

# Trees in many US cities may indirectly cool climate cities may increase atmospheric carbon by altering building energy use

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## 3 **Abstract**

4 Urban trees are a critical part of the "green infrastructure" intended to make our growing  
5 cities more sustainable in an era of climate change. The potential for urban trees to modify  
6 microclimates and thereby reduce building energy use and the associated carbon emissions is  
7 a commonly cited ecosystem service used to justify million tree planting campaigns across the  
8 countryUS. However, what we know of this ecosystem service comes primarily from unvalidated  
9 simulation studies.

10 Using the first dataset of actual heating and cooling energy use combined with tree cover  
11 data, we show that that contrary to the predictions of the most commonly used simulations,  
12 trees in a cool climate city increase carbon emissions from residential building energy use.  
13 This is driven primarily by near east ( $< 20\text{m}$  from building) tree cover. Further analysis  
14 of urban areas in the US shows that this is likely the case in cool climates throughout the  
15 country, encompassing approximately 39% of the US population and 62% of its area (56%,

16 excluding Alaska). Our results add This work adds geographic nuance to quantification of the effect of  
17 urban trees on our understanding of how urban shade trees affect the carbon budgetand , and it  
18 could have major implications for tree planting programs in cool climates.

## 19 Introduction

20 Two global trends of the 21st century, climate change and increasing urbanization, have  
21 deepened our need to make cities more sustainable, and urban trees are . Urban trees are often  
22 championed as a means to that end. Several large cities in the U.S. have recently committed  
23 to large tree planting programs (see Million Trees New York City and Million Trees Los  
24 Angeles). Spending hundreds of millions of dollars, these cities hope that the environmental  
25 benefits, particularly the reduction in building energy use and the associated carbon (C)  
26 emissions from power plants, will outweigh the cost (Young, 2011).

27 A single urban tree has a much stronger impact on the carbon cycle than a non-urban  
28 counterpart because an urban tree induces or reduces more C emitting human behaviors  
29 than a rural one does. Both trees sequester carbon C from the atmosphere, but the urban  
30 tree requires more management (planting, watering, pruning, removal, chipping) and, by  
31 modifying the microclimate, it can alter building energy use and the associated C emissions  
32 (ACE) from power plants.

33 Trees primarily alter micro climates microclimates by 1) shading, 2) reducing wind speed, and  
34 3) cooling via transpiration. With the exception of transpirative cooling, which is mostly  
35 active in summer, these effects can both increase or decrease ACE. Shading to the west of  
36 buildings greatly reduces summer cooling loads, but shading to the south of buildings, even  
37 by deciduous trees, may increase winter heating loads (Heisler, 1986). Reduced wind speeds  
38 have complex effects. They: 1) decrease convective heat loss, which is beneficial for winter  
39 heating but detrimental for summer cooling, 2) decrease air infiltration which decreases both  
40 heating and cooling energy use, and 3) decrease natural ventilation, increasing the need for  
41 mechanical cooling (Huang et al., 1990). The strength of the effect of a tree on ACE attenuates  
42 with distance to a building. Trees far from a house have little affect on ACE via shading and  
43 wind reduction, but they likely affect ACE via evapotranspiration and the associated reduction in  
44 temperature (Ziter et al., 2019).

45 Whether the net effect of trees is to increase or decrease ACE depends on the balance of

beneficial and detrimental effects on heating and cooling energy use. This is largely mediated by the location of tree cover, the prevailing climate (e.g. number of heating- and cooling-degree days), building characteristics , (orientation, insulation, size and surface area, etc.), occupant behavior and the carbon C content of a kWh, which varies across the country depending on the fuel mix in the electrical grid.

Our current understanding of how trees affect building energy use and ACE suggests that there are contexts in which trees may increase ACE. But despite this potentially detrimental effect of trees, it is often not mentioned in the literature. In an extensive review of the effect of the urban forest on CO<sub>2</sub> emissions, Weissert et al. (2014) did not consider that trees could increase ACE. In a paper critical of many ecosystem services provided by trees, Pataki et al. (2011) nevertheless state that trees reduce energy use and ACE. Our work here builds on past simulation studies and uses empirical energy use data from thousands of houses in a city to demonstrate that trees may actually increase ACE in cool climate cities.

## Previous research

Decades worth of research primarily by two research groups, the US Forest Service 's (USFS) Southwest Research Station Urban Ecosystems and Processes group and and the Lawrence Berkeley National Lab Heat Island Group (LBNL), have reported that, on average, trees reduce C emissions. In 2002, Akbari published a paper summarizing their group's findings: "Shade trees reduce building energy use and CO<sub>2</sub> emissions from power plants". In 1999, McPherson and Simpson wrote a technical report that was the basis of the iTree software, which has been used by thousands of communities around the U.S. to estimate ACE avoided. Their methodology was recently applied to estimate the effects of trees on ACE for the entire conterminous US (Nowak et al., 2017). Despite the number of publications on the topic, the length of time we have been researching the matter, and the many large cities with massive tree planting initiatives, our uncertainty about the effects of trees on building energy use is actually quite

high (Pataki et al., 2006; McPherson and Simpson, 1999). The effect of trees on nearby building energy use is difficult and expensive to measure directly and complex to model.

