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The impact of urban form on daily mobility demand and energy use: Evidence from the United States

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ABSTRACT

The causal relationship between urban form, in particular density, and travel demand is subject to debate. Here, we investigate this relationship using a structured regression approach applied to a large-scale layered dataset of travel patterns and urban form. We find that residents of the densest urban areas use 80% less energy for transportation than residents of rural areas and explore the causal factors influencing this relationship. We find that the primary driver of the density–energy use relationship is the larger number of nearby destinations available to urban dwellers, followed by differences in road network properties and public transit infrastructure. The energy benefits of urban dwelling are weakened when there are more destinations available 10–100 km away due to urban sprawl. While these causal factors are correlated with density, urban form can substantially affect travel energy use even within a given density bracket. We also show that urban form predominantly influences how and where people travel, rather than how often and how long. These results outline pathways for cities and communities to reduce the environmental impact of travel while increasing access to relevant destinations.

1. Introduction

Personal mobility accounts for a substantial fraction of urban greenhouse gas and air pollutant emissions [1], including in the United States [2]. Travel patterns and energy demand of travel have been found to correlate with certain aspects of the built environment, in particular density [3,4]. As a result, land use and urban design policies may contribute to energy consumption reduction and emissions mitigation strategies [5].

The built environment influences travel behavior differently at different distance scales. At the macro scale, residents of larger cities have been found to travel further each day than those of smaller cities [6,7]. At the intermediate or meso scale, some of the strongest effects have consistently been found [8–11], including factors such as density and land use diversity (land use entropy). At the micro scale, local urban design can affect modal choice, in particular the likelihood of someone to walk [9,12]. Effects at the meso- and micro-scale have been dubbed the “3 Ds” of travel demand: density, (land use) diversity, and design [9]. This is what we define to be ‘urban form’ here: the physical characteristics of the built environment that can affect travel behavior, including the density, size, and configuration of settlements and their transport network.

The observed magnitude of the causal relationship between urban form and travel demand at different scales is contested (e.g. [13,14]) and can vary substantially based on study design [4,15]. Differences among existing studies include how urban form and travel behavior are measured. For example, most existing studies focus on vehicle miles traveled (VMT), often per household and year (e.g. [9,16]). Such analysis does not explicitly reflect travel on non-automotive modes, limiting insights on aggregate travel demand and substitutions between modes. More direct measures of travel energy use have been rare.

Studies also differ in whether they measure urban form through density as a proxy, or explicitly through concepts such as access (e.g., the typical distance or travel time to key destinations). Some consider both, thus potentially confounding the two (e.g. [3,17]). Further differences exist in whether and how residential self-selection and other forms of endogeneity are treated, a commonly discussed issue in existing literature [4,18–20]. Finally, most existing studies focus on a specific city or set of neighborhoods within a city [4], thus not capturing the full set and magnitude of differences that can exist between different areas. We include a tabularized comparison between key existing studies and this work in Table S1. In summary, existing studies have often limited in their geographical scope and the comprehensiveness in which they represent urban form and travel demand. In this work, we aim

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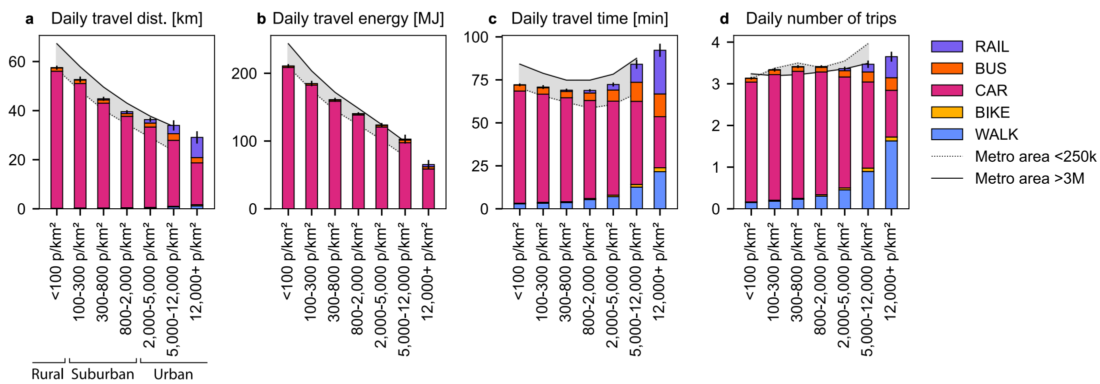

Fig. 1. Correlation between density (residential population and jobs, in people-equivalents, measured at the household location) and travel demand, based on the 2017 U.S. National Household Travel Survey [21]. Rural, suburban, and urban brackets are defined in Table 1. Confidence intervals show the bootstrapped 95% range of the daily totals. Shaded areas reflect the range between people living within large (population >3M) metropolitan areas and people living in a small or no metro area. Default sample weights were used. n = 245,431 people.

to address these gaps by analyzing data at the national scale and combining it with information from other sources.

Initial insights on the correlation between travel across all land-based modes and urban form at a national scale can be obtained from the National Household Travel Survey (NHTS, [21]). The NHTS contains information on travel behavior and demographic characteristics of 129,696 sampled households, spanning the entire United States. Each household was randomly assigned a specific travel day during which each person of the household compiled a detailed travel diary. Sample weights allow to correct for sampling and response biases. This data can be used to compile aggregate travel statistics. In this work, we measure travel using cumulative daily statistics, as opposed to per-trip statistics, allowing us to consider shifts between modes (e.g., is a reduction in the number of trips made by car per person and day directly correlated with a corresponding increase in walking trips?) and evaluate patterns in terms of total time spent traveling and total number of trips made per day (e.g., if higher density causes trips to be shorter, do people make more trips instead?).

The NHTS data indicate that density, spanning rural environments to dense urban areas, is strongly correlated with travel demand (Fig. 1). People living in the densest urban areas (with a density of 12,000 people per km^2) travel 50% less far per day and spend 70% less energy doing so than people living in rural areas. People in urban areas also spend more time traveling each day, on average, than people living in rural to suburban areas. The average number of trips made per person and day is relatively constant. At the same time, people living in large metropolitan areas travel further and longer each day, but with fewer trips, than people living outside of metropolitan areas but in a similarly dense environment.

