

# Trees in many US cities may indirectly increase atmospheric carbon

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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 country. 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 geographic nuance to quantification of the effect of urban  
17 trees on the carbon budget and could have major implications for tree planting programs in  
18 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 championed as  
22 a means to that end. Several large cities in the U.S. have recently committed to large  
23 tree planting programs (see Million Trees New York City and Million Trees Los Angeles).  
24 Spending hundreds of millions of dollars, these cities hope that the environmental benefits,  
25 particularly the reduction in building energy use and the associated carbon (**C**) emissions  
26 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 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 by 1) shading, 2) reducing wind speed, and 3) cool-  
34 ing via transpiration. With the exception of transpirative cooling, which is mostly active  
35 in summer, these effects can both increase or decrease ACE. Shading to the west of build-  
36 ings greatly reduces summer cooling loads, but shading to the south of buildings, even by  
37 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 attenu-  
42 ates with distance to a building. Trees far from a house have little affect on ACE via shading  
43 and wind reduction, but they likely affect ACE via evapotranspiration and the associated  
44 reduction in temperature Ziter et al. (2019).

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

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

## 50 Previous research

51 Decades worth of research primarily by two research groups, the US Forest Service's (USFS)  
52 Southwest Research Station Urban Ecosystems and Processes group and the Lawrence Berke-  
53 ley National Lab Heat Island Group (LBNL), have reported that, on average, trees reduce  
54 C emissions. In 2002, Akbari published a paper summarizing their group's findings: "Shade  
55 trees reduce building energy use and CO<sub>2</sub> emissions from power plants". In 1999, McPherson  
56 and Simpson wrote a technical report that was the basis of the iTree software, which has  
57 been used by thousands of communities around the U.S. to estimate ACE avoided. Their  
58 methodology was recently applied to estimate the effects of trees on ACE for the entire  
59 conterminous US (Nowak et al., 2017). Despite the number of publications on the topic, the  
60 length of time we have been researching the matter, and the many large cities with massive  
61 tree planting initiatives, our uncertainty about the effects of trees on building energy use is  
62 actually quite high (Pataki et al., 2006; McPherson and Simpson, 1999). The effect of trees  
63 on nearby building energy use is difficult and expensive to measure directly and complex to  
64 model.

65 Direct measures of the effect of trees on building energy use are rare, focused on cooling  
66 energy use, and limited in their ability to be extrapolated. To our knowledge, there are the  
67 only 5 studies that test the effect of trees on measured building energy use data (Akbari  
68 et al., 1997; Donovan and Butry, 2009; DeWalle et al., 1983; Parker, 1983; McPherson et al.,  
69 1989). Only two of these studies were of actual houses (not mobile homes nor models) and  
70 both are from Sacramento, CA and did not measure heating energy use (Akbari et al., 1997;

71 Donovan and Butry, 2009). Only one of the studies was from a cool, heating dominated  
72 climate (typical of much of the US) and it studied a single mobile home in a forest (DeWalle  
73 et al., 1983).

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

78 The work from LBNL assumes: millions more trees are planted in an urban area (ex-  
79 tremely ambitious); trees are planted to the west and south of buildings (ideal placement for  
80 reducing cooling loads); and winter tree canopy transmissivity is 0.9 (0.7 is more realistic,  
81 Heisler, 1986). In later work, microclimate wind effects are ignored (Akbari and Konopacki,  
82 2005), and in earlier work, they use a three parameter equation fit to four data points to  
83 estimate how wind speed is reduced by canopy cover (Heisler, 1990; Huang et al., 1990). Fi-  
84 nally, the LBNL work uses potential evapotranspiration to predict cooling, and their model  
85 uses parameters derived from crops. Given these assumptions, the authors note that their  
86 work provides an upper boundary for the indirect effect of trees (Akbari and Konopacki,  
87 2005; Huang et al., 1987).

88 USFS studies assume: lookup tables for the effect of tree shade on building energy use  
89 are reliable (even though they may deviate from more detailed simulations by up to 10%,  
90 Simpson, 2002); wind reduction only affects heating use in the winter, even though we know  
91 cooling use is also affected, and they also use an overfit summertime leaf-on equation from  
92 Heisler (1990). Evergreen trees are modeled as if they are windbreaks for rural farmhouses  
93 in winter, even in suburban neighborhoods where other buildings and trees already block  
94 significant winds; and estimated evapotranspirative cooling is optimistically high, higher  
95 even than the self declared upper limit of Huang et al. (1987) (McPherson and Simpson,  
96 1999).

97 The consequence of these assumptions is that simulations may overestimate the energy

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

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

## Results

### Effect of trees on building associated C emissions

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



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.

