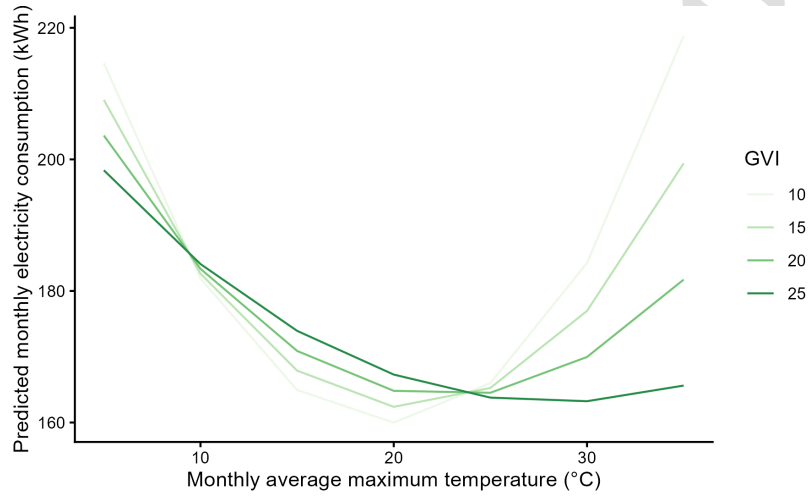


Figure 5. Predicted value and change in monthly electricity demand at different levels of GVI and for different maximum temperatures.

## 405 5.2 Exploring mechanisms: street green space and local temperature levels

406 In our main specification, we find that SGS has a mediating role in the relationship between electricity consumption  
407 and temperatures. As previously discussed, one of the key underlying mechanisms is that SGS can decrease urban  
408 temperature and, in turn, affect the usage of temperature mitigating household appliances. We evaluate the impact  
409 of SGS on urban heat by estimating Equation 10. Table 3 presents the regression results based on granular SGS  
410 and microclimate data for within-city locations in the ten large municipalities in Italy covered by the PROVIDE  
411 dataset (as discussed in the Data section). Results show that areas of cities with higher *GVI* level warm less in  
412 relation to the average warming experienced throughout the city. This finding is consistent across the linear (column  
413 1), quadratic (column 2) and quantile piecewise (column 3) specifications, where the  $\beta_2$  interaction coefficient of  
414 local *SGS* and local  $T_{max}$  is found to be negatively associated with the average maximum temperature of the city,  
415 net of month and grid cell fixed-effects. Specifically, the linear specification (1) shows that, for every 1-unit of  
416 local *GVI* index, we estimate around a 1% reduction in the local maximum air temperature value with respect to  
417 the city-scale average maximum air temperature. Considering the average values of 20.2 of  $T_{max}$  and of 20 of *GVI*  
418 across the ten cities assessed in this supplementary analysis, we estimate a total average reduction of 0.2° C in  
419 the average maximum temperature ( $T_{max}$ ) due to SGS cooling role within each municipality. The magnitude of  
420 this result is within the range of the literature when referring to the cooling efficiency of urban green space on air  
421 temperature (Li et al., 2025) and it reflects the average effect across all months of the year. We also find evidence of  
422 non-linearity in the effect of *GVI*: the estimated coefficients demonstrate that *GVI* is mildly non-linear, in particular  
423 in the right-hand-side of the distribution, where higher *GVI* values determine a more than linear reduction in the  
424 heat metrics, consistently with what noted in the literature (Ouyang et al., 2020). To conclude, column (4) displays  
425 the result of an alternative specification where cell-level fixed effects are omitted so as to directly include in the  
426 specification the local *GVI* and additional time-invariant cell-level variables. Consistently with the results of the  
427 other columns, the specification of column (4) provides evidence of a local negative association between *GVI* and  
428  $T_{max}$ , net of cell-level covariates. Consistent with our empirical design, the results are unchanged when preserving  
429 inter-yearly variation while including month-of-year level fixed effects (Table A-17).

430  
431 The results of this supplementary analysis further reinforce the theoretical foundation for evaluating the impli-  
432 cations of SGS for residential electricity use in relation to the temperature-energy demand relation. As a remark,  
433 the mediating role of SGS for decreasing heat-related electricity use in building is likely larger in magnitude the  
434 direct air temperature reduction found in the 100-meter resolution microclimate model output data only. These data  
435 display only moderate spatial variation within each city, contrarily to surface temperature, which is found to vary by  
436 much larger ranges within cities (Cao et al., 2021). *SGS* levels are also strongly related to factors such as reduced  
437 solar radiation through shading (Hsieh et al., 2018; Pandit and Laband, 2010), which has a strong impact on indoor  
438 heat stress but is not directly observable in our meteorological data.

**Table 3.** Regression results for the granular analysis to assess the role of street green space (net of additional urban feature covariates) for local heat levels, relative to the city-wide level. The regression is based on the ten large municipalities covered by the PROVIDE dataset.

Dependent Variable: Model:	Local monthly maximum temperature ( $Tmax_{c,a,t}$ )			
	(1)	(2)	(3)	(4)
<i>Variables</i>				
$Tmax_{a,t}$	1.012*** (0.0046)	1.040*** (0.0068)	1.016*** (0.0048)	
$GVI \times Tmax_{a,t}$	-0.0005*** ( $7.12 \times 10^{-5}$ )	-0.0034*** (0.0004)		
$GVI \text{ square} \times Tmax_{a,t}$		$7.9 \times 10^{-5}$ *** ( $9.21 \times 10^{-6}$ )		
Q1 $GVI \times Tmax_{a,t}$			-0.0138*** (0.0019)	
Q2 $GVI \times Tmax_{a,t}$			-0.0126*** (0.0018)	
Q3 $GVI \times Tmax_{a,t}$			-0.0117*** (0.0017)	
Q4 $GVI \times Tmax_{a,t}$			-0.0126*** (0.0017)	
GVI				-0.0061*** (0.0018)
Pop. dens				0.0011*** (0.0001)
Elevation				0.0006 (0.0004)
Water bodies				0.0017 (0.0024)
<i>Fixed-effects</i>				
Grid cell	Yes	Yes	Yes	
Month	Yes	Yes	Yes	Yes
Municipality				Yes
<i>Fit statistics</i>				
Observations	147,396	147,396	147,384	147,396
R <sup>2</sup>	0.99692	0.99694	0.99693	0.96996
Within R <sup>2</sup>	0.85584	0.85671	0.85646	0.00527