While valuable as a starting point, these insights obtained directly from travel survey data leave many questions unanswered. Where does the strong effect of density on travel behavior come from and how much is it confounded by other aspects of urban form that correlate with density? How much is the effect confounded by demographic characteristics and residential self-selection (i.e., people with an inherent preference toward certain travel characteristics choosing to live in an environment that enables those preferences)? And is the increase in average daily travel time in higher density areas the result of decreased car travel speeds (and correspondingly longer typical travel times for trips made by car), or the result of an increase in public transit and walk mode share?

To address these types of questions, we extend a restricted (i.e., non-public) version of the 2017 NHTS data that contains the approximate location (the census tract) of each traveler's household by matching that household location with additional information from the Smart Location database [22], OpenStreetMap (accessed using OSMnx [23]), and the Typical Meteorological Year [24]. We then apply a path analysis to this comprehensive dataset that enables us to explain which aspects of urban form affect travel behavior and how they are correlated with density while controlling for residential self-selection and other characteristics (Fig. 2). While it has previously been used to study the relationship between the built environment and travel (e.g. [11,16,25,26]), the lack of detailed contextual data on urban form has been limiting its use. Our combined dataset allows us to investigate this relationship using a large, weighted sample that representatively spans the entire United States while considering detailed information on urban form at the local level.

Our work reveals the quantitative relationship between different aspects of urban form and daily travel demand. It also contributes meaningfully to the discussion of how urban form can be effectively measured and quantified in the context of mobility, and how various features of urban form relate to each other. Therefore, this work supports the fundamental understanding of the role that urban planning and design can play in the decarbonization of our cities. In doing so it uncovers specific, actionable policy measures that can contribute to decarbonization goals, as well as quantifying some of the potential benefits and risks of urban form interventions.

2. Material and methods

We evaluate the relationship between urban form and daily travel demand per capita while controlling for demographic and other properties. We implement the model structure shown in Fig. 2 using a path analysis, a subtype of structural equation models (SEMs) without latent variables. Similar techniques have previously been used in the context of travel demand modeling [16,26,27]. All relationships are implemented as linear equations. Full mathematical equations are available in section 1 of the Supplementary Material.

The model is applied to the weighted National Household Travel Survey (NHTS) data, consisting of randomly sampled travel days made by 245,431 people after filtering. This travel survey data is complemented with data from other sources at the census block group (CBG) level that have been aggregated to the census tract (CT) to enable an integration with the NHTS data. The average CBG has a population of about 1500 people, meaning that there are about 220,000 CBGs in the United States. There are about 3 CBGs per CT. A summary of properties of all variables used in the analysis is available in Table S3 in the Supplementary Material. The estimated coefficients, along with their significance levels, are shown in Tables S4–S7.

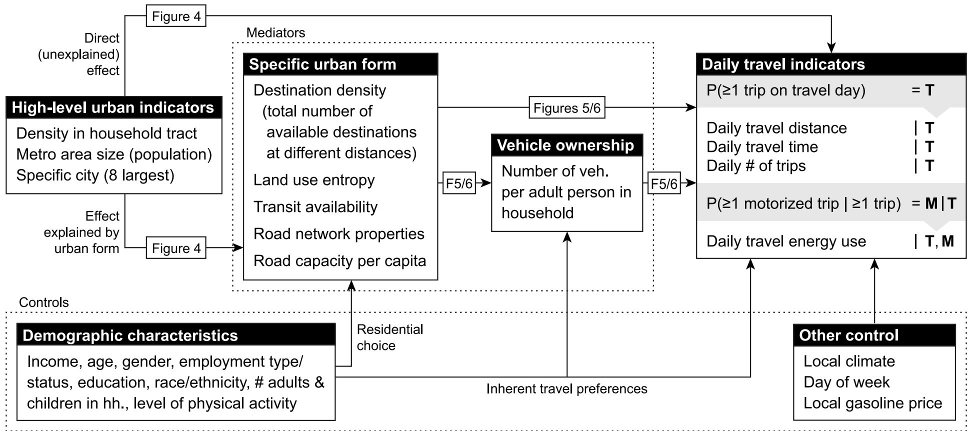

Fig. 2. Schematic of the path analysis. A detailed description of each group and the specific features representing a given indicator is available in the Methods section. Solid arrows reflect links related to urban form; dotted arrows reflect controls. Arrows labeled 'Fig. 4' and 'Figs. 5/6' or 'F5/6' indicate the figures in which the estimated effect sizes (results) of those pathways are visualized.

2.1. Measuring mobility demand

Existing analyses of mobility demand in relation to the built environment can be grouped along three axes: the modes they consider (usually either car trips only, or all urban trips), unit of analysis (individual people, households, or neighborhoods/cities), and the unit of time over which they measure mobility (annual, daily, or individual trips). The most common metric to gauge travel demand in the context of energy use and sustainability is daily or annual household vehicle miles traveled (VMT; see Table S1 for a list of examples). However, VMT do not include trips made with other travel modes, making it difficult to determine whether and how trips are substituted when they are not made by car. Household VMT are also confounded by household size and structure. Finally, in many travel surveys, VMT are self-reported, making the metric prone to noise and potentially response biases.

Modal choice studies, on the other hand, often focus on individual trips. While this mitigates some of the issues associated with measurements of annual household VMT, analysis of individual trips does not capture unobserved aspects of travel behavior that may be correlated with the characteristics of individual trips. For example, if higher density means trips become shorter, do people make more trips instead?

Here, we measure travel behavior in terms travel days. Each travel day represents the cumulative sum of travel activity (such as travel distance) made by a given person on a single day. This approach allows us to combine the benefits of annual travel miles with the benefits of measuring individual trips. Specifically, we consider four indicators of travel behavior: daily total (cumulative) travel distance per person, daily travel energy use per person, daily travel time per person, and number of individual trips made per person and day. Since energy consumption is not directly available in the NHTS data, we estimate the energy use for each trip. For trips made by car, this estimate is based on the officially rated fuel economy of the corresponding vehicle, trip distance, and average trip speed. Details are available in the Supplementary Material.

2.2. Measuring urban form

Early efforts to quantify the impact of urban form on travel demand often focused on population density. In the late 90's, the notion of the "3 D's" of travel demand (density, land use diversity, and design) was popularized, based on evidence from travel surveys [9]. The list of D's kept expanding, often including measures of access (access to relevant destinations and/or infrastructure, including public transit infrastructure). Access as well as street network properties are closely related to density, however, and may reflect one of the key mechanisms through which density affects travel behavior rather than being separate factor [4,28].

