

Trees in cool climate cities may increase atmospheric carbon by altering building energy use

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9 **Abstract**

10 Urban trees are a critical part of the "green infrastructure" intended to make our growing
11 cities more sustainable in an era of climate change. The potential for urban trees to modify
12 microclimates and thereby reduce building energy use and the associated carbon emissions
13 is a commonly cited ecosystem service used to justify million tree planting campaigns across

14 the US. However, what we know of this ecosystem service comes primarily from unvalidated
15 simulation studies.

16 Using the first dataset of actual heating and cooling energy use combined with tree cover
17 data, we show that that contrary to the predictions of the most commonly used simulations,
18 trees in a cool climate city increase carbon emissions from residential building energy use.
19 This is driven primarily by near east ($< 20\text{m}$ from building) tree cover. Further analysis
20 of urban areas in the US shows that this is likely the case in cool climates throughout the
21 country, encompassing approximately 39% of the US population and 62% of its area (56%,
22 excluding Alaska). This work adds geographic nuance to our understanding of how urban
23 shade trees affect the carbon budget, and it could have major implications for tree planting
24 programs in cool climates.

25 Introduction

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

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

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

51 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 C content of a kWh, which varies 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 (a gray literature exception is Nowak et al. (2010)). In an extensive review of the effect of the urban forest on CO₂ 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 (USFS) 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 CO₂ 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

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

80 Direct measures of the effect of trees on building energy use are rare, focused on cooling
81 energy use, and limited in their ability to be extrapolated. To our knowledge, there are the
82 only 5 studies that test the effect of trees on measured building energy use data (Akbari
83 et al., 1997; Donovan and Butry, 2009; DeWalle et al., 1983; Parker, 1983; McPherson et al.,
84 1989). Only two of these studies were of actual houses (not mobile homes nor models) and
85 both are from Sacramento, CA and did not measure heating energy use (Akbari et al., 1997;
86 Donovan and Butry, 2009). Only one of the studies was from a cool, heating dominated
87 climate (typical of much of the US) and it studied a single mobile home in a forest (DeWalle
88 et al., 1983).

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

93 The work from LBNL assumes: millions more trees are planted in an urban area (ex-
94 tremely ambitious); trees are planted to the west and south of buildings (ideal placement for
95 reducing cooling loads); and winter tree canopy transmissivity is 0.9 (0.7 is more realistic,
96 Heisler, 1986). In later work, microclimate wind effects are ignored (Akbari and Konopacki,
97 2005), and in earlier work, they use a three parameter equation fit to four data points to
98 estimate how wind speed is reduced by canopy cover (Heisler, 1990; Huang et al., 1990). Fi-
99 nally, the LBNL work uses potential evapotranspiration to predict cooling, and their model
100 uses parameters derived from crops. Given these assumptions, the authors note that their
101 work provides an upper boundary for the indirect effect of trees (Akbari and Konopacki,
102 2005; Huang et al., 1987).

103 USFS studies assume: lookup tables for the effect of tree shade on building energy use

104 are reliable (even though they may deviate from more detailed simulations by up to 10%,
105 Simpson, 2002); wind reduction only affects heating use in the winter, even though we know
106 cooling use is also affected; and they also use an overfit summertime leaf-on equation from
107 Heisler (1990). Evergreen trees are modeled as if they are windbreaks for rural farmhouses
108 in winter, even in suburban neighborhoods where other buildings and trees already block
109 significant winds; and estimated evapotranspirative cooling is optimistically high, higher
110 even than the self declared upper limit of Huang et al. (1987) (McPherson and Simpson,
111 1999).

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

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

131 Results

132 Effect of trees on building associated C emissions

133 Trees increased C emissions associated with residential building energy use (**ACE**) in Madi-
 134 son, WI. This effect was the result of a trade-off between their electricity (cooling) saving
 135 and gas (heating) penalty. We estimated that 100m² of tree cover within 20m of a house
 136 increased ACE from gas use by 0.77% (95% CI: 0.68%, 0.85%), and decreased ACE from
 137 electricity use by 0.21% (95% CI: 0.34%, 0.080%). Our model for net ACE estimated that
 138 100m² of tree cover increased ACE by 0.17% (95% CI: .09%, .27%).