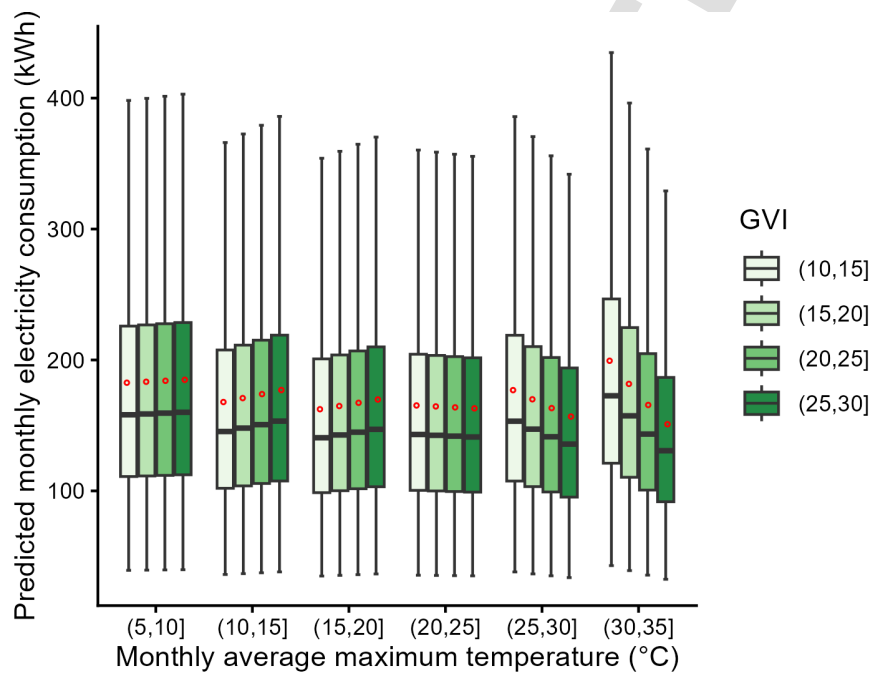
Clustered (id & variable) standard-errors in parentheses

Signif. Codes: \*\*\*, 0.01, \*\*, 0.05, \*, 0.1

## 439 6 Heterogeneity, robustness, and potential limitations

440 **Heterogeneity analysis.** To explore the heterogeneous role of SGS in mediating the temperature-energy demand  
 441 relation, we evaluate the range of different effects across PODs, municipalities, regions, and conditional to different  
 442 municipality-level features such as income level and population density. Figure 6 illustrates the range of model-  
 443 predicted electricity consumption across PODs in the sample conditional on different levels of monthly average  
 444 maximum temperature and GVI. The plot shows that the range of variation in predicted values becomes significantly  
 445 larger as temperature grows. GVI reduces energy use, but has the opposite effect at low temperatures, where energy  
 446 use among PODs living in more SGS-dense municipalities slightly increases.

447  
 448 An analysis of variance model (ANOVA) further highlights that the difference in means across bins of GVI  
 449 (i.e., the role played by GVI in mediating the temperature–electricity demand relation) is statistically significant  
 450 across all temperature intervals (Table A-10). The magnitude of the F-statistics notably increases with temperature  
 451 — from around 246 in the [5,10]°C bin to over 130,000 in the [30,35]°C bin — suggesting that the moderating effect  
 452 of GVI becomes increasingly pronounced as temperatures rise. This pattern supports the interpretation that SGS  
 453 plays a stronger role in reducing electricity demand during hotter conditions, consistent with the idea that vegetation  
 454 mitigates heat-related energy use through local cooling effects.



**Figure 6.** Box-plots of the range of impact of GVI on the effect of maximum temperature on electricity consumption. Red dots identify the mean value across each whisker.

455 We conduct two additional sets of regressions to evaluate if municipalities that are characterized by higher and  
 456 lower than median summer heat (municipality-level median 2020-2022 June-August = 27.73°C) and GVI levels  
 457 (municipality-level median 2020-2022 June-August = 21.327) respond differently to hot temperatures and show  
 458 differences in the mediating role of SGS identified in our main specification. Specifically, we first estimate if  
 459 households living in each of these subsets of municipalities respond differently to  $T_{max}$  over cold and hot months,  
 460 respectively; then, we test for the mediating role of GVI in the relation between  $T_{max}$  and electricity consumption.

461  
 462 Tables A-13 and A-14 display the results of these specifications. We find that hotter municipalities have a nearly  
 463 60% higher response to temperature during hot months than less hot municipalities (2.7% vs. 1.7% growth per °C),

464 likely reflecting the wider availability of cooling appliances in buildings; on the other hand, colder municipalities  
465 are more responsive to high temperatures in decreasing consumption during cold months of the year. Looking at  
466 the mediating role of GVI, we find that GVI mediates 60% more the maximum temperature-driven in electricity  
467 consumption in hotter than in colder municipalities.

468  
469 Moving to the municipality SGS level heterogeneity analysis, we find that households in less SGS-dense  
470 municipalities react twice as much (1.9% vs. 0.6% per GVI point) to hot temperatures during hot months of the  
471 year compared to those living in more SGS-dense municipalities, while they react half to hot temperatures during  
472 cold months of the year. With regards to the mediating role of GVI, we find that GVI mediates 80% more the  
473 maximum temperature-driven in electricity consumption in less SGS-dense than in more SGS dense municipalities.  
474 This finding can be interpreted as evidence of the decreasing returns of investing in SGS (i.e., increasing GVI is  
475 more efficient in municipalities where it is less available).

476  
477 In addition, we also conduct regression analysis for stratified sub-samples by the degree of urbanization of the  
478 municipality and its wealth level (Table A-6), showing that households in rural and semi-urban (vs. urban) and in  
479 lower income municipalities are both more sensitive to temperature and benefit more from GVI for their electricity  
480 consumption level. We also aggregate the data to carry out an analysis where each unit of observation represents the  
481 average of the POD consumption at each municipality and time period (Table A-2 for descriptive statistics and Table  
482 A-8 for regression results).

483  
484 Finally, we conduct a set of supplementary regressions where re-estimate the double interaction quadratic model  
485 among our two treatment variables of interest ( $T_{max}$  and GVI) for each of the twelve months of the year, and we  
486 derive model-based predictions to evaluate heterogeneity in the moderating effect of GVI across months of the year.  
487 Figure A-10 reports the results of such analysis. The slope patterns suggest that GVI tends to mitigate the negative  
488 association between higher temperatures and the outcome during the warmer months (e.g., June–July), when greener  
489 areas are associated with lower predicted values as temperatures rise. Conversely, during some of the cooler months,  
490 the moderating role of GVI appears weaker or even slightly reversed, indicating that vegetation exerts a seasonally  
491 dependent buffering effect that is strongest in mid-summer and less pronounced in winter.