To preserve the intuitive concept of density but also understand the relevance of specific aspects of urban form, such as access, land use diversity, and road network properties, we measure urban form in two layers. Initially, we consider three high-level urban indicators: (1) population density; (2) metropolitan area population of the core statistical area (CSA); and (3) fixed effects for individual metropolitan areas with sufficient sample sizes. These indicators are readily available in most travel surveys and are intuitive to understand.

To measure density, we consider the combined and normalized population and job density at the census tract level, using data from the smart location database [22]. First, we normalize the number of jobs across the country to equal the total population:

$$N_{jobs,norm,i} = N_{jobs,i} \frac{\sum_i N_{pop,i}}{\sum_i N_{jobs,i}} \tag{1}$$

where $N_{jobs,i}$ is the number of jobs in census tract i and $N_{pop,i}$ is the population in census tract i. Then, we calculate the adjusted population density as the combination of original population density and normalized job density, assigning a weight of 50% to each:

$$d_{p,adj,i} = \frac{N_{pop,i} + N_{jobs,norm,i}}{2A_i} \tag{2}$$

where $d_{p,adj,i}$ is the adjusted population density in census tract i and A is the area of that tract.

This approach alleviates issues with residential population density where dense but predominantly commercial or industrial areas would be considered low-density due to the lack of residents in the area. Normalizing the adjusted population density to the same scale as the original population density should the final numbers more intuitively familiar. We also tested other approaches (e.g. combined household units and jobs per area), but they resulted in less consistent modeling results. For example, measuring density in terms of household units is confounded by the average household size.

To further improve the intuitive understanding of density, we classify different density brackets into rural, suburban, and urban. These terms are not standardized, and different approaches to define them exist (e.g. [29]). The official definition by the U.S. Census Bureau does not include the term 'suburban' and only distinguishes between 'urban' and 'rural' [29,30]. Some definitions blend the rural–suburban–urban distinction with metropolitan area size or presence (e.g. [31]). The geographical resolution (e.g. census tract, zipcode, or even county) at which areas are defined to be rural, suburban, and urban can vary as well. Here, we define rural, suburban, and urban at the census tract

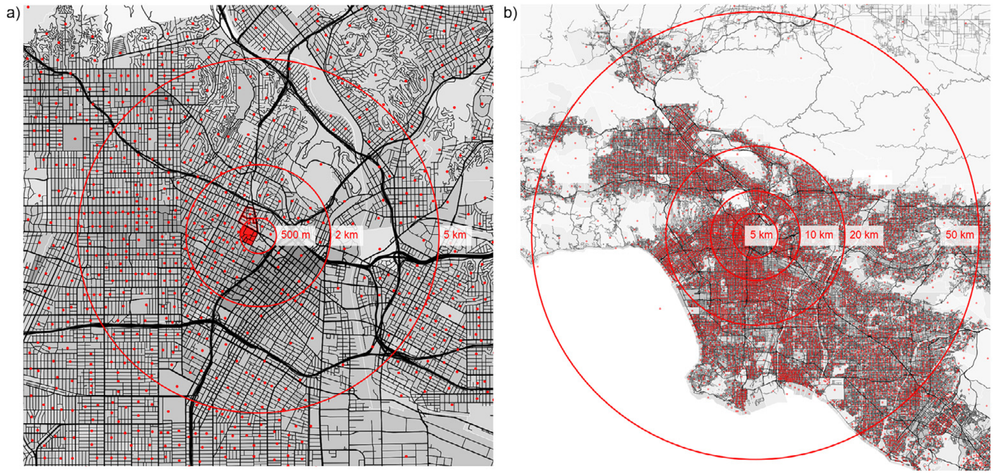

Fig. 3. Illustration of the spatial scale of urban form metrics, showing Los Angeles (CA). The area shaded red in subfigure (a) indicates a census block group (CBG), the adjacent areas with a red border the rest of the census tract consisting of 3 CBGs total. The red dots in both subfigures represent the centroids of other CBGs. The shade of gray reflects density. In (a), the 500 m, 2 km, and 5 km radii around the centroid of the red shaded CBG are indicated; in (b) the 5, 10, 20, and 50 km radii. Similar to the density brackets in Table 1, the radii are approximately equally apart from each other in log-space.

Table 1
Definition of 'rural', 'suburban', and 'urban' in this work, compared to Kolko [32]. p_{adj} refers to the adjusted population density in Eq. (2). HH refers to (occupied) households. 'Equivalent to' refers to the average density in HH/mi^2 of the census tracts to the bracket limits in p_{adj}, illustrating that our thresholds are similar to those in Kolko [32].

	Kolko [32]	This work	Equivalent to
Rural	<102 HH/mi^2	<100 p_{adj}/km^2	<118 HH/mi^2
Suburban	102–2213 HH/mi^2	100–2000 p_{adj}/km^2	118–2204 HH/mi^2
Urban	>2213 HH/mi^2	>2000 p_{adj}/km^2	>2204 HH/mi^2

level, based on the adjusted population density in Eq. (2). Metropolitan area size is considered separately. We use thresholds similar to [32] (see Table 1).

In a second step, we tie the high-level indicators (density at the census tract level and metropolitan area population) to specific measures of urban form: the number to destinations available within a certain distance range (destination density within different distance brackets, which is strongly related to access), land use diversity or entropy, access to public transit network, and various street network and road design properties (see Fig. 2).

Notably, removing this second layer from the model would not substantially alter the total measured effect of the first-layer urban indicators on daily travel demand. The purpose of the second layer is to explain where the total effect of density and metropolitan area population on travel comes from and which aspects of urban form and urban design could be leveraged most effectively to reduce daily travel energy use. In addition, the direct (unexplained) effects from each density bracket help us identify whether there are non-linear relationships or missing relationships between the specific measures of urban form and travel demand. Such relationships would be compensated by the unexplained effect of certain density brackets.

We measure destination density in 7 distance bands, destination entropy in 3 distance bands, and other properties within a certain radius from the census block group of each household (Fig. 3). These properties are then aggregated (averaged) to the census tract based, and combined with the NHTS data (whose household location is available at the tract, not the block group level). More details of how each urban form characteristic was defined and calculated are available in section 1 of the Supplementary Material.