Direct measures of the effect of trees on building energy use are rare, focused on cooling energy use, and limited in their ability to be extrapolated. To our knowledge, there are the only 5 studies that test the effect of trees on measured building energy use data (Akbari et al., 1997; Donovan and Butry, 2009; DeWalle et al., 1983; Parker, 1983; McPherson et al., 1989). Only two of these studies were of actual houses (not mobile homes nor models) and both are from Sacramento, CA and did not measure heating energy use (Akbari et al., 1997; Donovan and Butry, 2009). Only one of the studies was from a cool, heating dominated climate (typical of much of the US) and it studied a single mobile home in a forest (DeWalle et al., 1983).

Given the challenges inherent in collecting direct measurements, simulation studies are useful attempts to extend our understanding of how trees affect building energy use and ACE. But these simulations necessarily contain simplifications and generalizations which are sometimes unrealistic or untestable due to lack of data.

The work from LBNL assumes: millions more trees are planted in an urban area (extremely ambitious); trees are planted to the west and south of buildings (ideal placement for reducing cooling loads); and winter tree canopy transmissivity is 0.9 (0.7 is more realistic, Heisler, 1986). In later work, microclimate wind effects are ignored (Akbari and Konopacki, 2005), and in earlier work, they use a three parameter equation fit to four data points to estimate how wind speed is reduced by canopy cover (Heisler, 1990; Huang et al., 1990). Finally, the LBNL work uses potential evapotranspiration to predict cooling, and their model uses parameters derived from crops. Given these assumptions, the authors note that their work provides an upper boundary for the indirect effect of trees (Akbari and Konopacki, 2005; Huang et al., 1987).

USFS studies assume: lookup tables for the effect of tree shade on building energy use are reliable (even though they may deviate from more detailed simulations by up to 10%,

98 Simpson, 2002); wind reduction only affects heating use in the winter, even though we know  
99 cooling use is also affected, ; and they also use an overfit summertime leaf-on equation from  
100 Heisler (1990). Evergreen trees are modeled as if they are windbreaks for rural farmhouses  
101 in winter, even in suburban neighborhoods where other buildings and trees already block  
102 significant winds; and estimated evapotranspirative cooling is optimistically high, higher  
103 even than the self declared upper limit of Huang et al. (1987) (McPherson and Simpson,  
104 1999).

105 The consequence of these assumptions is that simulations may overestimate the energy  
106 reducing power of trees. What little validation we have has confirmed the general effects  
107 of trees on energy use that we expect in hot climates, but also highlight the imprecision  
108 of simulations as well as occasional discrepancies from empirical observations. Simulations  
109 of Akbari et al. (1997) were off by 2-fold, though trees were about twice as beneficial as  
110 predicted for the two houses studied. Donovan and Butry (2009) found trees to the north  
111 actually increasing electricity use, unlike the predictions of McPherson and Simpson (1999).

112 Despite providing estimates for the effects of trees on building energy use and ACE for  
113 anywhere in the country (Akbari and Konopacki, 2005) and the entire country (Nowak et al.,  
114 2017), we still have no empirical validation of the effect of urban trees in a cool climate. More  
115 than 3 out of every 4 people in the U.S. live in places with more heating degree days than  
116 cooling degree days, and Americans use much more energy for heating than for cooling (U.S.  
117 Department of Energy, 2009). To properly assess simulations of the role of urban trees in the  
118 C budget, comprehensive analyses are needed to test the relationship between tree location  
119 and energy usage (both heating and cooling). Our work in Madison, WI was the first to [begin](#)  
120 [address this need. In 2016, we downloaded average annual energy use data for approximately](#)  
121 [32 thousand single family residential homes and built a regression model between the amount of](#)  
122 [tree cover near each house and the C produced from electricity and natural gas use, controlling](#)  
123 [for other factors such as building characteristics.](#)



Figure 1: Simulated shadows of trees on a house at the latitude of Madison, WI. In the summer, trees to the west of buildings provide the most effective shade since solar angles are lower and cooling demand highest in the afternoon. In winter, even deciduous trees can significantly reduce solar gain.

124 **Results**

125 **Effect of trees on building associated C emissions**

126 Trees increased C emissions associated with residential building energy use (**ACE**) in Madi-  
127 son, WI. This effect was the result of a trade-off between their electricity (cooling) saving  
128 and gas (heating) penalty. We estimated that 100m<sup>2</sup> of tree cover within 20m of a house  
129 increased ACE from gas use by 0.77% (95% CI: 0.68%, 0.85%), and decreased ACE from  
130 electricity use by 0.21% (95% CI: 0.34%, 0.080%). Our model for net ACE estimated that  
131 100m<sup>2</sup> of tree cover increased ACE by 0.17% (95% CI: .09%, .27%).