123 100m<sup>2</sup> of tree cover increased ACE by 0.17% (95% CI: .09%, .27%).

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

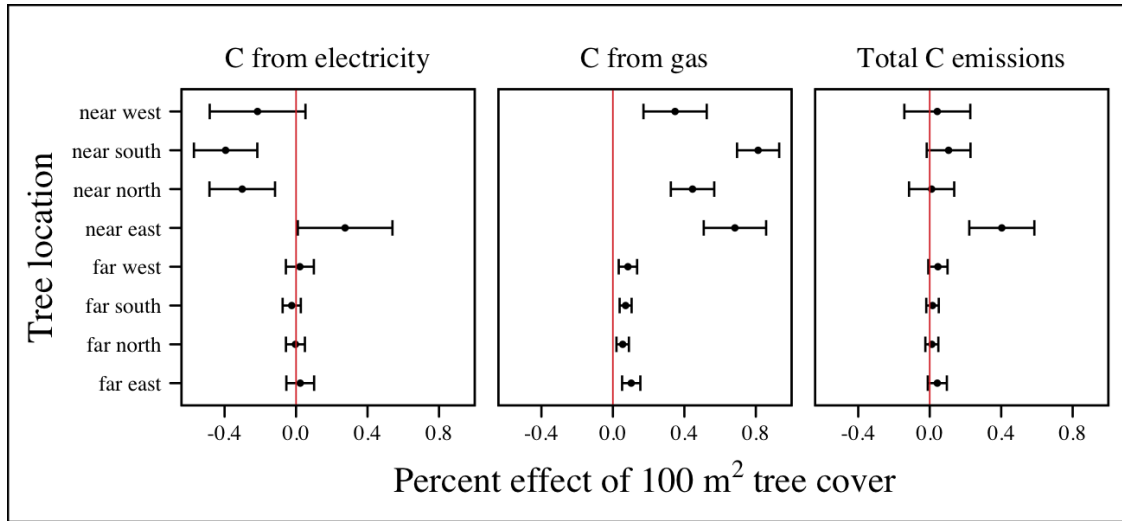


Figure 2: The percent effect of 100m<sup>2</sup> tree cover in different locations on C emissions from residential building energy use. n = 25095, bars indicate standard errors.

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

130 The median house in our sample was responsible for 1084 and 954 kg C annual emissions  
 131 due to electricity use and gas use, respectively. Multiplying the median tree cover in each  
 132 region (see table 1) by its coefficient we estimated the effects of typical tree cover on a typical  
 133 house in Madison: electricity C emissions were reduced by 33.8 kg C / yr (95% CI: 14.7,  
 134 52.7), but gas C emissions were increased by 102.3 kg C / year (95% CI: 92.9, 111.8). Our  
 135 combined model estimated the net effect of existing tree cover is to increase C emissions by  
 136 about 62 kg C/year (95% CI: 38.7, 85.3) for a typical house. This is 2.5% of the median  
 137 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

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

## 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  $100\text{m}^2$ . 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).

## Discussion

### Interpreting Tree Effects

In the cool climate city of Madison, with 7283 HDD and 597 CDD and a electricity emission factor of 0.206 kg C / kwh, the effect of trees on ACE was clear: trees increased ACE from