Through the structure in Fig. 2, we assume that there are no strong causal links between the individual aspects of urban form measured here that would need to be included explicitly. We believe this assumption to be justified, since the different properties can be planned, designed, and adjusted simultaneously and largely independently. Correlations, however, are likely to exist, and need to be evaluated carefully to avoid over- or underestimation of coefficients due to strongly correlated predictors. We discuss this further in section 1 of the Supplementary Material.

In a final step of the analysis, we apply the same model to two subsets of the data: one only containing households living in census tracts with an adjusted density of <2000 people/km^2, and one only containing households living in census tracts with an adjusted density of >500 people/km^2. These submodels let us evaluate whether the direction or magnitude of the effect of urban form characteristics on travel demand varies with density.

2.3. Identification of causal relationships

Causal inferences derived from observational data, such as the ones used in this study, tend to be more tentative than those drawn from a randomized study [33,34]. This is an inherent limit to investigating the impact of aspects of the built environment on behavior or energy use.

Observed relationships between two variables can either be the result of causation, confounders, or colliders [34,35]. To support causal claims, confounders therefore need to be addressed. This is achieved by selecting the right controls. Good controls blocks non-causal paths from the treatment to the outcome and do not interfere with any mediating paths from the treatment to the outcome.

However, controlling for the wrong variables can introduce colliders into the model [35,36]. Specifically, conditioning on the common outcome of two variables (i.e., a collider) induces a spurious association between them. For example, controlling for air travel (which we do not measure as part of travel demand) would likely introduce bias into the model, since air travel is likely to be partially an outcome of urban form (our intervention) and the amount of land-based travel done (our effect). This bias is also called endogenous selection bias. A related problem is simultaneity, where an explanatory variable and the dependent variable cause each other [33]. In many cases, instances of simultaneity can potentially be converted to non-simultaneous (acyclic) structures by resolving the temporal sequence of events more granularly [34].

In this study, we control for residential self-selection and three other confounders (local climate, gasoline price, and day of the week of the sampled travel day). At the same time, we carefully avoid controlling for potential colliders. These considerations are discussed in more detail in the subsequent sections.

2.4. Residential self-selection and attitude

A potential source for biases in analyzing the relationship between urban form and travel behavior is residential self-selection: people with specific attitudes (e.g., preference to walk) may choose to live in specific areas (e.g., dense urban areas), meaning that the built environment does not necessarily cause the choice to walk [37]. Self-selection preferences are sometimes measured by some form of attitude. Prior evidence suggests that urban form does affect travel behavior even when attitude is controlled for [12,18,37,38]. While these previous studies include a measure of attitude towards travel to account for self-selection, the NHTS data used here does not contain sufficient data to evaluate inherent attitude towards travel.

However, attitude itself can be shaped by the built environment [18, 20,38,39], implying that a direct inclusion of attitude into the model may lead to underestimations of the effect of urban form on travel. This is because if attitude is the result of urban form travel behavior, controlling for it introduces a collider into the model.

Here, we control for residential self-selection by incorporating a wide variety of demographic characteristics that cannot be or are very unlikely to be altered by urban form or travel behavior. We allow these characteristics to moderate the link between the urban indicators and travel demand through the included endogenous variables, as well as the final travel demand itself (see Fig. 2). Despite this, however, a certain overestimation of the causal links between measured aspects of urban form and travel demand cannot be ruled out in the final model. The results presented here should be considered evidence for, but not proof of, the magnitude of causal relationships.

2.5. Additional potential sources of endogeneity

Residential self-selection is not the only aspect that can introduce endogeneity into the model when controlling for it in a certain manner. For example, it might be tempting to include some measure of effective travel speed or congestion. However, effective travel speed is jointly determined by the built environment (the treatment) and by travel demand (the dependent variable). In addition, travel speeds are inherently linked to travel distance: shorter trips may have inherently lower travel speeds and higher levels of congestion because they take place in denser areas, but that does not mean that low travel speeds or congestion caused a trip to be shorter than it otherwise would have been.

Similarly, it might seem tempting to measure the population density at the origin and destination of each trip instead of at the traveler's household location, yielding a more accurate picture of the urban environment in which the trips took place. However, relating urban form to individual trips can introduce bias. For example, we may find that if both trip origin and trip destination are located in a high-density area, trips are shorter than if only the origin is located in a high-density area. However, this could simply be the result of the fact that two high-density areas are inherently more likely to be close to each other than a randomly chosen high-density and a randomly chosen low-density area. Once again, the variable in question (population density at the origin and destination of a given trip) is both the result of the treatment (urban form) and effect (revealed travel behavior).

For these reasons, we measure all properties of urban form at and around the traveler's household, rather than the origin or destination of each trip. We exclude direct measures of trip speed or congestion in favor or measured properties of the built environment that may affect these characteristics, but are not immediately affected by travel demand, such as road capacity and speed limits. Further details on the method, including equations and detailed descriptions of each included variable, can be found in section 1 of the Supplementary Material.

3. Results

Explaining the relationship between density and travel through urban form

We confirm the previous observation (see Fig. 1) that population density has a substantial impact on daily travel demand, now controlling for demographics and other factors (Fig. 4a,b). Compared to rural areas, dense urban areas (>12,000 p_{adj}/km^2) show a reduction of 72%[1] in daily average travel distance and a reduction of 78% in daily travel energy use. While a larger fraction of the population travels on a given day in dense urban areas (+8.1%, Fig. 4e), fewer travelers make any motorized trips (−16.8%, Fig. 4f). Combining these probabilities with the reduction in energy consumption of people who do make at least one motorized trip (Fig. 4b), the densest urban areas cause a reduction in daily travel energy use of 80% as compared to the least dense rural areas.

Figures S8 and S9 in the Supplementary Material add further insight into why demographic factors do not substantially affect the previously identified relationship between density and travel demand: while demographic factors explain a large fraction of daily travel demand, they are barely correlated with specific characteristics of urban form such as destination density, road network properties, and public transit infrastructure.

Of the total effect of density on travel demand, a large portion (40% in terms of daily travel distance, 28% in terms of daily travel energy use given that at least one motorized trip was made) can be attributed to the correlation between density and access to locations no more than 2 km away. The combination of different road network properties have a similarly large effect. The remaining impact can be explained by public transit infrastructure, road capacity per capita, and destination density at a distance of 2–10 km. Land use entropy does not mediate the relationship between density and travel demand. As we will show in the next section, this is because entropy is barely correlated with density (but is correlated with travel demand).