132 The magnitude and direction of the effect depended on tree location relative to the  
133 building. Figure 2 shows the percent change in the ACE from 100m<sup>2</sup> of tree cover. Trees  
134 reduced ACE from electricity for all near regions except the east. Trees increased ACE from  
135 gas for all regions, especially in the near south and east. For net ACE, tree cover in the near  
136 east was the most important, having the only estimate with a 95% CI that excluded 0.

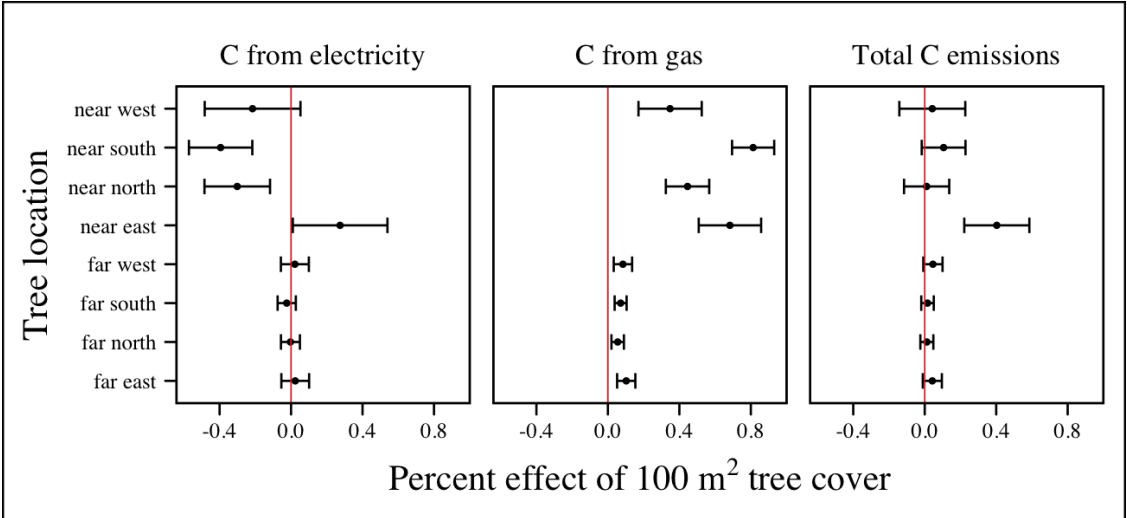


Figure 2: The percent effect of 100m<sup>2</sup> tree cover in different locations on C emissions from residential building energy use. n = 25095, bars indicate standard errors.



## 137 Effect of existing tree cover on a typical house

138 The median house in our sample was responsible for 1084 and 954 kg C annual emissions  
 139 due to electricity use and gas use, respectively. Multiplying the median tree cover in each  
 140 region (see table 1) by its coefficient we estimated the effects of typical tree cover on a typical  
 141 house in Madison: electricity C emissions were reduced by 33.8 kg C / yr (95% CI: 14.7,  
 142 52.7), but gas C emissions were increased by 102.3 kg C / year (95% CI: 92.9, 111.8). Our  
 143 combined model estimated the net effect of existing tree cover is to increase C emissions by  
 144 about 62 kg C/year (95% CI: 38.7, 85.3) for a typical house. This is 2.5% of the median  
 145 house's annual ACE.

Table 1: Summary statistics for amount of tree cover ( $\text{m}^2$ ) in each region around houses in Madison, WI.

Region	min	mean	median	max
near west	0	193	179	742
near south	0	372	363	1443
near north	0	357	345	1197
near east	0	193	179	764
far west	0	974	960	2640
far south	0	1676	1653	4376
far north	0	1673	1661	4602
far east	0	967	955	2677

146 While tree cover in far regions had smaller per unit area effects than in near regions,  
 147 there was more tree cover in farther regions, so when median tree cover was multiplied by  
 148 the smaller coefficients some of the farther regions had larger typical effects than near ones  
 149 (figure 3). Typical tree cover in the far east and far west regions had a greater estimated  
 150 effect than cover in the near north and near west.