492  
493 **Summer tourism heterogeneity.** We evaluate the heterogeneity across municipalities that are classified by  
494 ISTAT (the Italian national statistical office) as summer-tourism destination (maritime, mountainous, and lake  
495 tourism). Hot periods of the year may bear a confounding signal owing to the fact that a significant proportion of  
496 residents in non-touristic municipalities may temporarily relocate to holiday homes towards touristic municipali-  
497 ties. Hence, we aim at evaluating whether there is a significant difference in the temperature-electricity demand  
498 relation across summer-tourism destinations municipalities and non summer-tourism municipalities. Table A-11  
499 illustrates the results of the comparative regressions analysis. While coefficients' signs and statistical significance  
500 are unchanged between the two sub-samples, we find that summer touristic municipalities show stronger energy  
501 consumption responses to hot temperatures, as well as a more salient moderating role of SGS. We attribute this to the  
502 fact that individuals on holiday may behave differently from residents: for example, they may more intensively use  
503 cooling systems in holiday homes or in rented properties due to behavioral biases or moral hazard on electricity prices.

504  
505 **Treatment variables and specifications.** We evaluate the sensitivity of the results to the choice of the treatment  
506 variable for measuring heat exposure, as well as to the model specifications, fixed-effects inclusion, and clustering  
507 of standard errors. Table A-4 and Table A-8 demonstrate that the main results presented above - in terms of their  
508 sign, magnitude, and significance - are robust to such checks. We quantify the relation using Cooling Degree Days  
509 (CDD), Cooling Degree Hours (CDH), and temperature quantile bins as the treatment heat metric (Table A-7). We  
510 also add a binary variable for COVID in year 2020 and we appraise the relevance of different spatial resolution of  
511 entity-specific yearly time trend (municipality and/or province). Finally, we evaluate the uncertainty in the statistical  
512 significance of the effect in our main quadratic temperature specification when clustering standard errors at different

513 levels of aggregation, as shown in Figure A-12, demonstrating robustness in the significance of the estimate of the  
 514 main coefficients of interest.

515  
 516 **Across-municipality sorting and endogeneity concerns.** Based on the established physical understanding of  
 517 the process through which SGS regulate urban temperatures, as well as the exogeneity of the latter with respect  
 518 to city-scale decision variables different than land use, we can be confident about the lack of omitted variables in  
 519 shaping the estimates of the ancillary regression linking within-city variation in SGS and temperature. On the other  
 520 hand, concerns relating to the possibility that more SGS-dense municipalities might be non-random with respect  
 521 to the distribution of households energy behaviors need to be addressed. For instance, SGS may be non-randomly  
 522 distributed with respect to households showing a lower propensity to increase electricity during warm days. Another  
 523 sorting mechanism may lay in the possibility that more SGS-dense municipalities might be systematically cooler,  
 524 and thus electricity consumption may simply follow this pattern.

525  
 526 We are aware that there might be factors simultaneously affecting electricity consumption at the POD level  
 527 and the measured level of SGS at the municipality level. For example, individuals living in a more green space-  
 528 dense neighborhood have been found to spend more time outside (Feng, Toms and Astell-Burt, 2021); in parallel,  
 529 households living in more SGS-dense areas might also display stronger preferences for energy efficiency and green  
 530 behaviors (Alcock et al., 2020) or the use of housing and/or appliances retrofitting incentives, including through  
 531 peer and network effects (Huang, 2024). These unmeasurable factors and dynamics might potentially bias our main  
 532 regression estimate of the role of SGS for moderating the electricity use response to temperature. Specifically, all  
 533 these concerns might imply smaller-than-estimated direct effects of SGS on household electricity consumption.

534  
 535 To seek to address these concerns, we calculate propensity score weights to evaluate the hypothesis of sorting of  
 536 households across municipalities based on the GVI level, conditional on other characteristics of the municipality  
 537 which are potentially correlated with GVI levels. These include the average income level of households living in  
 538 the municipality; log of total population and population density in the municipality (potential proxies of energy  
 539 behavior); the distribution of maximum temperature across months of the years (local climate); the summer tourism  
 540 destination classification of the municipality; the latitude and elevation of the municipality; and a vector of variables  
 541 providing the share of buildings in the municipality by 10-year age of construction classes. Note that these variables  
 542 might also indirectly capture unobserved factors of which they are jointly strong predictors, and crucially in the  
 543 context of this study, the probability of AC prevalence (De Cian et al., 2025).

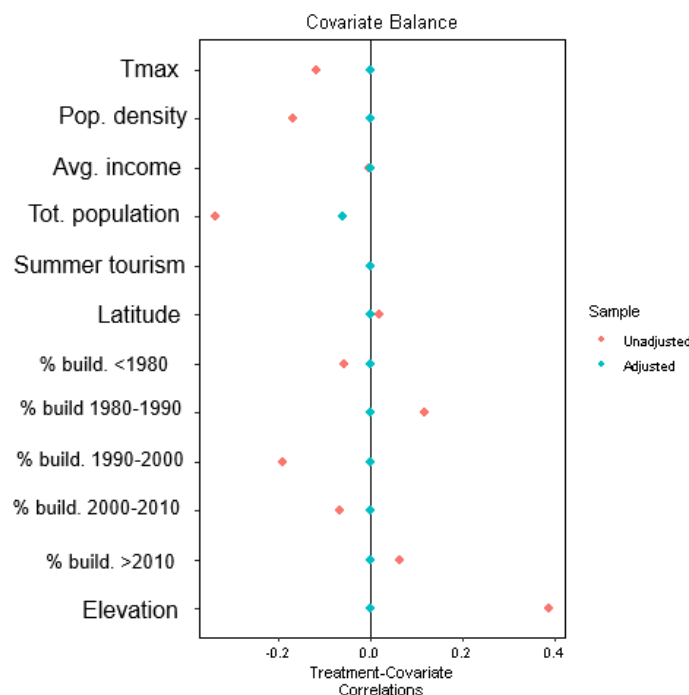
544  
 545 We first calculate observation weights based on the following equation:

$$SGS_{a,t} = INCOME_{a,t} + Tmax_{a,m,t} + POPDENS_a + \log(POP_a) + SUMMERDESTINATION_a + \quad (11)$$

$$LATITUDE_a + ELEVATION_a + BUILDAGECLASSES_a + \varepsilon_{a,m,t}$$

546 where weights are estimated using entropy balancing (Tübbicke, 2021; Vegetabile et al., 2021). We then evaluate  
 547 weighted and unweighted covariates-treatment correlations, as shown in Figure 7. Then, in a second step, we  
 548 re-estimate the main specification (Eq. 9) in both its unweighted (original) and its (propensity weights) weighted  
 549 formulations. Table A-12 shows that the propensity score weighted regression results are consistent with those of  
 550 our main specification in terms of sign, significance and shape and magnitude of the estimated curves (Figure A-11)  
 551 - with weighted regression coefficients decreasing slightly in magnitude. This finding rules out that the observed  
 552 covariates are meaningfully biasing the coefficient estimates due to non-random across-municipality sorting of  
 553 households.