We also confirm that the size of a metropolitan area has a considerable effect on daily travel distance, energy use, and travel time (Fig. 4a–c). People living in large cities (with a metropolitan area population of 3 million or more) travel 28% further each day, for 23% more time, than people living outside of a metropolitan area, all else being equal. This is predominantly the result of an increased number of possible destinations at least 10 km away.

Daily average travel time and in particular the number of trips per day are affected less by density than daily travel distance and travel energy use, even when controlling for demographics (Fig. 4c–d; note the y-axis scale). Increased access to public transit in dense urban areas does lead to an overall increase in typical daily travel times, which acts opposition to the correlation between density and the presence to nearby destinations. This increased access to public transit in combination with an increase in destination density between 10 and 100 km, associated with large metropolitan areas, causes the observed increase in average daily travel time in dense areas in Fig. 1.

Notably, the direct or unexplained effect of density and metropolitan area size is small for all travel metrics, in particular for daily travel distance and energy use (Fig. 4a–f). This implies that the measures of urban form that we include comprehensively cover the mechanisms through which density reduces daily travel distance and energy use. It also indicates that the identified relationships in their sum are unlikely to be strongly under- or overestimated, or non-linear. If they were, the free coefficients for the unexplained effect would need to correct an overestimated effect for some, but not all, density or metropolitan area size brackets.

[1] $e^{-1.39+0.12} - 1 = -0.72$; see section on coefficient interpretation in section 1 of the Supplementary Material.

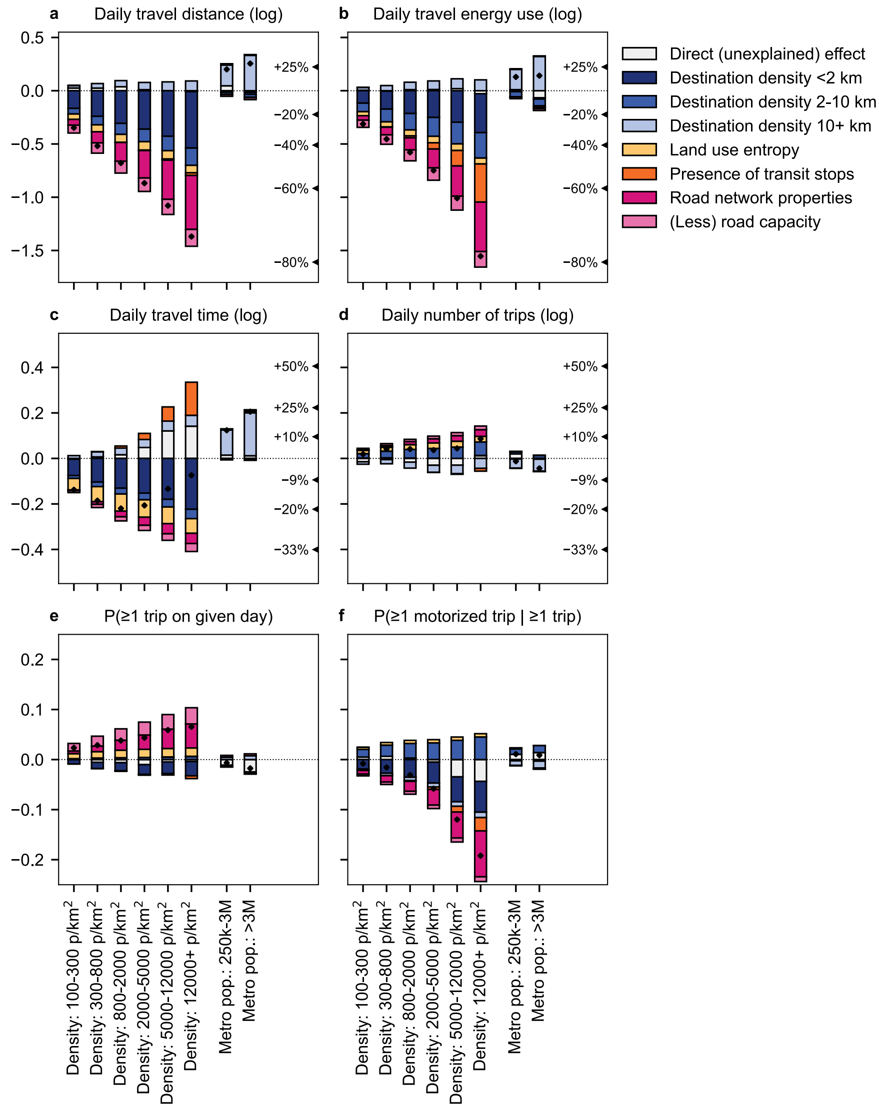

Fig. 4. Estimated effects of density (reflecting residents and jobs) and metropolitan area size on travel demand, mediated through specific aspects of urban form (see Fig. 2). The baseline (0.0) reflects a household located in an area with <100 p_{adj}/km^2 and outside of metropolitan area. The percentage impacts shown are calculated using $p = \exp(-\upsilon) - 1$, where υ is the original y-axis value. The black diamond markers show the net effect size. Supplementary results for the fixed effects of 8 metropolitan area codes (see Fig. 2, top left) are shown in Figure S10.

Investigating specific aspects of urban form

Next, we explore individual measures of urban form and their impact on daily travel energy use, daily travel time, and the probability of making at least one motorized trip during a given day (results for the other three indicators are shown in Figure S5). Contrary to the results in the previous section, where aspects of urban form were evaluated in the context of density and metropolitan area population size, the results of this section are independent of the extent to which individual aspect of urban form are correlated with these high-level indicators.

We find that destination density less than 10 km away (whose individual effects are cumulative) has the largest impact on daily energy use, closely followed by rail station access and the fraction of 1-way streets (Fig. 5). We suspect that the latter is closely correlated with limited parking availability and pedestrian-friendly street design. Increased entropy does lead to a decrease in daily average travel energy use. Part of the benefit of increased entropy (more convenient access to a variety of destinations nearby), however, is already captured by access to nearby destinations.

In our formulation, urban form can impact travel demand directly, or it can impact vehicle ownership, which in turn impacts travel demand. We find that most of the effect of urban form on travel demand is direct, but that vehicle ownership still plays a substantial role. This suggests that the choice to walk or take public transit is less tied to the lack of availability of a car than it is to the availability of destinations that are accessible by these alternative modes. Similarly, it may suggest that policies leading to marginal changes to car ownership, when isolated from other impacts on urban form, are unlikely to effectively reduce (or increase) travel energy demand. The two features more directly tied to car ownership rates are public transit access and the fraction of 1-way streets. The latter may be strongly correlated with street parking availability.