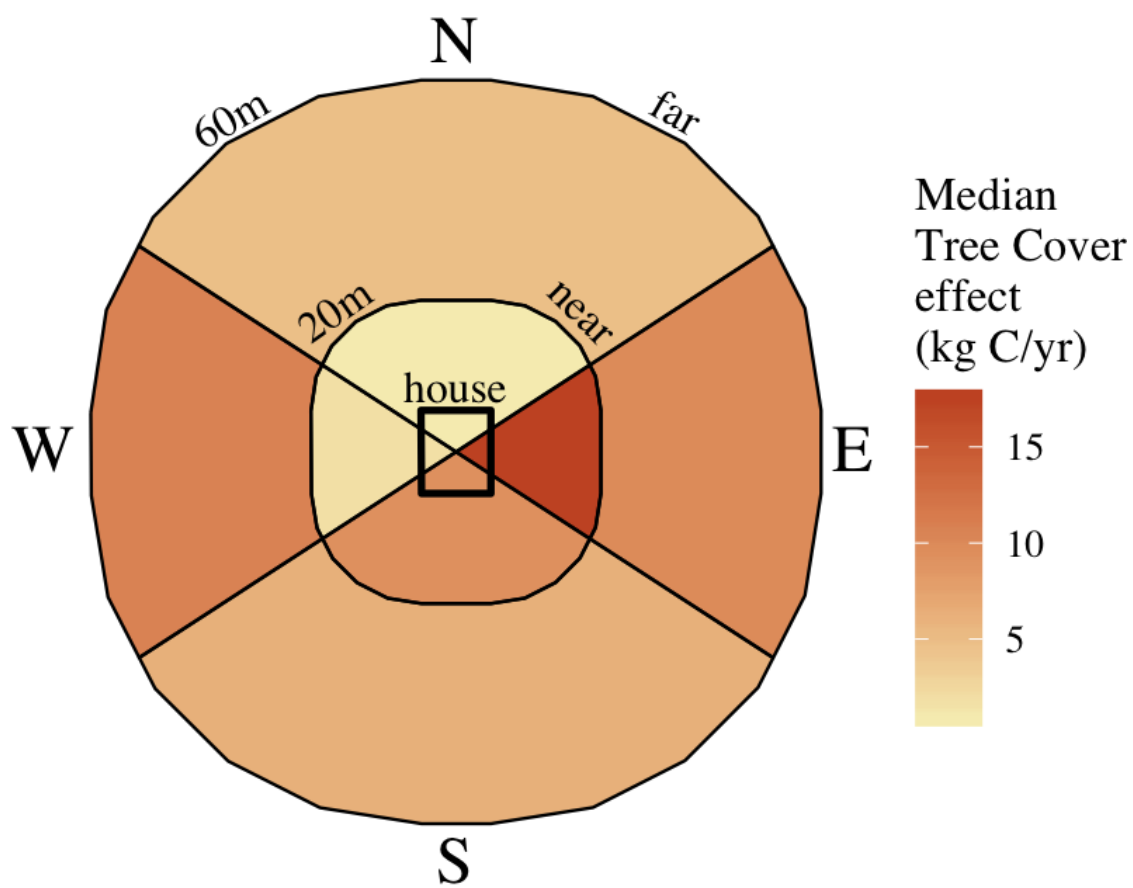


Figure 3: Effect of typical tree cover on a typical building's C emissions.

Comparing C emissions from energy use due to trees to C stored and sequestered.

For comparison, consider a green ash tree with a crown area of 100m<sup>2</sup>. This tree would store approximately 1360 kg C in above ground biomass and it could sequester around 34 kg C / year. That same tree in the near east region of a typical house in Madison was estimated to increase C emissions by 9.8 kg C/yr (95% CI: 6.7, 12.9). In the near west the estimated effect was 1.0 kg C/yr (95% CI: -2.1, 4.1). The the transfer of carbon from atmosphere to the biosphere is an order of magnitude larger than the transfer from the lithosphere to atmosphere.

## Discussion

### Interpreting Tree Effects

The effect of trees on ACE had strong statistical significanceIn the cool climate city of Madison with 7283 heating degree days, 597 cooling degree days and a electricity emission factor of 0.206 kg C / kwh, the relationship of trees with ACE was clear: trees increased ACE from gas use more than they decreased ACE from electricity use, resulting in a net increase in ACE. This result

According to past studies, if shade were the only effect on ACE (winter wind speed reduction was not included) trees in cool climate cities would cause an increase in ACE. Since we found an increase in ACE with increased tree cover this suggests that shading was the most important process and that whatever gas savings trees may have provided in winter by reducing wind speeds was swamped by the penalty in of reduced solar radiation.

By separating tree cover into different locations, it appeared that for the most regions, the beneficial effects of trees on electricity ACE *mostly* canceled out the detrimental effects of trees on gas ACE, with the exception of the near east. This suggests that trees to the east may have been responsible for most of the net increase in ACE. Eastern trees did not provide electricity savings since houses require less cooling in the morning hours, but still

175 caused an increased gas use in winter. This agrees with Donovan and Butry (2009) who also  
176 found trees to the east had no effect on electricity use.

177 As expected, trees to the near south had a strong effect on electricity savings, but they  
178 also had a stronger gas penalty. Trees in the near west and near north had the weakest gas  
179 penalty, which may have been due to the savings they provided by reducing wind speed.  
180 Somewhat surprising was the weakness of the estimated electricity savings of trees in the  
181 near west, which all simulations have predicted has the strongest effect. Also surprising was  
182 that trees to the north are associated with an increase in gas use, something no other study has  
183 predicted. Since tree cover is measured north of each building's centroid, it could be that there  
184 is still some shading from trees on the northern roof. It is also possible that there could be some  
185 transpirative cooling occurring during the early spring and late fall when trees have their leaves  
186 and it is still the heating season in Madison.

187 The inability to discern causation and identify clear mechanisms is one of the limitations of this  
188 observational study. While the overall association between tree cover and ACE is clear, uncertainty  
189 increases when distance and direction of tree cover are considered. Where our coefficients disagree  
190 with past studies, they should be considered cautiously.