554



**Figure 7.** Covariate balancing robustness: love plot of pre and post-weighting co-variates correlation.

555 **Residual sorting concerns and limitations.** Despite the extensive supporting evidence illustrated so far on the  
 556 energy-saving effect of SGS, there exist residual limitations to our findings that cannot be tackled in the context of the  
 557 data and empirical settings of this paper. Existing unobservable household-specific and time-sensitive characteristics  
 558 might still be correlated with both variation in GVI and electricity consumption levels, inducing spatial sorting  
 559 and self-selection in our sample of consumers that would not be captured by either our controls or fixed-effects  
 560 structure. These may include, for instance, preferences and energy efficiency of households: individuals who adopt a  
 561 more sustainable consumption profile, as well as those living in more energy-efficient homes, and may prefer to  
 562 live in high SGS areas within each municipality. Moreover, unobservable house refurbishment programs affecting  
 563 space heating and cooling energy use in specific types of households, as well as other targeted policy measures (e.g.  
 564 air-conditioning purchase subsidies), may occur, though the short duration of the panel makes major changes in  
 565 building insulation or household environmental preferences unlikely to occur at scale.

566  
 567 While residual limitations exist, the relationship described in this paper is robust to considering a set of measures  
 568 at the municipality level (such as income and composition of buildings) that are a reasonably good proxy for  
 569 these unobservable characteristics. Future research may explore the possibility to combine granular data on urban  
 570 microclimate and SGS with higher spatio-temporal resolution of electricity demand across cities, as well as a more  
 571 comprehensive set of household characteristics.

## 572 7 Climate change and policy impact simulations

573 Based on the estimated models, we carry out a set of policy and climate change impact simulations to appraise the  
 574 potential influence, *ceteris paribus*, on household electricity use of i) SGS densification policies, ii) climate change,  
 575 and iii) their interaction. Specifically, we evaluate policies increasing SGS and the impacts of climate change on  
 576 temperature around 2050. For climate, we focus on the RCP 8.5 climate change scenario<sup>3</sup> from the CMIP6 models  
 577 ensemble, which produces downscaled climate projections for the climatological period 2045-2055. The data are

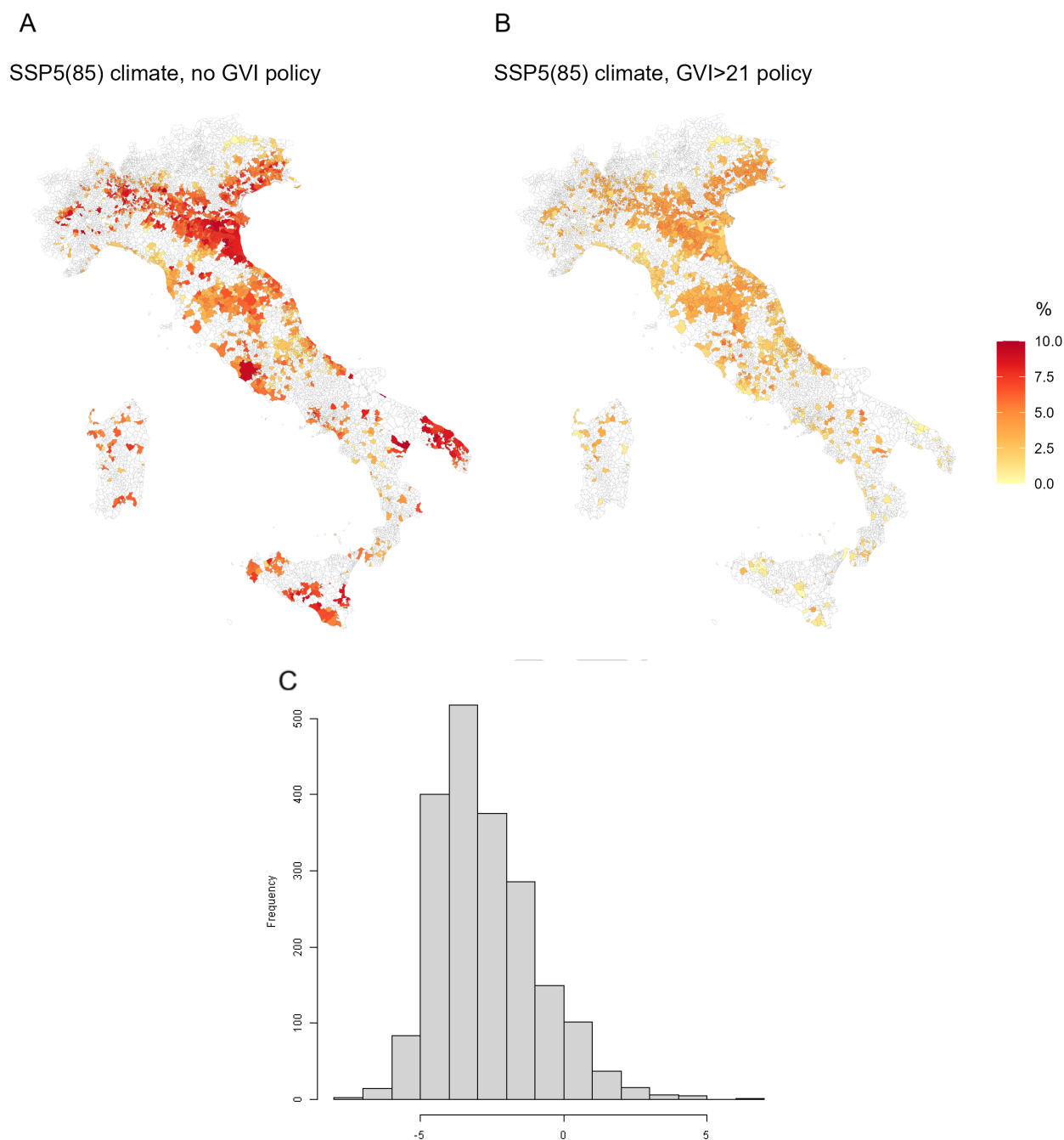
<sup>3</sup>See <https://www.ipcc.ch/report/ar6/wg1/chapter/chapter-4/> for details.

578 obtained from the NASA NEX-GDDP-CMIP6 database (Thrasher et al., 2022). We consider monthly maximum  
 579 temperature ( $T_{max}$ ) and compare two cases: future temperatures under RCP 8.5 projections for around 2050 ( $H_{cc}$ ) and  
 580 historical forcing temperatures ( $H_{hist}$ ), both based on the CMIP6 climate model outputs. In parallel, SGS increase  
 581 policy scenarios ( $SGS_s$ ) are defined, where  $s$  indicates a minimum target value for mean GVI at the municipality  
 582 level assigned to all municipalities in our sample. We compare current GVI levels scenario ( $\bar{s}$ ) with five alternative  
 583 levels, i.e.  $s \in [\bar{s}, 15, 20, 21, 24, 27]$ . In each scenario, all municipalities  $a$  where  $GVI_a < s$  are set to exactly match  
 584 the target value  $s$ . These target GVI values correspond approximately to the 5th, 35th, 50th, 75th and 90th percentiles  
 585 of the distribution of municipality-level GVI in the sample covered by our analysis. This translates into 6%, 37%,  
 586 47%, 74% and 90% of the count of unique municipalities in our sample being targeted by the five GVI target-driven  
 587 policies, respectively.