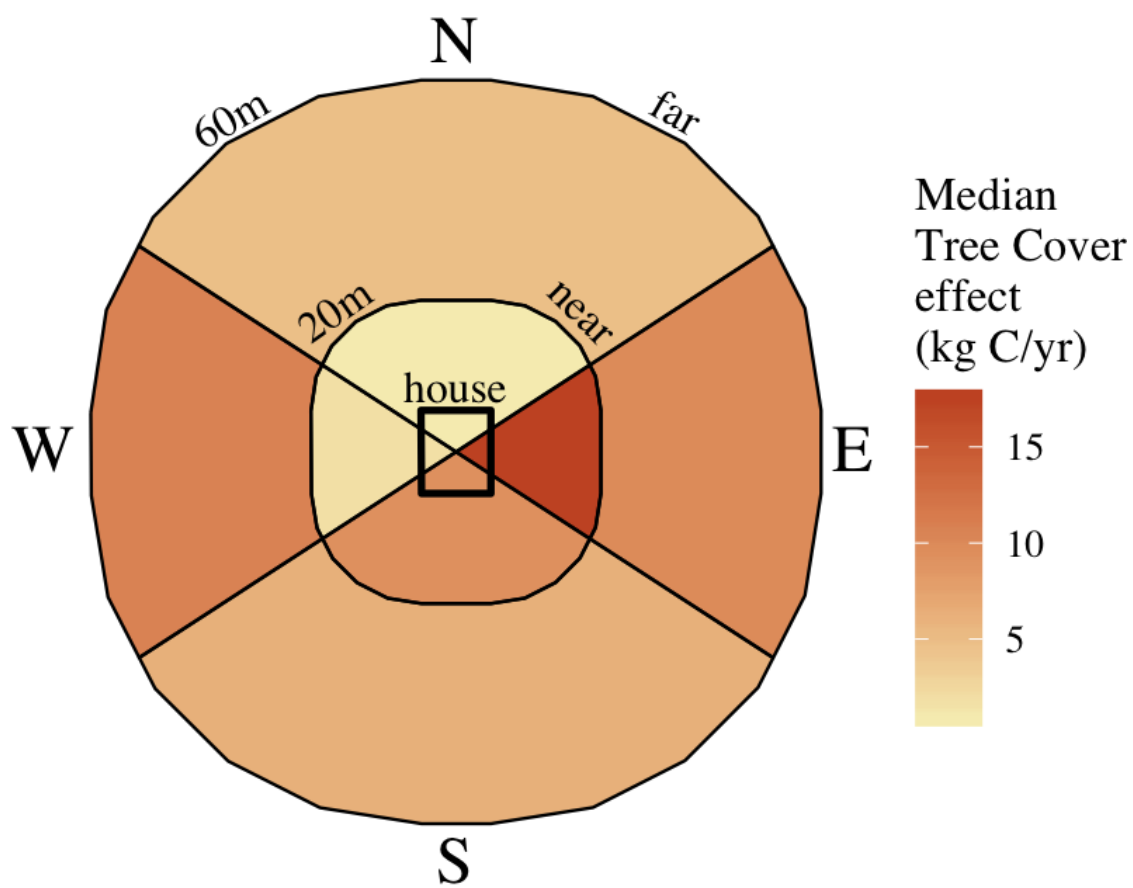


Figure 3: Effect of typical tree cover on a typical building's C emissions.

154 gas use more than they decreased ACE from electricity use, resulting in a net increase in  
155 ACE. This result suggests that shading was the most important process and that whatever  
156 gas savings trees may have provided in winter by reducing wind speeds was swamped by the  
157 penalty in reduced solar radiation.

158 By separating tree cover into different locations, it appeared that for the most regions,  
159 the beneficial effects of trees on electricity ACE *mostly* canceled out the detrimental effects  
160 of trees on gas ACE, with the exception of the near east. This suggests that trees to the  
161 east may have been responsible for most of the net increase in ACE. Eastern trees did not  
162 provide electricity savings since houses require less cooling in the morning hours, but still  
163 caused an increased gas use in winter. This agrees with Donovan and Butry (2009) who also  
164 found trees to the east had no effect on electricity use.

165 As expected, trees to the near south had a strong effect on electricity savings, but they  
166 also had a stronger gas penalty. Trees in the near west and near north had the weakest gas  
167 penalty, which may have been due to the savings they provided by reducing wind speed.  
168 Somewhat surprising was the weakness of the estimated electricity savings of trees in the  
169 near west, which all simulations have predicted has the strongest effect.

## 170 **Comparing to past work**

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

180 the U.S. Figure 4 illustrates an application of their method to every census tract in the  
 181 conterminous US for pre-1980s houses using updated energy emission factors. About 40%  
 182 of the US population live in areas where the Akbari and Konopacki (2005) model predicts  
 183 that trees increase C emissions. While their methods were limited as mentioned above, and  
 184 they modeled theoretical, not existing, tree cover, their work suggests that many large cities  
 185 especially in New England, the Northwest, the Mountains and the Upper Midwest would  
 186 need to carefully consider the C implications of large tree planting programs.