## 191 Comparing to past work

192 Our findings agreed with some though not all of the past simulation studies, and the modeling  
193 of wind is the main cause of discrepancies. Thayer Jr and Maeda (1985) modeled the shading  
194 effects of south trees on building energy use and reported that trees increased emissions in  
195 cities with more heating degree days than cooling degree days. McPherson et al. (1988)  
196 investigated the shading and wind effects on building energy use in 4 cities, one of which  
197 was Madison, WI. Converting their results into C, trees in Madison caused a small increase  
198 in emissions, though their method for modeling wind was later criticized and abandoned  
199 (Simpson and McPherson, 1998). Akbari and Konopacki (2005) developed a method to  
200 predict the effect of a tree planting program and increasing roof albedo for any city in

the U.S. Figure 4 illustrates an application of their method to every census tract in the conterminous US for pre-1980s houses using updated energy emission factors. They identify places where trees increase ACE and others where trees decrease ACE, however they are most often cited for the average effect found: "Shade trees reduce building energy use and CO<sub>2</sub> emissions from power plants", the title of from Akbari's 2002 paper. Clearly climate largely drives the relationship between ACE and trees at large scales, but there is significant regional variation due to differences in electricity C emission factors. Trees are more beneficial in places with "dirtier" (more C per kWh) electricity and less beneficial in places with "cleaner" (less C per kWh) electricity. For example, despite its cool climate, trees in Chicago reduce ACE because the electricity has more C per kWh and therefore the electricity reduction benefit of trees leads to a greater reduction in C than in places with cleaner electricity.

About 40% of the US population live in areas where the Akbari and Konopacki (2005) model predicts that trees increase C emissions. While their methods were limited as mentioned above, and they modeled theoretical, not existing, tree cover, their work suggests that many large cities especially in New England, the Northwest, the Mountains and the Upper Midwest would need to carefully consider the C implications of large tree planting programs.

Our empirical findings disagree with those simulation studies that model the relationship between tree cover and wind speed following Heisler (1990) and McPherson and Simpson (1999). When the beneficial effects of wind are excluded for models of several cool climate cities: Toronto (Akbari and Taha, 1992), Chicago (Jo and McPherson, 2001), Minneapolis, Sacramento, and Washington (Huang et al., 1990), trees either have no effect or increase energy use and ACE, which agrees with our general findings. The iTree model which uses the methods of McPherson and Simpson (1999) predicts that the shading effects of a large deciduous tree in the Norther Northern Tier, North Central, Mountains, Pacific Northwest, and California Coast regions increases ACE of a 1950-1980 vintage house by 0.136 to 9.52 kg, depending on the region. This is comparable to our results. However, the wind effect in the iTree model of that same tree on the same house decreases heating ACE by 1.23 to 66.14

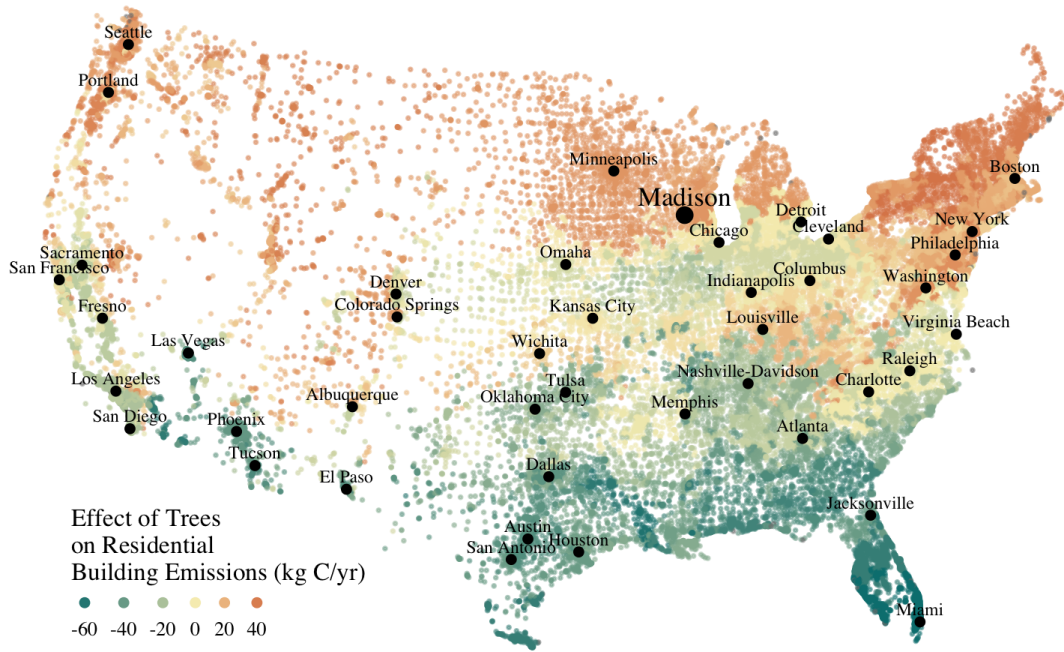


Figure 4: Each census tract in the conterminous US shaded by magnitude of building C emissions effect of trees planted to west and south of a pre-1980's home and increasing roof albedo. Differences in regional emission factors (C/kWh) cause deviations from climate trend. New England has especially high ACE for the climate because their electricity is cleaner (low C/kWh). About 40% of Americans live in places where trees increase ACE. Model based on Akbari and Konopacki (2005).

