Property Values Not Hurt by Wind Farms

Studies find properties that host wind farms are worth more after turbines installed. Nearby properties are unaffected.

https://www.energyandpolicy.org/wind-energy-does-not-hurt-property-values/

Ten major studies in three countries of 1.3 million property transactions over 18 years of data have found no connection between wind farms and property values. Yet the fear of property value loss persists and is exploited by anti-wind campaigning groups in their attempts to turn local populaces against wind developments.

By comparison, only two moderately reliable studies with some statistical significance found property value impacts, and they are both challenged in different ways. Five other often referenced studies are merely case studies with no statistical significance, done by appraisers who show strong evidence of bias, and in one case there is clear evidence that they ignored the reality of the property they appraised.

The evidence that wind farms don't harm property values is robust, methodologically sound and from reliable organizations. The evidence that wind farms harm property values is much weaker, methodologically challenged at best and usually from much less reliable organizations.

Respect the people and their concerns
Whether it is a home or a vacation property, people who buy or own rural property have deep emotional drivers attached to it. For some older people, it is the home they have been in for decades. For others, it is a rural idyll, the fantasy of a hobby farm or country estate. For others, it is an escape from the vertical canyons,

concrete, steel and noise of the city. For most of them, it represents a very large percentage of their finances, with all of the attendant concerns that it might turn to dust as happened in the US with the subprime mortgage collapse in 2008. It is worthwhile to respect the deep emotions involved in this subject. Anti-wind advocacy groups certainly do, and while some are directly motivated by fears of falling properties, many broader groups are using those fears to directly motivate grassroots organizations to form to fight wind turbines.

Property values show no long-term correlation to wind turbine presence
There have been several major reports released in 2013 and 2014 that substantially add to the evidence base for wind farms and property values.

Most recently, the largest and longest duration study was released by the Center for Economics and Business Research (Cebr) in the UK. They were commissioned by RenewableUK, the industry body for wind and marine energy generation, which in many minds will reduce the merit of the study, however, it covers over one million property transactions in counties with wind farms over 18 years, making it the study with by far the largest statistical base and longest perspective. The methodology and statistics are sound. Their findings?
Our analysis of the raw house price data for transactions completed within the vicinity of the wind farms yielded no evidence that prices had been affected by either the announcement, construction or completion of the wind farms for six out of seven sites. In fact, the analysis shows that on average, house prices near wind farm sites grew faster for the periods between the start of construction and mid-2013 (0.8% annual growth) than at the wider county-level (0.5% annual growth). One site did see a noticeable downturn following the announcement that a wind farm would be built; however once the turbines were erected, local house price growth returned to the county-wide norm.
As can be seen from a key graph, the average house prices within five kilometres of wind farms track the county averages very closely over the eighteen years. What's also of relevance to the discussion is that house prices dropped in 2008 and have continued downward. Once again, the visibility of wind farms makes them lightning rods for concerns that are actually caused by other things.

As a side note, Cebr excluded two wind farms from the statistical analysis because they had too few properties within five kilometres of them for statistical validity. This is interesting because the transactions near those wind farms — 470 and 2,384 respectively — are greater than the total transactions in virtually all of the studies finding harm to property values, casting those studies even more deeply into doubt.

The most substantive is the **2013 update of the 2009 Lawrence Berkeley National Laboratory (LBNL) study**, described below in detail.
To ensure that the seriousness of this organization and its devotion to academic excellence and scientific truth is understood, thirteen Nobel Prize winners have been associated with the Lab and thirteen have been awarded the US National Medal of Science, the top US honor for lifetime achievements in science. Dozens more have received other extraordinary levels of recognition. This is an organization that is not for sale. This is an organization that takes its independence and excellence seriously, and accusations leveled at the studies it performs related to being bought and paid for by the wind industry are specious and without basis. Pertinent points are extracted here:

We collected data from more than 50,000 home sales among 27 counties in nine states. These homes were within 10 miles of 67 different wind facilities, and 1,198 sales were within 1 mile of a turbine—many more than previous studies have collected. The data span the periods well before announcement of the wind facilities to well after their construction. We find no statistical evidence that home values near turbines were affected in the post-construction or post-announcement/pre-construction periods.
This major study controlled for significantly more variables and concerns than previous studies and found no impact on property values from wind farms.