588  
 589 We obtain a total of 12 combinations, 11 projected scenarios and one benchmark (current climate and current  
 590 GVI level combination). For all the simulated policy combinations, we compute predictions from our empirically-  
 591 estimated preferred quadratic model specification presented above to calculate the simulated change in household  
 592 electricity consumption and spending from the status quo ( $\Delta q$ ). Formally, we compute:

$$\Delta q_{E,i,a} = (\widehat{q_{E,i,a}}|SGS_a = SGS_s, H_a = H_{cc}) - (\widehat{q_{E,i,a}}|SGS_a = SGS_{\bar{s}}, H_a = H_{hist}) \quad (12)$$

593 The results of the simulation analysis are provided in Table 4. Under the current climate, SGS enhancing policies  
 594 would reduce residential electricity consumption in the municipalities covered by our analysis. For instance, the  
 595 summer months municipality-level average reduction in response to SGS increase policies ranges from 0.07 to  
 596 3.3% (compared to current consumption levels), depending on the GVI target value simulated. On the other hand,  
 597 while simulating the impact of climate change on temperature and hence on electricity demand by 2050 under  
 598 RCP scenario 8.5, we find that in the absence of SGS policy, on average the summer consumption would increase  
 599 by 4.3%. However, if a SGS increase policy is implemented, such climate-induced increase in energy use would  
 600 be reduced substantially, up to a net reduction of -1.8% under an ambitious SGS policy ( $s=27$ ). As a remark, the  
 601 climate change-driven increase in electricity demand estimated is likely to be a lower bound due to the projected  
 602 increase in air conditioning penetration (De Cian et al., 2025) and other temperature-sensitive appliances, which  
 603 are not explicitly captured in our model (but implicitly captured by POD and municipality-level fixed effects in the  
 604 short-term panel) and might drive a more extensive hot temperature-related surge in household electricity use as  
 605 penetration grows. For reference, Figure 8 visually illustrates the spatial heterogeneity in the estimated average  
 606 percentage impact of climate change (RCP 8.5, year 2050) on residential electricity demand in each municipality  
 607 covered by the analysis under a policy aimed at increasing SGS to a minimum level of municipality-level mean GVI  
 608 of 21 - a value at around the median of the current distribution across municipalities. Such policy would reduce by  
 609 more than two thirds the climate change-driven projected increase in summer residential electricity consumption  
 610 under RCP 8.5 climate conditions around 2050 (compared to a scenario without SGS policy).



**Figure 8.** Climate change-induced, municipality-level average change (%) in summer monthly electricity consumption under a RCP 8.5 climate in year 2050 with (A) current GVI levels; (B) a GVI  $\geq$  21 policy; (C) histogram of municipality-level average change between (A) and (B).

611 As seen from Table 4, we use the model to extrapolate over all Italian municipalities and 26 million households  
612 in the country<sup>4</sup> to estimate the corresponding reduction (or negative reduction, i.e. net increase) in the quantity of

<sup>4</sup>We feel confident in assuming that the POD-level metered consumption dataset used in our analysis provides a good representation of the universe of Italian PODs across the whole country for two main reasons: (i) first, as displayed in Figure 2, our consumption dataset represents municipalities across the whole Italian territory, providing evidence of good geographical coverage. (ii) Second, we show that the

energy consumed (TWh/summer) and its weight on the total yearly residential electricity consumption (TWh · yr<sup>-1</sup>).  
 Finally, we also estimate emission reductions under the current average carbon intensity of the electricity sector in  
 Italy of 372 gCO<sub>2</sub>e · kWh<sup>-1</sup>.

**Table 4.** Policy and climate change simulations results summary: reduction in electricity use (TWh) and related CO<sub>2</sub> emissions (metric tons) with minimum GVI target values ( $\geq$ ) compared to current climate and SGS levels in the universe of Italian households.

	avg. % change	$\Delta$ TWh summer	% yearly resid. electr. cons.	$\Delta$ CO <sub>2</sub> (Mt)	Ely. tot (TWh/summer)
GVI $\geq$ 15, historical $T_{max}$	-0.08	-0.10	-0.15	-0.04	18.50
GVI $\geq$ 20, historical $T_{max}$	-0.85	-0.44	-0.68	-0.16	18.16
GVI $\geq$ 21, historical $T_{max}$	-1.17	-0.53	-0.83	-0.20	18.06
GVI $\geq$ 24, historical $T_{max}$	-2.36	-0.83	-1.29	-0.31	17.77
GVI $\geq$ 27, historical $T_{max}$	-3.77	-1.13	-1.76	-0.42	17.46
GVI current*, SSP5(85) $T_{max}$	4.91	1.26	1.95	0.47	19.87
GVI $\geq$ 15, SSP5(85) $T_{max}$	4.76	1.08	1.68	0.40	19.68
GVI $\geq$ 20, SSP5(85) $T_{max}$	3.37	0.46	0.72	0.17	19.06
GVI $\geq$ 21, SSP5(85) $T_{max}$	2.79	0.29	0.45	0.11	18.89
GVI $\geq$ 24, SSP5(85) $T_{max}$	0.56	-0.25	-0.39	-0.09	18.34
GVI $\geq$ 27, SSP5(85) $T_{max}$	-2.08	-0.81	-1.26	-0.30	17.78