kg depending on the region and existing canopy: an order of magnitude greater savings for gas ACE from wind reduction than the penalty from shading. However, Given that our model coefficients derived from measured gas use suggest show that trees increases ACE, it suggests that shading is a more important process than wind shielding. speed reduction. In other words, our results agree with the shading but not wind reduction effects proposed by others, and therefore may suggest that shading is being more accurately modeled than wind in existing simulations. McPherson and Simpson (1999) note that the uncertainty in their methods was high, and, given our contradictory findings, it is clear that more data and improved models are needed to better parameterize the complex and uncertain relationship between tree cover, wind, and building energy use.

## 238 Considering the larger C cycle

The effect on ACE of a tree with a 100 m<sup>2</sup> canopy area is an order of magnitude smaller than that tree's C sequestration. However, it is important to make the distinction between different pools of C. Discounting increased ACE as irrelevant because C sequestration more than compensates, fails to recognize that ACE is an input of fossilized C while sequestration is a temporary transfer of C from the atmosphere to biosphere. Unless In the short term, sequestration may assist in climate change mitigation, but unless forested land is permanently expanded or wood products are forever prevented from decay, in the long run (hundreds of years) sequestration by trees can never offset fossil C emissions. Indeed this same conclusion was made for fossilized C emissions due to tree management (Nowak et al., 2002). The avoided ACE from trees had has been estimated to more than offset these management emissions in a life-cycle analysis of the Million Trees Los Angeles program (McPherson and Kendall, 2014). However, our results suggest that for cool climate communities in much of the US, shade trees actually increase ACE and, especially when combined with the C emissions from management, are atmospheric C sources in the long term.

## 253 **Trees relative to other factors that affect ACE and the ACE effect** 254 **of trees relative to other ecosystem services/disservices.**

255 Considering all of the factors that determine building energy use and ACE, trees play a very  
256 minor role, which we estimated to be about 2.5% of the ACE of a median house. [As buildings](#)  
257 [become better built and insulated the effect of trees on ACE will decrease.](#) Far greater ACE  
258 savings are possible with improved construction and savvy occupant behavior. However, the  
259 effect of trees on energy use and ACE is one of the most often cited ecosystem services of  
260 trees (Roy et al., 2012), and evidence that ACE is increased by trees highlights the large  
261 uncertainty in software used by thousands of communities to justify urban forest costs.

262 Still, effects on ACE are just one of the ecosystem effects that trees have in cities. Trees  
263 may also improve air quality, reduce stormwater runoff, reduce noise, and provide wildlife  
264 habitat. The aesthetic value of trees is often far greater than the value of the ecosystem  
265 services or disservices provided (McPherson et al., 2005). Even after publishing that trees  
266 reduced ACE on average, Akbari (2002) noted that this benefit alone may not justify the  
267 cost of tree planting. Our opposing results have a similar caveat: even after finding the  
268 detrimental impacts of trees on ACE in cool climates, management decisions need to consider  
269 these results as just one of the many benefits and costs of trees. Our results suggest that  
270 trees planted on all but the near east side of a house are net neutral in terms of ACE, so  
271 that the other benefits of tree planting, such as aesthetics, could be accomplished in cool  
272 climates through careful selection of planting locations.

## 273 **Future work**

274 Using actual energy use data from over 25,000 houses, we provide a much needed complement  
275 to simulation models of tree effects on ACE in cool climates. However, there is need for  
276 continuing work to address remaining shortcomings. The observational nature of our data is  
277 strengthened by the size of the dataset, but ultimately causal inference depends on our physical



278 knowledge of how trees alter building energy use. More experimental studies are needed especially in cool  
279 climate cities to better understand that relationship. Not all coefficients in our model agree with our existing  
280 physical understanding of how trees affect building energy use. For example, it is surprising  
281 that trees to the near west have such a weak effect on electricity use . and that trees to the  
282 north increase gas use. While the overall association between greater tree cover and greater ACE  
283 in Madison is clear from our work, how that relationship changes with distance and direction is  
284 less clear. Our work is an important complement to simulation studies and highlights the need  
285 for more experimental studies especially in cool climate cities.

286 Our data on tree cover was also limited by a lack of information about tree height, which  
287 means we could not address how adjusting the size of trees planted in an urban area affects  
288 ACE. Incorporating lidar could provide more accurate estimates of tree shading and wind  
289 reduction. Furthermore, the scale of the effects that our study could detect is much smaller  
290 than the city-wide effects many simulation studies address. Ultimately, this work is a sample  
291 of one year from one city with the accompanying limitations. The warm December during  
292 the sampling period may mean the effect of trees is even more detrimental than we report,  
293 but more years are needed to say. The location of Madison near the boundary that Akbari  
294 and Konopacki (2005) identified between trees being a sink and a source is useful, but more  
295 cities are needed to empiracally empirically determine this boundary.