139 The magnitude and direction of the effect depended on tree location relative to the
 140 building. Figure 2 shows the percent change in the ACE from 100m² of tree cover. Trees
 141 reduced ACE from electricity for all near regions except the east. Trees increased ACE from
 142 gas for all regions, especially in the near south and east. For net ACE, tree cover in the near
 143 east was the most important, having the only estimate with a 95% CI that excluded 0.

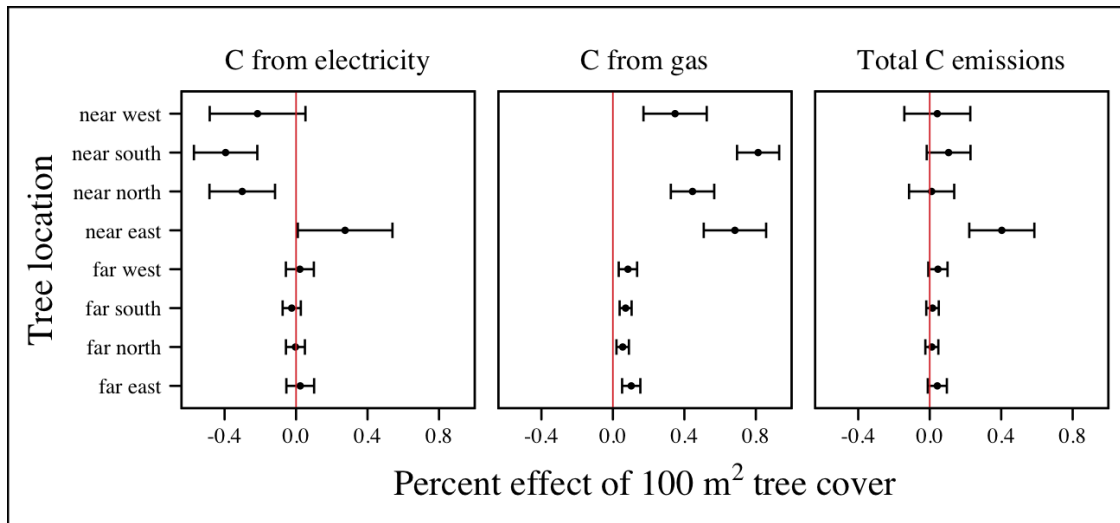


Figure 2: The percent effect of 100m² tree cover in different locations on C emissions from residential building energy use. n = 25095, bars indicate standard errors.

144 Effect of existing tree cover on a typical house

145 The median house in our sample was responsible for 1084 and 954 kg C annual emissions
 146 due to electricity use and gas use, respectively. Multiplying the median tree cover in each
 147 region (see table 1) by its coefficient we estimated the effects of typical tree cover on a typical
 148 house in Madison: electricity C emissions were reduced by 33.8 kg C / yr (95% CI: 14.7,
 149 52.7), but gas C emissions were increased by 102.3 kg C / year (95% CI: 92.9, 111.8). Our
 150 combined model estimated the net effect of existing tree cover is to increase C emissions by
 151 about 62 kg C/year (95% CI: 38.7, 85.3) for a typical house. This is 2.5% of the median
 152 house's annual ACE.

Table 1: Summary statistics for amount of tree cover (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