Changes in observed daily travel time can result from changes to daily travel distance, from passengers switching from one mode to a faster or slower one, or from changes to the travel speed associated with a given mode (in particular, from roadway congestion). Destination entropy (land use diversity) and access to destinations less than 500 m away (within walking distance) are both associated with decreases in typical average daily travel time, implying that they allow travelers to take shorter-distance trips and spend less time traveling overall. On the other hand, increased rail station access is associated with increased daily travel time through changes in mode split, and an increase in

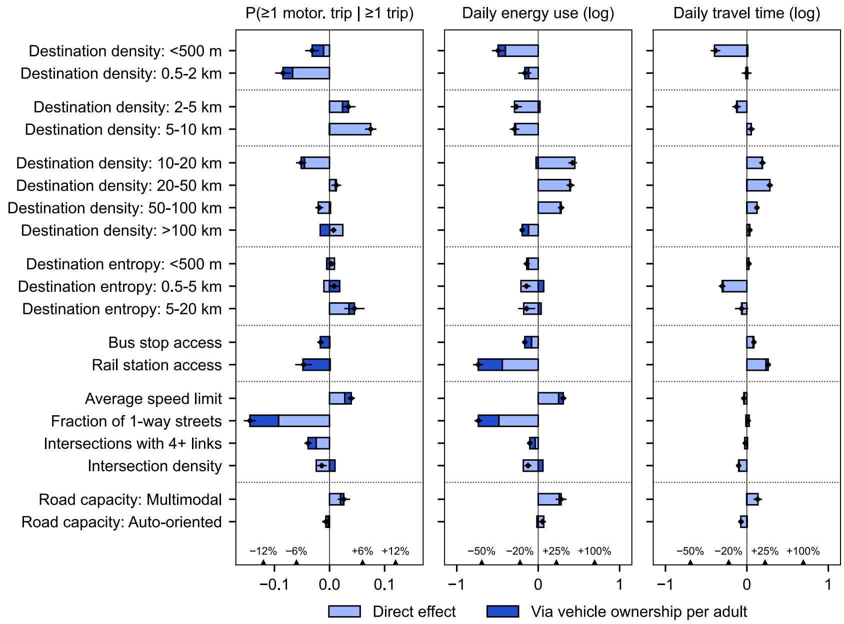

Fig. 5. Estimated effect size of individual aspects of urban form on three key travel indicators (see Fig. 2). Results for the other three indicators are shown in Figure S8. All features are normalized to a range between 0 and 1, meaning that the shown effect size indicate the maximum effect. For a version of this figure showing the average contribution of each indicator to the variation in the travel indicator instead, see Figure S6.

destinations 10–100 km away is associated with an increase in daily travel time through longer trips. Overall, however, average daily travel time is less affected by different aspects of urban form than daily travel energy use.

From rural to suburban to urban: assessing effect heterogeneity

For this part of the analysis, we separately consider the transition from rural to suburban and from suburban to urban spaces, as defined in Table 1, using two submodels. We also show the mean average deviation (how much each aspect varies across the United States) and correlation (how much each aspect is correlated with density) for additional context.

From rural to suburban areas, access to destinations less than 10 km away, higher intersection density, and lower road capacity per capita dominate the reduction in energy use. Urban sprawl, through a corresponding increase in destination availability between 10 and 100 km, partially cancels out those reductions.

From suburban to urban areas, the effects become more varied. Public transit presence and the fraction of one-way streets, which were excluded from the rural to suburban model due to their low variance, become substantially more relevant. In addition, we note that it is predominantly the availability of destinations less than 2 km away that is driving a decrease in travel demand, with destination density at the 5–10 km interval being associated with an increase in motorized travel.

Notably, rail station access and the fraction of 1-way streets, two of the aspects with the largest individual impact on daily energy use, vary little across the country (column 'MAD' in Fig. 6) because they are often close to 0. At the same time, they are both strongly correlated with density (column 'Corr'). Destination entropy is not strongly correlated with density, especially in suburban to urban environments, which is why its effect is small in Fig. 4, even though it can affect daily travel energy use and travel time considerably.

If you build it, they will come

Road capacity per capita is strongly correlated with daily travel energy use when transitioning from suburban to urban areas (Fig. 6). In particular, increased road capacity may enable access to destinations 10–100 km away (whose presence drives overall energy demand), and appears to disincentivize travelers from using non-motorized modes. This finding is consistent with the expected impacts of induced demand—a phenomenon that takes place when roadway congestion is acting as a binding constraint on demand for car travel, and by which increasing roadway capacity leads to more car travel. Were induced demand to be unimportant, one would expect increases in roadway capacity to be associated with *decreases* in travel time owing to reduced congestion, suggesting that the travel-inducing impacts of increases in roadway capacity outweigh the congestion-mitigating ones.

Increases in roadway capacity are associated with more car trips, more energy use, and more travel time. The observed effect of automotive road capacity (where pedestrians are not allowed) is smaller than that of pedestrian-accessible roads. This is likely because we only measure road capacity around the traveler's household in a radius of 3 km, not around each trip origin or destination, thus only partially capturing the effect of automobile road capacity on the prevalence of longer car trips. We discuss this modeling choice more extensively in section 1 of the Supplementary Material.

Evidence for induced demand can also be found elsewhere. In particular, urban form characteristics associated with faster or easier driving do not tend to lead to overall reductions in travel time. For instance, an increase in the average speed limit can be expected to be associated with an increase in typical travel speeds for car trips, but higher speed limits lead to no net decrease in travel time, suggesting that travel speed increases due to higher speed limits (and the associated higher-speed roadway design) are entirely counteracted by increases in congestion and longer distance trips. A smaller share of one-way streets and a lower intersection density (e.g. longer blocks) increase the likelihood of taking at least one car trip, appearing to make car travel more, and non-motorized travel potentially less convenient. Fewer four way intersections (associated with a suburban rather than a typical urban street layout) are not associated with the same increase in car trips, but these factors all lead to an increase in daily travel energy use while hardly affecting daily travel time, suggesting that car-friendly urban form leads to either more or longer-distance car trips.