296 Our work reveals a blind spot in urban forest ecosystem studies. In an extensive review of the effect  
297 of the urban forest on CO<sub>2</sub> emissions, Weissert et al. (2014) did not consider that trees could increase ACE. In a paper critical of  
298 many ecosystem services provided by trees, Pataki et al. (2011) nevertheless state that trees reduce energy use and ACE Many  
299 studies only report that trees reduce ACE (Pataki et al., 2011; Weissert et al., 2014). While this  
300 may be true in most of the US, and the potential ACE reduction is larger than the potential  
301 ACE increase, it ignores geographical nuance geographic variation (Akbari and Konopacki, 2005).  
302 In many ways it is not surprising, given the climatic diversity across the country, that the  
303 effects of trees on ACE might also vary and that our prescriptions for how to plant trees  
304 to minimize ACE could be different between Los Angeles and New York City. However our

305 Our study is only the first study to use a large number of both gas and electric energy use  
306 observations, and the first study of its kind in a cool climate. Much more work with observed  
307 energy use is needed to identify the border between atmospheric C sink and source where trees switch from  
308 increasing to decreasing ACE.

## 309 Conclusion

310 Using observed energy use data, we have shown that trees near residential houses in Madison,  
311 WI increase are associated with increased energy use and associated C emissions and near ACE. Near east  
312 tree cover has appears to have the strongest net effect relationship. Extending past simulation  
313 studies, we show that this is likely the case for a large area of the US and cool climate regions  
314 generally. The magnitude and direction of the effect association is dependent on tree location  
315 relative to buildings, climate, building characteristics, occupant behavior, and the C content  
316 of electricity. Disagreements between our results and past work is may be due to how wind  
317 effects are modeled and much more work is needed to better understand this process. While  
318 we do not invalidate past simulation studies of how trees affect building energy use and ACE, our  
319 empirical results raise questions about simulation assumptions and highlight the need for more  
320 research. We add critical geographic nuance to research that could have major implications  
321 for tree planting programs in cool climates.

## 322 Methods

### 323 Building Energy Use

324 In April 2016, we obtained the annual energy use summary table (April 2015 - April 2016)  
325 from Madison Gas and Electric's publicly available website for approximately 32 thousand  
326 single family residential houses in Madison, WI. This included average monthly gas and  
327 electricity use. This period exhibited a much warmer than average December (about 6° C)

and had low snowfall. We removed from our sample outliers that used fewer than 120 therms (which is less than the 0.5% quantile) or fewer than 240 kWh (which is less than the 0.05% quantile) annually. We included only buildings that used natural gas for heating and had central air conditioning. Our final sample size used to build models was 25095.

## **Carbon Emissions**

We converted energy use to C emissions using emission factors published by the US EPA's Emissions & Generation Resource Integrated Database, eGRID (Emissions & Generation Resource Integrated Database, 2016). 100% of the carbon in natural gas is oxidized to CO<sub>2</sub> when burned for heating. The carbon coefficient for natural gas is 1.446 kg C / therm (United State Environmental Protection Agency, 2017). For electricity, Madison, WI is a part of the Midwest Reliability Organization East (MROE) region of the North American electric grid. The estimated carbon coefficient for power generated in this region is 0.2063698 kg C/kWh (Emissions & Generation Resource Integrated Database, 2016). We had originally used emission factor for MROE from 2012 (.1567988 kg C / kWh) and by switching to the updated and higher 2016 emission factor (0.2063698 kg C/kWh), the overall detrimental effects of trees on ACE was diminished from about 3.4% to 2.5%.

## **Building Characteristics**

Energy use is strongly determined by building characteristics. For every address in the city, the City of Madison releases the assessor's property information, which includes information on building age, size, materials, type of heating and cooling, as well as which schools serve the address. We removed any houses that had bad or missing data. Many of the covariates, such as size and price, were strongly correlated. Given that our primary interest was how tree cover affected building energy use, not how building characteristics affect building energy use, we reduced the dimensionality of building characteristics using principal components analysis. This reduced the number of building covariates from 20 (Lot area, length of water

frontage, year built, number of stories, number of bedrooms, number of bathrooms (full and half), number of fireplaces, living area on each floor, finished attic area, finished basement area, total basement area, crawl space area, year roof was replaced, number of stalls in each garage, land value, improvement value) to 5 orthogonal vectors, accounting for 55% of the variance.