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

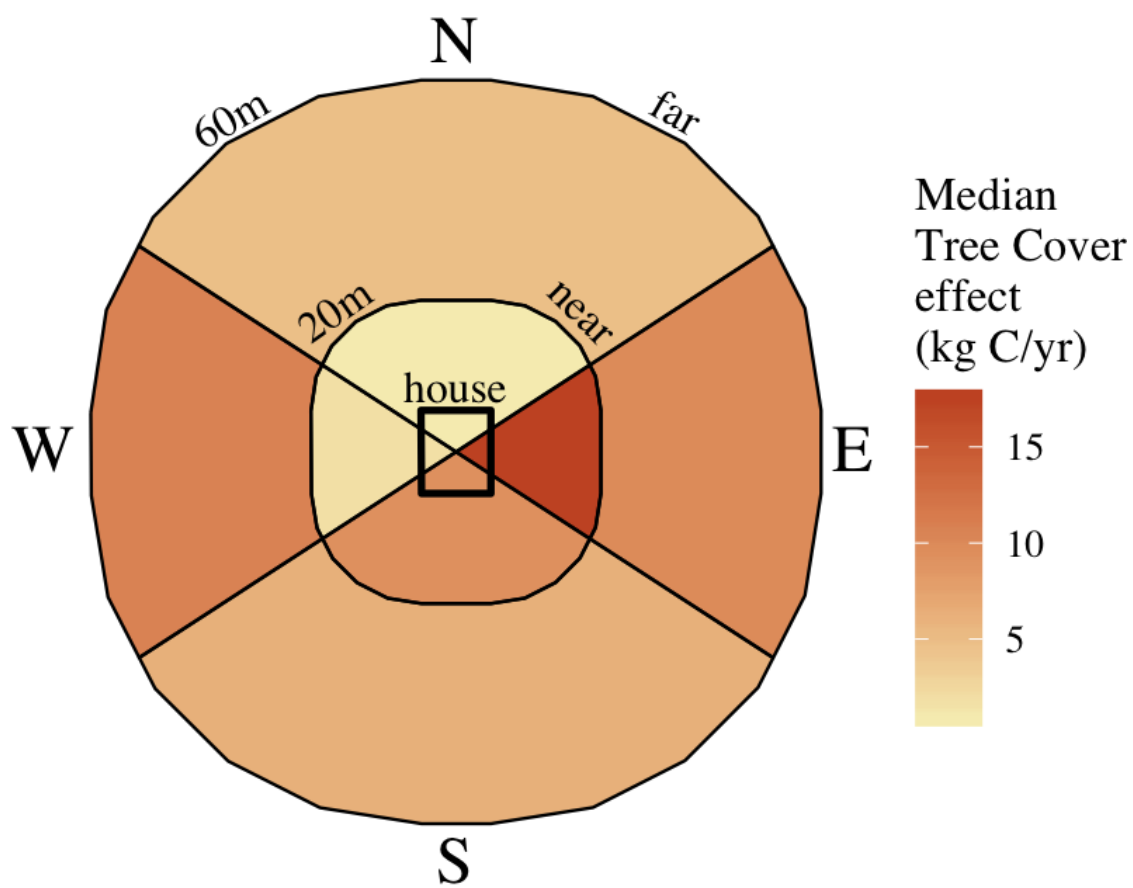


Figure 3: Effect of typical tree cover on a typical building's C emissions.

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

160 For comparison, consider a green ash tree with a crown area of 100m². This tree would store
161 approximately 1360 kg C in above ground biomass and it could sequester around 34 kg C /
162 year. That same tree in the near east region of a typical house in Madison was estimated
163 to increase C emissions by 9.8 kg C/yr (95% CI: 6.7, 12.9). In the near west the estimated
164 effect was 1.0 kg C/yr (95% CI: -2.1, 4.1). Therefore, the transfer of carbon from atmosphere
165 to the biosphere (sequestration) is an order of magnitude larger than the transfer from the
166 lithosphere to atmosphere (emissions).

167 **Discussion**

168 **Interpreting Tree Effects**

169 In the cool climate city of Madison with 7283 heating degree days, 597 cooling degree days
170 and a electricity emission factor of 0.206 kg C / kwh, the relationship of trees with ACE was
171 clear: trees increased ACE from gas use more than they decreased ACE from electricity use,
172 resulting in a net increase in ACE.

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

178 By separating tree cover into different locations, it appeared that for the most regions,
179 the beneficial effects of trees on electricity ACE *mostly* canceled out the detrimental effects
180 of trees on gas ACE, with the exception of the near east. This suggests that trees to the
181 east may have been responsible for most of the net increase in ACE. Eastern trees did not

182 provide electricity savings since houses require less cooling in the morning hours, but still
183 caused an increased gas use in winter. This agrees with Donovan and Butry (2009) who also
184 found trees to the east had no effect on electricity use.

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

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

199 **Comparing to past work**

200 Our findings agreed with some though not all of the past simulation studies, and the modeling
201 of wind is the main cause of discrepancies. Thayer Jr and Maeda (1985) modeled the shading
202 effects of south trees on building energy use and reported that trees increased emissions in
203 cities with more heating degree days than cooling degree days. McPherson et al. (1988)
204 investigated the shading and wind effects on building energy use in 4 cities, one of which
205 was Madison, WI. Converting their results into C, trees in Madison caused a small increase
206 in emissions, though their method for modeling wind was later criticized and abandoned
207 (Simpson and McPherson, 1998). Akbari and Konopacki (2005) developed a method to