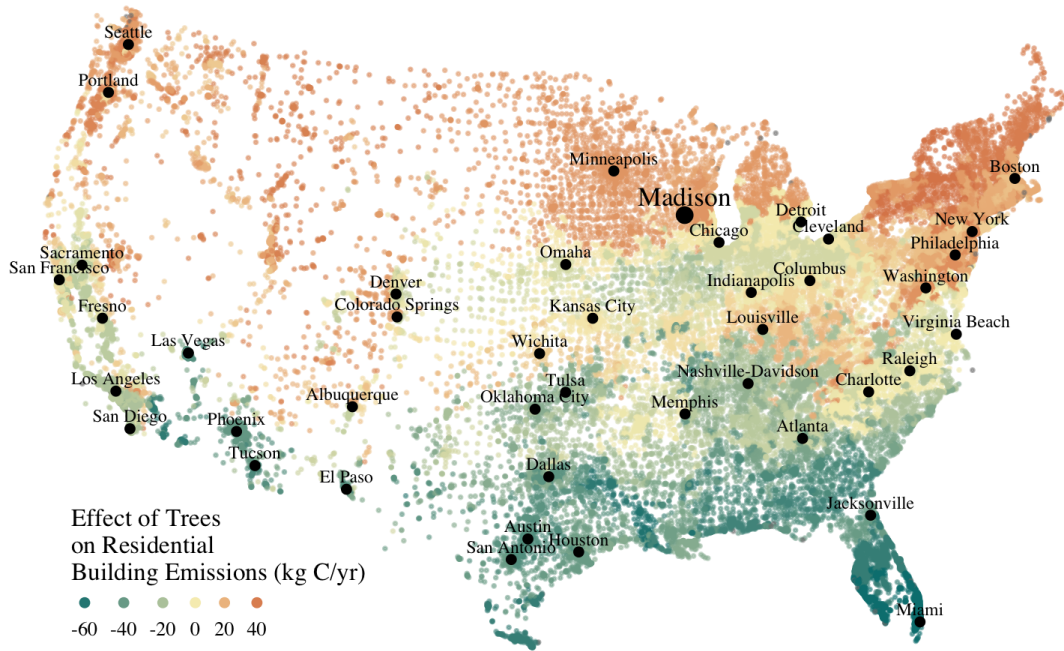


Figure 4: Each census tract in the conterminous US shaded by magnitude of building C emissions effect of trees planted to west and south of a pre-1980's home and increasing roof albedo. Differences in regional emission factors (C/kWh) cause deviations from climate trend. New England has especially high 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).

187 Our empirical findings disagree with those simulation studies that model the relationship  
 188 between tree cover and wind speed following Heisler (1990) and McPherson and Simpson  
 189 (1999). When the beneficial effects of wind are excluded for models of several cool climate

190 cities: Toronto (Akbari and Taha, 1992), Chicago (Jo and McPherson, 2001), Minneapolis,  
 191 Sacramento, and Washington (Huang et al., 1990), trees either have no effect or increase  
 192 energy use and ACE, which agrees with our general findings. The iTree model of McPherson  
 193 and Simpson (1999) predicts that the shading effects of a large deciduous tree in the Norther  
 194 Tier, North Central, Mountains, Pacific Northwest, and California Coast regions increases  
 195 ACE of a 1950-1980 vintage house by 0.136 to 9.52 kg, depending on the region. This is  
 196 comparable to our results. However, the wind effect in the iTree model of that same tree  
 197 on the same house decreases heating ACE by 1.23 to 66.14 kg depending on the region and  
 198 existing canopy: an order of magnitude greater savings for gas ACE from wind reduction than  
 199 the penalty from shading. However, our model coefficients derived from measured gas use  
 200 suggest shading is a more important process than wind shielding. McPherson and Simpson  
 201 (1999) note that the uncertainty in their methods was high, and, given our contradictory  
 202 findings, it is clear that more data and improved models are needed to better parameterize  
 203 the complex and uncertain relationship between tree cover, wind, and building energy use.

## 204 **Considering the larger C cycle**

205 The effect on ACE of a tree with a 100 m<sup>2</sup> canopy area is an order of magnitude smaller  
 206 than that tree’s C sequestration. However, it is important to make the distinction between  
 207 different pools of C. Discounting increased ACE as irrelevant because C sequestration more  
 208 than compensates, fails to recognize that ACE is an input of fossilized C while sequestra-  
 209 tion is a temporary transfer of C from the atmosphere to biosphere. Unless forested land is  
 210 permanently expanded or wood products are forever prevented from decay, in the long run  
 211 (hundreds of years) sequestration by trees can never offset fossil C emissions. Indeed this  
 212 same conclusion was made for fossilized C emissions due to tree management (Nowak et al.,  
 213 2002). The avoided ACE from trees had been estimated to more than offset these manage-  
 214 ment emissions in a life-cycle analysis of the Million Trees Los Angeles program (McPherson  
 215 and Kendall, 2014). However, our results suggest that for cool climate communities, trees ac-

216 tually increase ACE and, especially when combined with the C emissions from management,  
217 are atmospheric C sources.