## Tree Canopy

For tree cover we used a 1m resolution landcover map derived from 2013 National Agriculture Inventory Program (NAIP) visible and near-infrared digital aerial imagery (Erker et. al, in review). with an accuracy of 85% (Erker et al., 2018). Using building footprints from the Dane county, for each house for which we had energy use data, we divided the space around it into 8 regions defined by 2 buffers around the house of distance 20 m and 60m and 4 rays from the building's centroid. Tree cover closer than 20m was considered near, tree cover farther than 20m and closer than 60m was considered far. These buffers were subdivided into north, west, south, and east regions by rays of angles 57, 123, 237, 303 degrees from north. These angles are within 1 degree of the azimuth angle of sunrise and sunset at the two solstices. This defines the south region as the region that is exposed to direct sunlight year-round, and the north region as the region that is never exposed to direct sunlight (this relationship is approximate and complicated by individual building geometry). Within each of the eight regions we summed the area covered by trees, and then use the tree cover in each region as predictors in our models.

We tested buffers of different widths (every 3m from 3m to 60m), but found because of the observational nature of our data that we needed to aggregate regions to remove multicollinearity that caused unstable coefficient estimates. Using a distance of 18, 21, or 24 m instead of 20m to separate "near" from "far" cover only slightly changed coefficient estimates. By fitting a model with all tree cover close to a house aggregated into one variable and then a model with the tree cover separated into 8 variables defined by distance and direction

we tested the overall association of ACE with tree cover and then tested for specific associations by distance and direction.

## Building Cover

Nearby buildings likely also affect the energy use of a building. To test this hypothesis we calculated the area of buildings in each of the eight regions around every building and included these as covariates in our modeling. We used building footprints from Dane County which consists of structures the size of a single car garage or larger. The horizontal accuracy is +/- 6.6 feet for well-defined points, at a ninety percent confidence level.

## Modeling

We fit linear models where the response was log transformed annual ACE for gas use, for electricity use, or for gas and electricity combined (net). Because a separate model was built to explain net C emissions, coefficient estimates for the net model were not precisely the sum of the coefficients from the electricity and gas models. ACE was log transformed to meet assumptions of normality and diagnostic plots were assessed to check other model assumptions and potential sensitivity to influential observations. Variables Our first models aggregated all tree cover near buildings into one variable, and subsequent models separated tree cover based on direction and distance into eight variables. In addition to tree cover, variables in our model were: 5 principal components of building characteristics, building cover in each of the 8 regions, tree cover in each of the 8 regions and a random effect for elementary school which might capture neighborhood characteristics such as culture. We used AIC as a variable selection criterion and in our final models only used the first 5 building characteristics principal components and we dropped all the building cover covariates. Estimates for the coefficients of tree cover were not sensitive to the inclusion or removal of these covariates, but model fit improved. Although some tree cover covariates increased AIC, we kept all tree cover covariates in the model because we wanted estimates of their effects, however uncertain they

might be. We **fit models also fit models We fit models** using the R package lme4 (Bates et al., 2015).

## **Interpreting coefficients**

To improve interpretability of coefficients, we back transformed them to the original scale and expressed the multiplicative effects as a percentage (Gelman and Hill, 2007). We then multiplied this percent change by the median ACE (a better estimator of the central tendency because of the right skew in our data) to estimate the typical effect in absolute C terms. To get typical effects of tree cover, we multiplied median tree cover in each region by its coefficient estimate and back transformed to the original scale.

## **Estimating C storage and sequestration of a green ash with 100m<sup>2</sup> canopy**

To estimate C storage and sequestration by a single green ash tree with a canopy cover of 100m<sup>2</sup>, we used allometric equations to estimate that tree's diameter at breast height (DBH) and mass and then, assuming an annual DBH growth of 0.61 cm, predicted the change in mass to get C sequestration Nowak and Crane (2002); McPherson et al. (2016).

## **Extending Analyses from Published Literature**

To compare our work to past simulation studies we converted results that were in Therms or kWh to kg C. We did this for Thayer Jr and Maeda (1985), McPherson et al. (1988), and Huang et al. (1990) using updated emission factors corresponding to each study city's eGrid subregion (Emissions & Generation Resource Integrated Database, 2016). To extend Akbari and Konopacki (2005), we joined climate data (heating and cooling degree days) from the nearest NOAA weather station to census tract centroids U.S. Census Tract Centroids (2010); Arguez et al. (2012). **It was from this join of climate and census data that we determined that**

77% of the U.S. population lives in places with more heating than cooling degree days. Then for each census tract we predicted the effect of trees and increasing roof albedo on the energy use of a pre-1980's building with gas heating following their table that bins houses according to heating degree-days and using emission factors corresponding to the eGrid subregion containing the census tract centroid. Separating out the indirect effects of trees from the indirect effects of increasing roof albedo was not possible because these were not modeled separately. However, the general trend would be similar, but with a decreased electricity savings and a decreased heating penalty. Akbari and Konopacki (2005) found the effect of tree shade to be stronger than the indirect effects of increased roof albedo and transpirative cooling. We also used the join of climate and census tract data to estimate approximately 77% of the U.S. population lives in places with more heating than cooling degree-days.

## Code

All of the code and data for these analyses are present on Github (<https://github.com/TedwardErker/energy>). Code is provisional pending review.

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