208 predict the effect of a tree planting program and increasing roof albedo for any city in the U.S.
209 Figure 4 illustrates an application of their method to every census tract in the conterminous
210 US for pre-1980s houses using updated energy emission factors. They identify places where
211 trees increase ACE and others where trees decrease ACE, however they are most often cited
212 for the average effect found: "Shade trees reduce building energy use and CO₂ emissions
213 from power plants", the title of from Akbari's 2002 paper. Clearly climate largely drives the
214 relationship between ACE and trees at large scales, but there is significant regional variation
215 due to differences in electricity C emission factors. Trees are more beneficial in places with
216 "dirtier" (more C per kWh) electricity and less beneficial in places with "cleaner" (less C
217 per kWh) electricity. For example, despite its cool climate, trees in Chicago reduce ACE
218 because the electricity has more C per kWh and therefore the electricity reduction benefit
219 of trees leads to a greater reduction in C than in places with cleaner electricity.

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

225 Our empirical findings disagree with those simulation studies that model the relationship
226 between tree cover and wind speed following Heisler (1990) and McPherson and Simpson
227 (1999). When the beneficial effects of wind are excluded for models of several cool climate
228 cities: Toronto (Akbari and Taha, 1992), Chicago (Jo and McPherson, 2001), Minneapolis,
229 Sacramento, and Washington (Huang et al., 1990), trees either have no effect or increase
230 energy use and ACE, which agrees with our general findings. The iTree model which uses
231 the methods of McPherson and Simpson (1999) predicts that the shading effects of a large
232 deciduous tree in the Northern Tier, North Central, Mountains, Pacific Northwest, and
233 California Coast regions increases ACE of a 1950-1980 vintage house by 0.136 to 9.52 kg,
234 depending on the region. This is comparable to our results. However, the wind effect in the

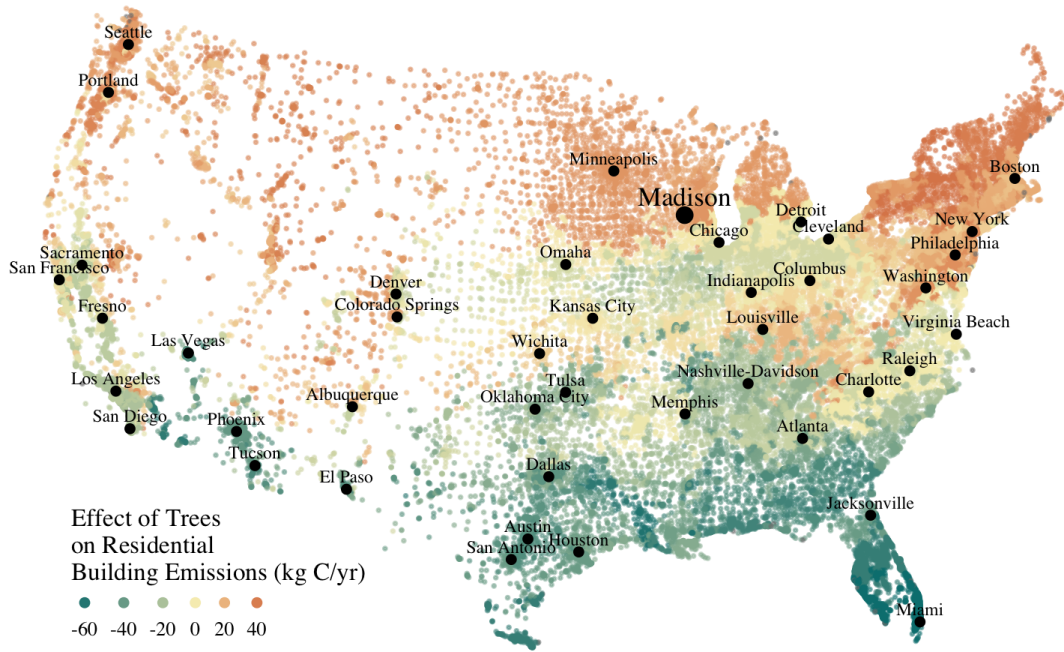


Figure 4: Each census tract in the conterminous US shaded by magnitude of building C emissions effect of trees planted to west and south of a pre-1980's home and increasing roof albedo. Differences in regional emission factors (C/kWh) cause deviations from climate trend. New England has especially high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

iTree model of that same tree on the same house decreases heating ACE by 1.23 to 66.14 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. Given that our model coefficients show that trees increases ACE, it suggests that shading is a more important process than wind 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.