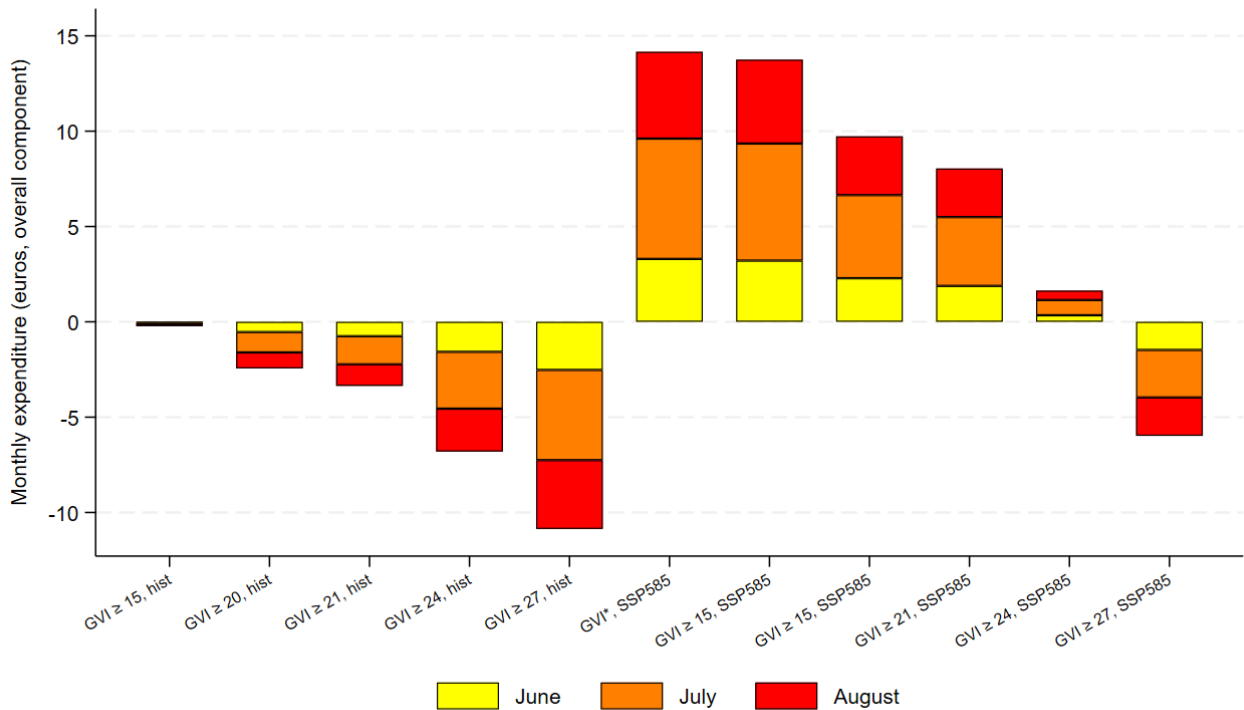
Note: \*Current (with current GVI and historical  $T_{max}$ ) estimated residential electricity consumption per summer (June-August) in the universe of Italian municipalities is 18.61 TWh.

#### Implications for household electricity expenditure

Simulated changes in household electricity consumption as a result of climate change impacts and SGS increase policies may directly translate into changes in private energy expenditure, hence having significant welfare repercussions. To estimate the magnitude of such potential changes, we derive the monthly and municipality-specific marginal price of electricity and cost per unit of energy consumed based on the energy billing information attached to the metered consumption data. Under the assumption of historical prices - justified by the challenge to project average retail electricity prices in year 2050 due to the plethora of factors involved - and marginal cost of energy, we conduct a back-of-the-envelope calculation that considers the representative household in our sample and projects the results of the expenditure change analysis on both (i) the households living in municipalities that are part of the sample of the metered consumption data of our empirical analysis, and (ii) on the universe of 26 million Italian households and 7,896 municipalities.

Figure 9 summarizes the results of the analysis showing, for each scenario, the simulated change (with respect to current consumption levels under the historical climate and GVI values) in the average household summer monthly expenditure for energy bills in year 2050. The numbers are computed by multiplying the projected variations in summer electricity consumption levels by the median price per kWh and overall expenditure per kWh paid by consumers in each municipality. The results show that such change spans between about an average saving of 3.2€/household/summer (in a scenario of historical climate and  $s=21$  GVI target) up to an expenditure increase of 13.5€/household/summer in a scenario of RCP 8.5 climate change and no SGS increase policy, which accounts for around 11.6% increase of the average of a household's summer expenditure for electricity. A similar figure based on the unit price of electricity (rather on the marginal cost of energy per unit consumed) is provided in Figure A-13.

distribution of consumption levels in our POD-level dataset is consistent with the country-level statistics reported by ARERA (the energy sector public regulatory agency of Italy, <https://www.arera.it/dati-e-statistiche>). Taking 2022 as an example, the most recent year in our dataset, we find that the median consumption level is at 143.5 kWh/POD/month, almost perfectly consistent with the value of 145 kWh/POD/month reported by ARERA for residential customers.



**Figure 9.** Estimated change in the household summer monthly expenditure for energy bills in the GVI policies and RCP 8.5 climate change impact simulations in year 2050. Average  $\Delta\text{€}$  per household per month under the assumption of historical marginal energy costs.

637 To summarize the expenditure analysis and gauge their magnitude across the entire population, Table 5 illustrates  
 638 the potential saving for (i) an average national household; (ii) the population of households living in the municipalities  
 639 represented in our metered consumption dataset, in aggregate; and (iii) for the entire population of Italian households  
 640 and municipalities, in aggregate. With regards to the latter, the results show that a scenario of RCP 8.5 climate  
 641 change and moderate SGS increase ( $s=21$ ) would only increase household electricity expenditure by €202 million,  
 642 while a scenario of RCP 8.5 climate change and no SGS increase policy would cause private increase in expenditure  
 643 up to €355 million per summer, translating into a gross private saving of €153 million per summer if the SGS  
 644 policy is implemented.

**Table 5.** Simulated changes in household electricity expenditure: average summer monthly bill, median price per kWh and median expenditure (sp). For each GVI policy and climate change scenario, the variation in summer consumption (c), energy components summer spending, and overall summer spending is calculated for an average Italian household (i), the aggregate of households in our sample of municipalities (ii), and the aggregate of households in the country (iii). The table also reports the total number of households in our sample of municipalities and in the country. These are used to calculate the variation in total spending ( $\Delta S$ ) for the two populations, expressed in thousands of euros.

	Household electricity expenditure			Population household numbers			
	avg. bill (euros/month)	P/kWh (med)	sp/kWh (med)	HHs (N, sample)		HHs (N, country)	
	116.57	0.103	0.389	7095696		26400326	
Simulated variations in electricity spending							
Scenario	i. Average Italian household			ii. Represented municipalities (aggregate)		iii. National (aggregate)	
	$\Delta c$ (kWh)	$\Delta sp$ (energy) (euros)	$\Delta sp$ (total) (euros)	$\Delta SP$ (energy) (1000 euros)	$\Delta SP$ (total) (1000 euros)	$\Delta SP$ (energy) (1000 euros)	$\Delta SP$ (total) (1000 euros)
GVI $\geq$ 15, hist	-0.587	-0.058	-0.221	-409.5	-1566.2	-1523.6	-5827.4
GVI $\geq$ 20, hist	-6.107	-0.618	-2.324	-4384.4	-16493.7	-16312.5	-61366.6
GVI $\geq$ 21, hist	-8.421	-0.854	-3.194	-6059.9	-22666.1	-22546.7	-84331.7
GVI $\geq$ 24, hist	-17.012	-1.748	-6.470	-12402.8	-45911.1	-46146.0	-170817.2
GVI $\geq$ 27, hist	-27.115	-2.802	-10.332	-19883.6	-73310.6	-73979.0	-272760.3
GVI*, SSP585	35.133	3.653	13.465	25920.1	95542.3	96438.7	355475.9
GVI $\geq$ 15, SSP585	34.092	3.550	13.070	25188.7	92739.6	93717.2	345047.9
GVI $\geq$ 20, SSP585	24.075	2.531	9.248	17959.4	65620.2	66820.1	244147.3
GVI $\geq$ 21, SSP585	19.820	2.096	7.646	14874.1	54250.4	55340.9	201844.8
GVI $\geq$ 24, SSP585	3.906	0.436	1.557	3096.2	11046.8	11519.7	41101.0
GVI $\geq$ 27, SSP585	-14.971	-1.536	-5.685	-10901.0	-40342.4	-40558.2	-150098.4