218 **Trees relative to other factors that affect ACE and the ACE effect**  
219 **of trees relative to other ecosystem services/disservices.**

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

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

## 239 **Future work**

240 Using actual energy use data from over 25,000 houses, we provide a much needed complement  
241 to simulation models of tree effects on ACE in cool climates. However, there is need for  
242 continuing work to address remaining shortcomings. The observational nature of our data is  
243 strengthened by the size of the dataset, but ultimately causal inference depends on our physical  
244 knowledge of how trees alter building energy use. More experimental studies are needed  
245 especially in cool climate cities to better understand that relationship. Not all coefficients in  
246 our model agree with our existing physical understanding of how trees affect building energy  
247 use. For example, it is surprising that trees to the near west have such a weak effect on  
248 electricity use. Our data on tree cover was also limited by a lack of information about tree  
249 height, which means we could not address how adjusting the size of trees planted in an urban  
250 area affects ACE. Incorporating lidar could provide more accurate estimates of tree shading  
251 and wind reduction. Furthermore, the scale of the effects that our study could detect is much  
252 smaller than the city-wide effects many simulation studies address. Ultimately, this work is  
253 a sample of one year from one city with the accompanying limitations. The warm December  
254 during the sampling period may mean the effect of trees is even more detrimental than we  
255 report, but more years are needed to say. The location of Madison near the boundary that  
256 Akbari and Konopacki (2005) identified between trees being a sink and a source is useful,  
257 but more cities are needed to empiracally determine this boundary.

258 Our work reveals a blind spot in urban forest ecosystem studies. In an extensive review of  
259 the effect of the urban forest on CO<sub>2</sub> emissions, Weissert et al. (2014) did not consider that  
260 trees could increase ACE. In a paper critical of many ecosystem services provided by trees,  
261 Pataki et al. (2011) nevertheless state that trees reduce energy use and ACE. While this  
262 may be true in most of the US, and the potential ACE reduction is larger than the potential  
263 ACE increase, it ignores geographical nuance (Akbari and Konopacki, 2005). In many ways  
264 it is not surprising, given the climatic diversity across the country, that the effects of trees  
265 on ACE might also vary and that our prescriptions for how to plant trees to minimize ACE

could be different between Los Angeles and New York City. However our study is only the first study to use both gas and electric energy use observations, and the first study of its kind in a cool climate. Much more work with observed energy use is needed to identify the border between atmospheric C sink and source.

## Conclusion

Using observed energy use data, we have shown that trees near residential houses in Madison, WI increase energy use and associated C emissions and near east tree cover has the strongest net effect. Extending past simulation studies, we show that this is likely the case for a large area of the US. The magnitude and direction of the effect is dependent on tree location relative to buildings, climate, building characteristics, occupant behavior, and the C content of electricity. Disagreements between our results and past work is due to how wind effects are modeled and much more work is needed to better understand this process. We add critical geographic nuance to research that could have major implications for tree planting programs in cool climates.

## Methods

### Building Energy Use

In April 2016, we obtained the annual energy use summary table (April 2015 - April 2016) from Madison Gas and Electric’s publicly available website for approximately 32 thousand single family residential houses in Madison, WI. This included average monthly gas and 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). 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.

## **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.

## 339 **Modeling**

340 We fit linear models where the response was log transformed annual ACE for gas use, for  
341 electricity use, or for gas and electricity combined (net). Because a separate model was  
342 built to explain net C emissions, coefficient estimates for the net model were not precisely  
343 the sum of the coefficients from the electricity and gas models. ACE was log transformed  
344 to meet assumptions of normality and diagnostic plots were assessed to check other model  
345 assumptions and potential sensitivity to influential observations. Variables in our model were:  
346 5 principal components of building characteristics, building cover in each of the 8 regions, tree  
347 cover in each of the 8 regions and a random effect for elementary school which might capture  
348 neighborhood characteristics such as culture. We used AIC as a variable selection criterion  
349 and in our final models only used the first 5 building characteristics principal components  
350 and we dropped all the building cover covariates. Estimates for the coefficients of tree cover  
351 were not sensitive to the inclusion or removal of these covariates, but model fit improved.  
352 Although some tree cover covariates increased AIC, we kept all tree cover covariates in the  
353 model because we wanted estimates of their effects, however uncertain they might be. We  
354 fit models using the R package lme4 (Bates et al., 2015).

## 355 **Interpreting coefficients**

356 To improve interpretability of coefficients, we back transformed them to the original scale  
357 and expressed the multiplicative effects as a percentage (Gelman and Hill, 2007). We then  
358 multiplied this percent change by the median ACE (a better estimator of the central tendency  
359 because of the right skew in our data) to estimate the typical effect in absolute C terms.  
360 To get typical effects of tree cover, we multiplied median tree cover in each region by its  
361 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). 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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480 McPherson and Simpson (1999)  
481 Heisler (1990)