Considering the larger C cycle

The effect on ACE of a tree with a 100 m² 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. 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 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, shade trees actually increase ACE and, especially when combined with the C emissions from management, are atmospheric C sources in the long term.

260 **Trees relative to other factors that affect ACE and the ACE effect** 261 **of trees relative to other ecosystem services/disservices.**

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

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

281 **Future work**

282 Using actual energy use data from over 25,000 houses, we provide a much needed complement
283 to simulation models of tree effects on ACE in cool climates. However, there is need for
284 continuing work to address remaining shortcomings. The observational nature of our data is

strengthened by the size of the dataset, but ultimately causal inference depends on our physical knowledge of how trees alter building energy use. Not all coefficients in our model agree with our existing physical understanding of how trees affect building energy use. For example, it is surprising that trees to the near west have such a weak effect on electricity use and that trees to the north increase gas use. While the overall association between greater tree cover and greater ACE in Madison is clear from our work, how that relationship changes with distance and direction is less clear. Our work is an important complement to simulation studies and highlights the need for more experimental studies especially in cool climate cities.

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

Our work presents more evidence for a known, but too often overlooked, result in urban ecology. Many studies only report that trees reduce ACE (Pataki et al., 2011; Weissert et al., 2014). While this may be true in most of the US, and the potential ACE reduction is larger than the potential ACE increase, it ignores geographic variation (Akbari and Konopacki, 2005). In many ways it is not surprising, given the climatic diversity across the country, that the effects of trees 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. Our study is only the first study to use a large number of 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

312 is needed to identify where trees switch from increasing to decreasing ACE.

313 Conclusion

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

326 Methods

327 Building Energy Use

328 In April 2016, we obtained the annual energy use summary table (April 2015 - April 2016)
329 from Madison Gas and Electric’s publicly available website for approximately 32 thousand
330 single family residential houses in Madison, WI. This included average monthly gas and
331 electricity use. This period exhibited a much warmer than average December (about 6° C)
332 and had low snowfall. We removed from our sample outliers that used fewer than 120 therms
333 (which is less than the 0.5% quantile) or fewer than 240 kWh (which is less than the 0.05%
334 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 CO₂ 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 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.

385 Building Cover

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

391 Modeling

392 We fit linear models where the response was log transformed annual ACE for gas use, for
393 electricity use, or for gas and electricity combined (net). Because a separate model was
394 built to explain net C emissions, coefficient estimates for the net model were not precisely
395 the sum of the coefficients from the electricity and gas models. ACE was log transformed
396 to meet assumptions of normality and diagnostic plots were assessed to check other model
397 assumptions and potential sensitivity to influential observations. Our first models aggregated
398 all tree cover near buildings into one variable, and subsequent models separated tree cover
399 based on direction and distance into eight variables. In addition to tree cover, variables in
400 our model were: 5 principal components of building characteristics, building cover in each of
401 the 8 regions, and a random effect for elementary school which might capture neighborhood
402 characteristics such as culture. We used AIC as a variable selection criterion and in our final
403 models only used the first 5 building characteristics principal components and we dropped all
404 the building cover covariates. Estimates for the coefficients of tree cover were not sensitive
405 to the inclusion or removal of these covariates, but model fit improved. Although some tree
406 cover covariates increased AIC, we kept all tree cover covariates in the model because we
407 wanted estimates of their effects, however uncertain they might be. We also fit models We
408 fit models using the R package lme4 (Bates et al., 2015).

409 **Interpreting coefficients**

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

416 **Estimating C storage and sequestration of a green ash with 100m²** 417 **canopy**

418 To estimate C storage and sequestration by a single green ash tree with a canopy cover of
419 100m², we used allometric equations to estimate that tree's diameter at breast height (DBH)
420 and mass and then, assuming an annual DBH growth of 0.61 cm, predicted the change in
421 mass to get C sequestration Nowak and Crane (2002); McPherson et al. (2016).