#### 645 Implications of policy costs for public budgets

646 SGS expansion and maintenance imply public costs to continuously provide a range of ecosystem services, including  
647 the indirect benefit of household electricity expenditure reduction through hot temperatures reduction, which is the  
648 focus of this paper. To assess the magnitude of such costs to achieve the policy goals simulated above, we produce  
649 a supplementary analysis of the public finances implications of SGS expansion and maintenance. We retrieve a  
650 panel dataset of every Italian local municipality's yearly budget, by cost entry, for the 2017-2023 period. The data is  
651 provided by OpenBDAP - the official portal of the Italian State General Accounting Department. Specifically, we  
652 select the cost entry classified as "*Maintenance of public green spaces and enhancement of the natural environment*")  
653 and we evaluate the responsiveness of municipality-level GVI levels to the yearly local capital investment and  
654 expenditure in such budget entry. The data are summarized in Table A-15 and Figure A-14, showing that the average  
655 values of municipality-level investment and expenditure are about €103,729 and €225,947 per year, respectively,  
656 but significant upper and lower tail exist in the distribution - driven by the high values in large municipalities and by  
657 the small average size of Italian municipalities.

658  
659 Table 6, shows the result of a municipality and yearly fixed effect regressions, implying an average requirement of  
660 €68.5 million and €13 million per year in the green space expenditure and investment of a municipality, respectively,  
661 for every additional local GVI point, net of average differences across municipalities and of country-wide shocks  
662 across years. It should be noticed that the estimated fiscal response to GVI is a lower-bound estimate, as tree  
663 canopies are a function of time after plantation, and it was shown that it takes between 30-60 years for a tree to  
664 provide its maximum level of benefits (Li et al., 2023).

665

**Table 6.** Regression results on responsiveness of public municipality investment and expenditure in the "maintenance of public green spaces and the enhancement of the natural environment" budget entry to variation municipality-level yearly GVI levels.

Dependent Variable:	GVI
<i>Variables</i>	
Million €/year × Expenditure	0.0146*** (0.0040)
Million €/year × Investment	0.0771*** (0.0227)
<i>Fixed-effects</i>	
Municipality	Yes
Year	Yes
<i>Fit statistics</i>	
Observations	76,998
R <sup>2</sup>	0.94475
Within R <sup>2</sup>	0.00027

*Clustered (Municipality) standard-errors in parentheses*  
*Signif. Codes: \*\*\*: 0.01, \*\*: 0.05, \*: 0.1*

666 Considering a time horizon of 25 years until 2050, we compute the total investment and expenditure requirement  
 667 (IER) for reaching the GVI targets simulated in each scenario as the ratio between the required increase in the GVI  
 668 to reach the target  $s$  in each municipality  $a$  and the estimated marginal cost (the coefficients of Table 6) of increasing  
 669 the GVI by one unit  $MC^{GVI}$ :

$$IER_a = \frac{\Delta GVI_a^s}{MC^{GVI}} \quad (13)$$

670 We then compute the net present value (NPV) by discounting the investment and expenditure cashflows with a  
 671 discount rate of 3% (following the European Commission CBA guidelines for social projects):

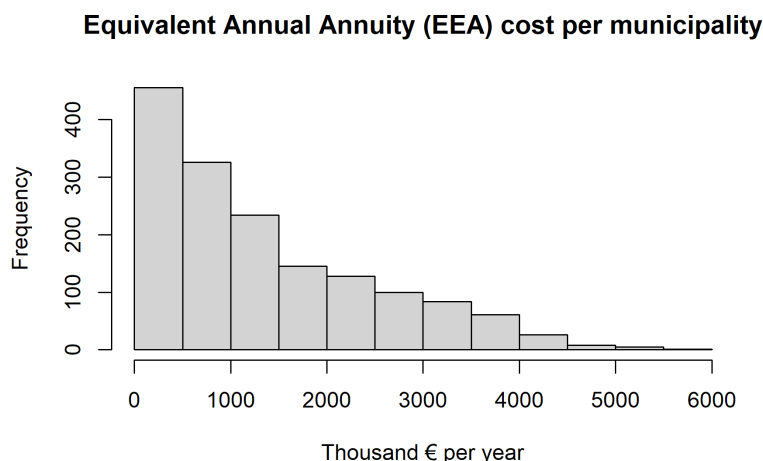
$$NPV_{IER_a} = \sum_{t=1}^{25} \frac{IER_{a,t}}{(1+0.03)^{t-1}} \quad (14)$$

672 Finally, we compute the Equivalent Annual Annuity (EAA) (i.e., the cost per year over the entire lifespan) from  
 673 the NPV as:

$$EAA_{a,t} = NPV_{IER_a} \times \frac{0.03}{1 - (1+0.03)^{-25}} \quad (15)$$

674 Across the municipalities covered by our analysis, we compute a  $NPV_{IER_a}$  of €24.8 billion over the 25-year  
 675 planning horizon, which translates into an  $EAA_{a,t}$  of €1.4 billion per year to achieve the GVI policy objective of  
 676  $s=21$ . Scaling the calculation to all Italian municipalities brings the  $NPV$  figure to a value of €36.9 billion and  
 677 the  $EAA$  figure to €2.1 billion per year. This figure corresponds to around €35 per capita. When looking at the  
 678 distribution of the  $EAA$  metric across municipality (illustrated in Figure 10), we find that achieving the  $s=21$  policy  
 679 implies a median  $EAA$  of about €1 million / municipality / year.

680  
 681 The  $NPV$  and  $EAA$  calculations are also applied to the estimated gross national-level private saving in energy  
 682 bills of about € 0.15 billion per summer if the GVI policy objective of  $s=21$  is achieved, so as to obtain comparable  
 683 cost and benefit metrics. This shows that private electricity expenditure savings yield an  $NPV$  of €2.7 billion and an



**Figure 10.** Distribution of the estimated Equivalent Annual Annuity (investment + expenditure) across municipalities to achieve the  $s=21$  GVI policy goal with a 25-year planning horizon and a 3% discount rate. The values sum to a total of about €2.1 billion per year across all Italian municipalities.

684 *EAA* of €0.15 billion per year, hence accounting for about 7.3% of the estimated policy costs. This finding should  
 685 be read under the lens of SGS being a provisioning source of a wide range of ecosystem services, which translate  
 686 into public and private benefits, with energy use reduction being only a component of such benefits. Moreover, our  
 687 analysis demonstrates that increasing urban SGS is costly, and it should be targeted in those areas where it is most  
 688 effective, rather than a one-size-fits-all solution.