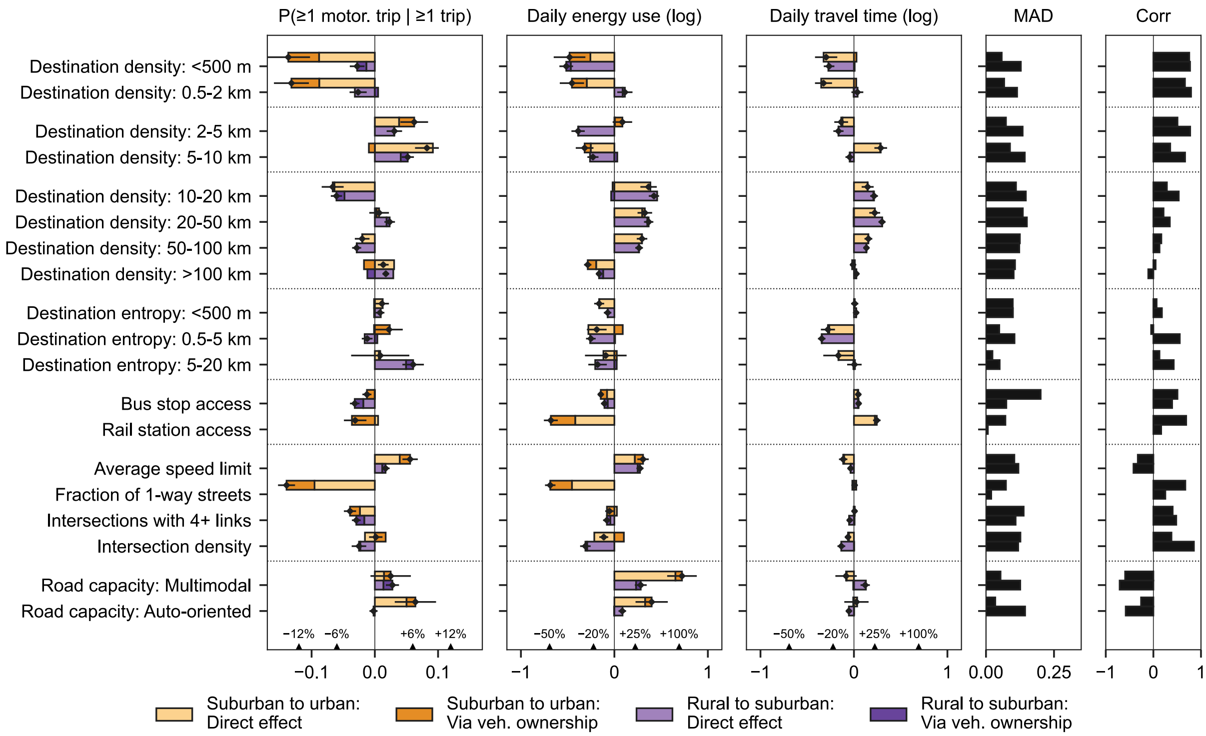

Fig. 6. As Fig. 5, but for two separate submodels: one for rural to suburban areas (up to 2000 p_{adj}/km^2), and one for suburban to urban areas (above 500 p_{adj}/km^2). The bracket from 500 to 2000 p_{adj}/km^2 is overlapping. In addition, column 'MAD' indicates the mean average deviation of each aspect and column 'Corr' indicates the correlation coefficient between each aspect and density (natural logarithm). For a version of this figure where each coefficient has been weighted by the corresponding MAD, showing the average instead the maximum effect size, see Figure S7.

Discussion

Our results suggest that higher density does indeed lead to substantially less travel energy use, in a large part due to increased access to nearby destinations less than 10 km away, and in particular destinations less than 2 km away. Part of the benefit of denser areas, however, is offset by the fact that most dense areas are located in large metropolitan areas. Combining these observations, our work suggests that promoting many urban centers no more than about 2–4 km apart from each other, to build 'cities within a city', may mitigate the demand-increasing effect of large cities while maximizing the demand-decreasing effect of local access.

While density is a good overall predictor of travel demand, properties of the local street network contribute as well. And while density and access to nearby destinations are correlated, they are not identical: an area with a given density can still have better or worse overall access to a variety of destinations closeby. For a given population density, lowest private vehicle travel energy use is therefore found in areas with strong local access, a highly connected street network, and low road capacity per capita (Fig. 7). These examples also illustrate that there are measures that can be taken to reduce travel energy use without having to increase density, accommodating people who prefer to live in lower-density areas.

Efforts to reduce travel energy use should not come at a cost of reduced access to opportunities for the population. Lowering road capacity for cars, for example, should be complemented by increasing walking access to nearby and public transit and cycling access to destinations further away (conversely, any increases to road capacity should be complemented by policies aimed at discouraging new, long-distance trips). Critically, our work indicates that providing access to a variety of destinations for all communities throughout a city is symbiotic with lowering energy consumption if all key measures are implemented simultaneously.

While in line with existing literature overall, our results indicate a stronger relationship between urban form and travel demand than some existing work [4] and appear to contradict certain previous findings that the impact of the built environment on travel is strongly confounded by demographic characteristics and attitude (e.g. [20,40]). While we observe that demographic factors indeed explain a large fraction of the variance in daily travel demand, they are weakly correlated with specific characteristics of urban form (see Figures S10 and S11). This means that the only attitudes that could cause the observed relationship between the built environment and travel demand are those that are entirely uncorrelated with any demographic control variable used in this study.

Instead, we postulate that there are two major drivers that distinguish our findings and those previous observations. First, we consider the most rural all the way to the densest urban areas, while incorporating detailed information on urban form for each location. Studies that attribute a strong confounding effect to attitude have predominantly compared individual, nearby neighborhoods (e.g. [18,40]). This design makes it more likely that differences in travel behavior are attributed to attitude, especially when those neighborhoods are relatively similar in terms of urban form, but distinct in terms of demographic characteristics. Second, attitudes themselves may be affected by the built environment over time (e.g. [18,20,38,39])—in fact, attitudes may exemplify a key mechanism through which urban form can affect travel demand: by modifying the perceived attractiveness of certain modes and destinations compared to other options.