422 **Extending Analyses from Published Literature**

423 To compare our work to past simulation studies we converted results that were in Therms
424 or kWh to kg C. We did this for Thayer Jr and Maeda (1985), McPherson et al. (1988),
425 and Huang et al. (1990) using updated emission factors corresponding to each study city's
426 eGrid subregion (Emissions & Generation Resource Integrated Database, 2016). To extend
427 Akbari and Konopacki (2005), we joined climate data (heating and cooling degree days) from
428 the nearest NOAA weather station to census tract centroids U.S. Census Tract Centroids
429 (2010); Arguez et al. (2012). It was from this join of climate and census data that we
430 determined that 77% of the U.S. population lives in places with more heating than cooling
431 degree days. Then for each census tract we predicted the effect of trees and increasing roof
432 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.

Code

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

References

- Akbari, H. (2002). Shade trees reduce building energy use and CO₂ emissions from power plants. *Environmental Pollution*, 116(nil):S119–S126.
- Akbari, H. and Konopacki, S. (2005). Calculating energy-saving potentials of heat-island reduction strategies. *Energy Policy*, 33(6):721–756.
- Akbari, H., Kurn, D. M., Bretz, S. E., and Hanford, J. W. (1997). Peak power and cooling energy savings of shade trees. *Energy and buildings*, 25(2):139–148.
- Akbari, H. and Taha, H. (1992). The impact of trees and white surfaces on residential heating and cooling energy use in four canadian cities. *Energy*, 17(2):141 – 149.
- Arguez, A., Durre, I., Applequist, S., Vose, R. S., Squires, M. F., Yin, X., Heim, R. R., and Owen, T. W. (2012). Noaa’s 1981-2010 u.s. climate normals: An overview. *Bulletin of the American Meteorological Society*, 93(11):1687–1697.

455 Bates, D., Mächler, M., Bolker, B., and Walker, S. (2015). Fitting linear mixed-effects models
 456 using lme4. *Journal of Statistical Software*, 67(1):1–48.

457 DeWalle, D. R., Heisler, G. M., and Jacobs, R. E. (1983). Forest home sites influence heating
 458 and cooling energy. *Journal of Forestry*, 81(2):84–88.

459 Donovan, G. H. and Butry, D. T. (2009). The value of shade: Estimating the effect of urban
 460 trees on summertime electricity use. *Energy and Buildings*, 41(6):662–668.

461 Emissions & Generation Resource Integrated Database (2016). Accessed Jul. 24, 2018.

462 Erker, T., Townsend, P. A., Wang, L., Lorentz, L., and Stoltman, A. (2018). A statewide
 463 urban tree canopy mapping method. *Remote Sensing of Environment (in review)*.

464 Gelman, A. and Hill, J. (2007). *Data Analysis Using Regression and Multilevel/Hierarchical*
 465 *Models*. Analytical Methods for Social Research. Cambridge University Press.

466 Heisler, G. M. (1986). Effects of individual trees on the solar radiation climate of small
 467 buildings. *Urban Ecology*, 9(3-4):337–359.

468 Heisler, G. M. (1990). Mean wind speed below building height in residential neighborhoods
 469 with different tree densities. volume 96. Proceedings of the American Society of Heating,
 470 Refrigeration and Air conditioning Engineers.

471 Huang, Y. J., Akbari, H., and Taha, H. (1990). The wind-shielding and shading effects
 472 of trees on residential heating and cooling requirements. volume 96. Proceedings of the
 473 American Society of Heating, Refrigeration and Air conditioning Engineers.

474 Huang, Y. J., Akbari, H., Taha, H., and Rosenfeld, A. H. (1987). The potential of vegetation
 475 in reducing summer cooling loads in residential buildings. *Journal of Climate and Applied*
 476 *Meteorology*, 26(9):1103–1116.

477 Jo, H.-K. and McPherson, E. (2001). Indirect carbon reduction by residential vegetation and
 478 planting strategies in chicago, usa. *Journal of Environmental Management*, 61(2):165–177.

479 McPherson, E., Simpson, J. R., and Livingston, M. (1989). Effects of three landscape
 480 treatments on residential energy and water use in tucson, arizona. *Energy and Buildings*,
 481 13(2):127–138.

482 McPherson, E. G., Herrington, L. P., and Heisler, G. M. (1988). Impacts of vegetation on
 483 residential heating and cooling. *Energy and Buildings*, 12(1):41–51.

484 McPherson, E. G. and Kendall, A. (2014). A life cycle carbon dioxide inventory of the
 485 million trees los angeles program. *The International Journal of Life Cycle Assessment*,
 486 19(9):1653–1665.