689

## 690 8 Discussion and conclusions

691 Our paper is the first quantitative assessment of the benefits of SGS in terms of reduced summer electricity con-  
 692 sumption with a large spatio-temporal coverage. Our work contributes to the understanding of the interaction  
 693 between public and private climate change adaptation (Tompkins and Eakin, 2012) and the related cost and benefit  
 694 streams. Our findings confirm the importance of SGS as a key regulating factor in the temperature-energy demand  
 695 relation. SGS density - as measured by the GVI - has a strongly significant non-linear effect on the impact of  
 696 temperature on household electricity demand, with the strongest impact being a consumption reduction effect under  
 697 high heat exposure. Such responses are heterogeneous, as they depend on morphological and socio-economic  
 698 characteristics such as the extent of greening, the degree of urbanization, temperature, and income characteristics,  
 699 as well as on a range of unobserved household and city-specific characteristics, such as behavioral responses.  
 700 The choice of the heat exposure metric also plays a role, as the type of indicator (i.e. cumulative vs. acute heat)  
 701 as well as the variables selected to measure it play a role in determining the magnitude of the mediating effect of SGS.

702

703 Despite some residual limitations to the strategy highlighted above, our study generates new knowledge in  
 704 relation to the intersection between climate change adaptation and mitigation, and the role of nature-based solutions  
 705 to reduce the feedback impacts of adaptation while providing ecosystem service co-benefits. This is potentially  
 706 achieved both through the energy demand and expenditure reductions in supporting climate change mitigation  
 707 efforts, and in the quest for sustainable solutions for adaptation to climate impacts such as heat exposure. For  
 708 instance, based on our empirical findings, we estimate that a policy aimed at increasing SGS to a minimum level of  
 709 municipality-level mean GVI of 21 - a value at around the median of the current distribution across the municipalities  
 710 covered by our analysis - would strongly contribute to offsetting more than two thirds of the climate-induced

711 increase in residential electricity consumption. Such policy would lead to a reduction of around three quarters of the  
 712 climate-induced expected increase in household summer electricity consumption under RCP 8.5 climate conditions  
 713 around 2050, compared to a scenario of current GVI levels. This corresponds to a gross national-level private saving  
 714 in energy bills of €0.15 billion per summer in year 2050. SGS increase and climate change impact scenarios on  
 715 residential electricity consumption could be assessed in energy and integrated assessment models to evaluate the role  
 716 of SGS for the mitigation-adaptation synergies and trade-offs in relation to the energy needs for adaptation to heat  
 717 exposure (which are found to be very significant (Colelli et al., 2022; Mastrucci et al., 2022; Van Ruijven, De Cian  
 718 and Sue Wing, 2019) and in the analysis of interactions among public and private adaptation actions, including  
 719 equity and social-ecological justice considerations in urban adaptation (Rocha et al., 2024).

720  
 721 Our proposed back-of-the-envelope calculation shows how private savings for electricity account for around  
 722 7.3% of the estimated yearly discounted maintenance costs. This, in turn, highlights a substantial, and potentially  
 723 overlooked, economic benefit of urban green spaces. Policymakers should incorporate energy savings - alongside  
 724 the wider range of ecosystem services, public health benefits, including mortality reduction and well-being (Van den  
 725 Berg et al., 2015b), and intrinsic economic values (Urban, 2018) - when performing comprehensive cost-benefit  
 726 analysis and evaluating the welfare implications associated with the expansion of green spaces.

727

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## 976 Author contributions

977 G.F. and E.D.C. designed the study and created the theoretical framework; G.F. assembled the data and carried out  
 978 the formal analysis; J.L. processed the metered electricity consumption data and conducted the expenditure change  
 979 calculations; G.F. produced the figures and tables; all authors wrote and edited the manuscript.

## 980 Competing interests

981 The authors declare no competing interests.

## 982 Data and materials availability

983 The replication code, instruction for accessing the input data, and the output data generated in this study are available  
 984 in a Github repository under: [https://github.com/giacfalk/sgs\\_electricity\\_replication](https://github.com/giacfalk/sgs_electricity_replication).

# Street green space and electricity demand: evidence from metered consumption data

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## ABSTRACT

Growing climate change impacts call for increased efforts to adapt and to reduce its adverse consequences on society. Adaptation responses can themselves be a source of climate risk, generating negative environmental externalities while entailing budgetary costs for both governments and private citizens. A key example is the private use of air-conditioning for indoor air temperature regulation in the face of rising urban heat. In this paper, we empirically evaluate the impact of street green spaces (SGS) on residential electricity demand through their urban temperature regulation effect. We exploit a monthly panel of household metered electricity demand data from 129,524 households located in 2,181 municipalities distributed across Italy, in the period between 2020 and 2022. We find evidence of a significant non-linear mediating role of SGS on the impact of temperature on household electricity demand. The most salient effect is a reduction in electricity consumption when hot temperatures occur - lowering monthly average electricity consumption by up to 11-25% (for monthly maximum temperatures of 30 and 35° C, respectively). The observed moderating effects of SGS are heterogeneous across municipalities, as they depend on contextual factors such as the degree of urbanization, baseline heat and SGS levels, and average income level. To dissipate across-municipality sorting concerns, we conduct propensity score weighting on a range of potentially confounding observables, and find our results remain consistent. We estimate that a policy increasing the average Green View Index (GVI) level across all municipalities to a value comparable to the median of the current distribution would reduce the growth in residential electricity consumption driven by climate change by more than two thirds (under Representative Concentration Pathway 8.5 climate conditions around 2050). This corresponds to a gross national-level private saving in energy bills of €150 million yearly in 2050. This is a noticeable benefit that represents about 7.3% of our estimated costs to implement such policy, and informs on a potentially substantial social and economic benefit of urban green spaces. Our results provide new quantitative evidence of the role of street green spaces for both energy demand reduction, and therefore climate change mitigation, and in terms of outdoor temperature reduction, supporting climate change adaptation.

## Keywords

Street green space; energy demand; public-private adaptation; urban heat islands; nature-based solutions; climate change impacts

## JEL classifications:

D12, O13, Q41, Q5

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## **Statements and Declarations**

### **Author contributions**

G.F. and E.D.C. designed the study and created the theoretical framework; G.F. assembled the data and carried out the formal analysis; J.L. processed the metered electricity consumption data and conducted the expenditure change calculations; G.F. produced the figures and tables; all authors wrote and edited the manuscript.

### **Competing interests**

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- Analysis of metered electricity consumption data from ~130,000 households in Italy.
- Street trees moderate electricity-temperature response non-linearly.
- Cooling effect of street trees reduces electricity demand at high temperatures.
- Benefits vary by urbanization, income, climate, and baseline greenery levels.
- Increasing SGS could cut 2050 climate-driven electricity growth by over two-thirds.