Our work also reaffirms that the daily travel time budget is relatively constant across very different urban environments [41,42], although we observe an even higher regularity for the average number of trips made per day. As such, our findings add to current literature on the underlying regularity of human travel patterns (e.g. [43]). These observations are closely related to induced demand: if the time spent traveling per day is constant for a given individual, then an increase in travel speed will lead to higher daily travel distance and energy use through longer trips and/or modal shifts. This indicates that the urban environment can influence how people travel and where, but not how

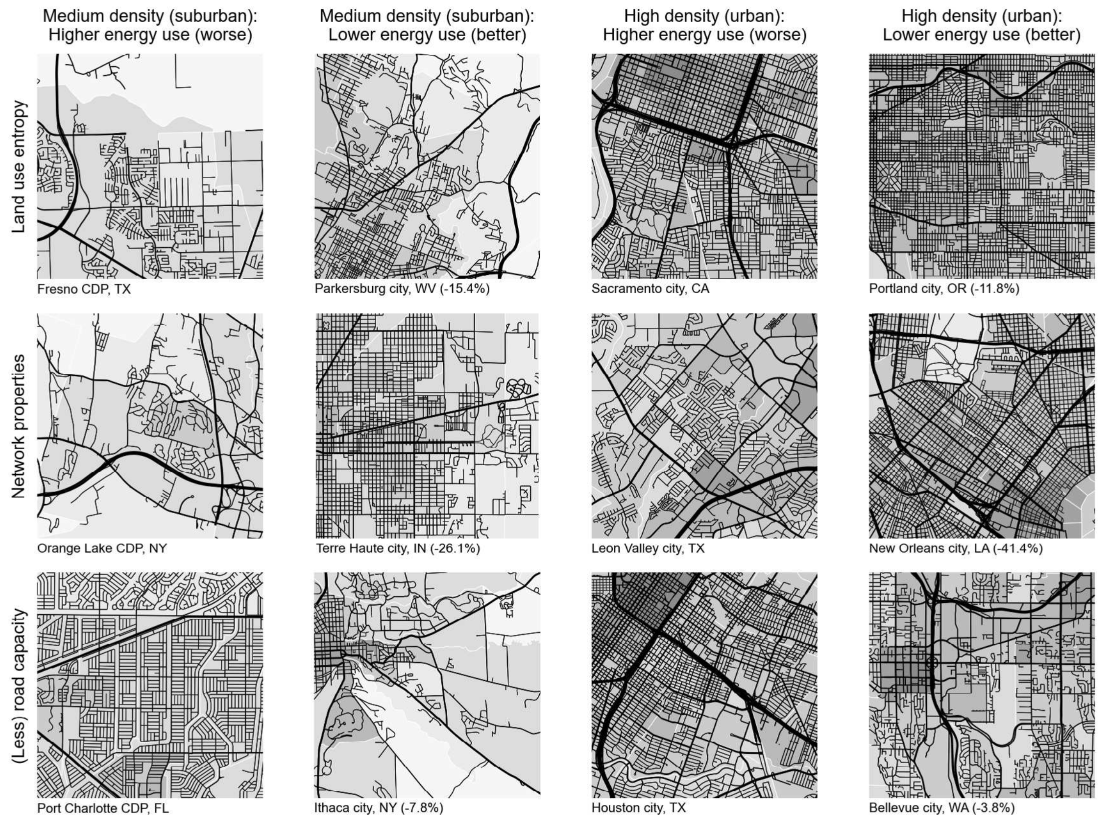

Fig. 7. Examples of areas with higher and lower predicted energy use while controlling for density and access to nearby destinations, for medium density (left two columns) and high density (right two columns). The percentages indicate the estimated difference in per-capita mobility energy use compared to the corresponding urban area to the left due to differences in the category of the corresponding row. This illustrates that population density is a reasonable but not definitive predictor of travel energy use, and that there are measures that can be taken to reduce travel energy use without having to increase density. Each map shows an area of 3 × 3 km. Public transit access, which also was found to have an impact on travel energy demand (see Figs. 4 and 5), is not shown. Plotted using network data from OpenStreetMap (accessed through OSMnx [23]).

often and for how long. Therefore, the former should be the focus of future policy and planning decisions aimed at decarbonization. Similarly, since travel patterns are largely derived from the built environment, we should plan for the patterns we want there to be, not for those that we project based on historical data.

A limitation of our study is the resolution and accuracy of certain measures of urban form. Since all data is collected at the census block group level, we are not able to investigate micro-scale effects of urban form on travel behavior. In addition, while we do identify an impact of land use entropy on travel demand, our measure of entropy is relatively coarse (see Methods). Finally, for street network properties, certain data had to be imputed, possibly mitigating the resulting effect size. Improvements in these measures would be unlikely to alter any of our key conclusions, but could improve our understanding of the relative importance of specific aspects of urban form in different contexts, especially for walking trips.

Future work could therefore improve how urban form is measured and find ways to integrate information on urban form measured at the origins and destinations of each trip, rather than just around the location of each traveler's household, and information on travel speed and congestion, without introducing simultaneity or other forms of endogeneity. Another key avenue for future work will be to achieve an increase in the spatial resolution of the analysis. Analyses based on travel survey data, such as ours, could be combined with crowd-sourced mobility pattern data to verify and further investigate the observations made here [44]. This increase in spatial resolution could be accompanied by additional measures of urban form. Image processing of satellite and street view images may assist in these measures, similarly to recent efforts for building energy modeling [45]. More sophisticated methods could also be used to include the impacts of climate, including urban microclimates, on travel.

Conclusion

Our work provides evidence for a strong causal link between properties of urban form and daily travel demand and energy use. Distributed urban centers that provide local access to a variety of destinations to a large part of the population, connected streets with low capacity for motorized vehicles, and public transit infrastructure should be prioritized in order to lower the energy consumption of travel. Notably, many of these measures can be implemented without requiring a substantially increase in density throughout existing built environments. This outlines a pathway for cities and communities to reduce the energy demand and traffic of personal mobility while maximizing access to destinations for all communities.

CRediT authorship contribution statement

Marco Miotti: Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Validation, Visualization, Writing – original draft, Funding acquisition. **Zachary A. Needell:** Conceptualization, Methodology, Writing – review & editing. **Rishee K. Jain:** Writing – review & editing, Funding acquisition, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Marco Miotti reports financial support was provided by Swiss National Science Foundation. Marco Miotti reports financial support was provided by Stanford University TomKat Center for Sustainable Energy. Marco Miotti reports financial support was provided by Stanford University Center for Integrated Facility Engineering.

Data availability

Key data has been made available on DataDryad and can be accessed at https://doi.org/10.5061/dryad.bvq83bkd4.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.apenergy.2023.120883. Method details (section 1), Supplementary Figures and Results S1–S11 (Section 2), and Supplementary Tables S1-S8 (section 3).

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