487 McPherson, E. G. and Simpson, J. R. (1999). Carbon dioxide reduction through urban
 488 forestry. *Gen. Tech. Rep. PSW-171, USDA For. Serv., Pacific Southwest Research Station*,
 489 *Albany, CA*.

490 McPherson, E. G., van Doorn, N. S., and Peper, P. J. (2016). Urban tree database and
 491 allometric equations.

492 McPherson, G., Simpson, J. R., Peper, P. J., Maco, S. E., and Xiao, Q. (2005). Municipal
 493 forest benefits and costs in five us cities. *Journal of Forestry*, 103(8):411–416.

494 Nowak, D. J., Appleton, N., Ellis, A., and Greenfield, E. (2017). Residential building energy
 495 conservation and avoided power plant emissions by urban and community trees in the
 496 united states. *Urban Forestry & Urban Greening*, 21:158–165.

497 Nowak, D. J. and Crane, D. E. (2002). Carbon storage and sequestration by urban trees in
 498 the usa. *Environmental Pollution*, 116(3):381–389.

499 Nowak, D. J., Robert III, E., Crane, D. E., Stevens, J. C., and Fisher, C. L. (2010). Assessing
 500 urban forest effects and values, chicago’s urban forest. *Northern Research Station Resource*
 501 *Bull.*, NRS-37.

502 Nowak, D. J., Stevens, J. C., Sisinni, S. M., and Luley, C. J. (2002). Effects of urban tree
503 management and species selection on atmospheric carbon dioxide.

504 Parker, J. H. (1983). Landscaping to reduce the energy used in cooling buildings. *Journal*
505 *of Forestry*, 81(2):82–105.

506 Pataki, D. E., Alig, R. J., Fung, A. S., Golubiewski, N. E., Kennedy, C. A., McPherson,
507 E. G., Nowak, D. J., Pouyat, R. V., and Lankao, P. R. (2006). Urban ecosystems and the
508 north american carbon cycle. *Global Change Biology*, 12(11):2092–2102.

509 Pataki, D. E., Carreiro, M. M., Cherrier, J., Grulke, N. E., Jennings, V., Pincetl, S., Pouyat,
510 R. V., Whitlow, T. H., and Zipperer, W. C. (2011). Coupling biogeochemical cycles in
511 urban environments: Ecosystem services, green solutions, and misconceptions. *Frontiers*
512 *in Ecology and the Environment*, 9(1):27–36.

513 Roy, S., Byrne, J., and Pickering, C. (2012). A systematic quantitative review of urban tree
514 benefits, costs, and assessment methods across cities in different climatic zones. *Urban*
515 *Forestry & Urban Greening*, 11(4):351–363.

516 Simpson, J. and McPherson, E. (1998). Simulation of tree shade impacts on residential
517 energy use for space conditioning in sacramento. *Atmospheric Environment*, 32(1):69–74.

518 Simpson, J. R. (2002). Improved estimates of tree-shade effects on residential energy use.
519 *Energy and Buildings*, 34(10):1067–1076.

520 Thayer Jr, R. L. and Maeda, B. T. (1985). Measuring street tree impact on solar performance:
521 a five-climate computer modeling study. *Journal of arboriculture (USA)*.

522 United State Environmental Protection Agency (2017). Inventory of u.s. greenhouse gas
523 emissions and sinks: Annex 2 methodology and data for estimating CO₂ emissions from
524 fossil fuel combustion. (430-P-17-001).

525 U.S. Census Tract Centroids (2010). Accessed Jul. 24, 2018.

526 U.S. Department of Energy, E. I. A. (2009). Wisconsin household energy report.

527 Weissert, L., Salmond, J., and Schwendenmann, L. (2014). A review of the current progress in
 528 quantifying the potential of urban forests to mitigate urban co2 emissions. *Urban Climate*,
 529 8(nil):100–125.

530 Young, R. F. (2011). Planting the living city. *Journal of the American Planning Association*,
 531 77(4):368–381.

532 Ziter, C. D., Pedersen, E. J., Kucharik, C. J., and Turner, M. G. (2019). Scale-dependent
 533 interactions between tree canopy cover and impervious surfaces reduce daytime urban heat
 534 during summer. *Proceedings of the National Academy of Sciences*, 116(15):7575–7580.

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