The LBNL also collaborated with the University of Connecticut on an assessment of property value impacts near wind farms in the US state of Massachusetts in 2013, publishing their results in January 2014. They spread the net even wider:
To determine if wind turbines have a negative impact on property values in urban settings, this report analyzed more than 122,000 home sales, between 1998 and 2012, that occurred near the current or future location of 41 turbines in densely- populated Massachusetts communities.
The results of this study do not support the claim that wind turbines affect nearby home prices. Although the study found the effects from a variety of negative features (such as electricity transmission lines and major roads) and positive features (such as open space and beaches) generally accorded with previous studies, the study found no net effects due to the arrival of turbines in the sample's communities. Weak evidence suggests that the announcement of the wind facilities had a modest adverse impact on home prices, but those effects were no longer apparent after turbine construction and eventual operation

commenced. The analysis also showed no unique impact on the rate of home sales near wind turbines.

In January 2014, **a Canadian study assessed the impacts of the Melancthon wind farms near Orangeville, Ontario** — at one point the largest in Canada — on home and farmland property values over another 7,004 property transactions. The study's conclusions:

The results of the hedonic models, which are robust to a number of alternate model specifications including a repeat sales analysis, suggest that these wind turbines have not significantly impacted nearby property values. Thus, these results do not corroborate the concerns raised by residents regarding potential negative impacts of turbines on property values.

Also in 2013, **the University of Rhode Island performed an assessment specifically of property transactions** in that US state. They covered 48,554 property transactions over thirteen years, both near and far from the twelve large and mid-sized wind turbines constructed in ten sites between 2006 and 2013.

Across a wide variety of specifications, the results indicate that wind turbines have no statistically significant impact on house prices. For houses within a half mile of a turbine, the point estimate of price change for properties within 1/2 mile relative to properties 3-5 miles away 3 is -0.2%. So our best estimate is wind towers have no virtually effect on prices of nearby properties.

The best study in this field prior to 2013 was funded by the US Office of Energy Efficiency and Renewable Energy. They mandated the *Lawrence Berkeley National Laboratory* to study the concern and the report was delivered in 2009. Here's what they found:

The present research collected data on almost 7,500 sales of single-family homes situated within 10 miles of 24 existing wind facilities in nine different U.S. states. The conclusions of the study are drawn from eight different hedonic pricing models, as well as both repeat sales and sales volume models. The various analyses are strongly consistent in that none of the models uncovers conclusive evidence of the existence of any widespread property value impacts that might be present in communities surrounding wind energy facilities.

It is worth noting and debunking the arguments used against the study, as they have been recycled constantly:

- The claim: it doesn't agree with what is obviously happening around the person observing. The reality: statistics have never had much success in convincing someone who believes something and receives sufficient evidence to support their confirmation bias.

- The claim: the Lab is government-funded. The reality: the bona fides and independence of the LBNL are top-notch and questioning them indicates the rhetorical or intellectual disposition of the questioner.

- The claim: the study excluded 34 statistical outliers. The reality: statistical studies of any size do this to eliminate unrepresentative data and 34 exclusions on a sample size of 7,500 is miniscule. This study is accurate and has not been manipulated.

The next study is the 2007 study by the Royal Institute of Chartered Surveyors (RICS) in conjunction with Oxfords Brookes University. These are serious, respectable and trusted institutes as well; RICS traces its history to chartering in 1792 and is a pre-eminent standards setting body world-wide. The researchers assessed property transactions within five miles (8 kilometers) of three wind farms from 2000 to 2007. This provides geographical, distance and time-frame perspectives. They eliminated transactions where significant other factors would impact prices: a large open cast slate mine, very expensive properties, very cheap properties and sea view properties. This was to provide a clear view of specifically wind turbines' impact on property values. This left them with 919 transactions, which is statistically valid. Their findings:
Despite initial evidence that there was an effect, when they investigated more closely, there were generally other factors which were more significant than the presence of a wind farm. Insofar as there was any impact on prices, the results seem to show that it is most noticeable for terraced and semi-detached houses, with there being a significant impact on properties located within a mile of a wind farm. The effect seems much less marked – if at all – for detached houses.
Regarding the terraced and semi-detached houses:

The view of the estate agents was that proximity to a wind farm simply was not an issue. What they did say, though, was that the properties close to one of the wind farms – St Eval – were, in fact, ex-Ministry of Defence properties, and so less desirable than similar properties.
To paraphrase, while people blamed wind turbines for property value decreases, other factors were much more significant, and detached homes, the dominant form of real estate near wind farms showed no price impacts. Unfortunately, RICS has removed this survey from their available publications on their website and appear to not be standing by the results of their research.

The third major study worth assessing is the Renewable Energy Policy Project's (REPP) 2003 study. While the oldest, it also assessed the largest pool of data prior to 2013, more than 25,000 property transactions in the USA. They looked at every home within 5 miles (8 kilometers) of ten greater than 10 MW wind developments that came online between 1998 and 2001. They gathered sales data for the control regions near the wind turbines but outside of the 5 mile (8 kilometer) boundary to ensure that they could assess differences accurately. They gathered six years worth of data covering the years leading up to and following the wind farms' online dates. It is worth noting that while this is by far the largest study with the least statistical adjustment of data, the creator of the study, REPP, is an organization whose public and stated goal is to accelerate the use of renewable energy. As such, while the study design is arguably very good and sample size the largest, it is the only one that might be possible to discount due to source. What REPP found:

- For 8 of the 10 of the wind projects, property values increased faster inside the five mile limit than outside of it over the six years.

- For 9 of the 10 wind projects, property values increased faster within the five mile limit after the wind projects came online than they had before.

- For 9 of the 10 wind projects, property values increased faster within the five mile limit after the wind projects came online than in the comparable communities.

Not only did this massive study not find negative impacts on real estate values, it found exactly the opposite: *wind turbines have a slight positive impact on real estate values.*

A fourth study is also worthy of a closer look: "Wind Farm Proximity And Property Values: A Pooled Hedonic Regression Analysis Of Property Values In Central Illinois" by Jennifer L. Hinman in partial fulfilment of a Master in Applied Economics with Illinois State University in 2010. Ms. Hinman's study evaluated 3,851 residential property transactions from January 1, 2001 through December 1, 2009 from McLean and Ford Counties, Illinois around the 240-turbine, Twin Groves wind farm (Phases I and II) in eastern McLean County, Illinois. Ms. Hinman's study found no correlation between a working wind farm and decreased property values, in fact saw **more rapid price increases nearer to the wind farm** as was observed in the REPP report. Her study most clearly shows that there is a statistical correlation between fears about a wind farm before it is erected, temporarily depressing property values, and that this temporary dip is rapidly eliminated once the wind farm is in operation.

A University of New Hampshire study published in December 2012 assessed another 4,600 property transactions and found:

While this study does not exclude the possibility of isolated cases of property value impacts attributable to the Lempster Wind Power Project, this study has found no evidence that the Project has had a consistent, statistically-significant impact on property values within the Lempster region. This is consistent with the near unanimous findings of other studies—based their analysis on arms-length property sales transactions—that have found no conclusive evidence of wide spread, statistically significant changes in property values resulting from wind power projects.

Two correlation graphs from this study paint a clear picture.

Note that distances are in kilometres.

Basically, there's no variance on home prices due to distance from wind turbines, and a huge correlation to size of dwellings.

A preliminary Australian study indicates that this is also true south of the equator. While the sample size of sales transactions is low, they found that 40 of 45 sales transactions had no evident reduction in value in close proximity to wind farms and that properties that were in sight of wind farms found no reduction in value.

What is the evidence that shows negative impacts?
There is a statistically valid, methodologically sound, peer-reviewed study which contradicts the preponderance of evidence above, and is worth detailed assessment as a result. Martin Heintzelman and Carrie Tuttle did a study of 11,331 property transactions over 9 years in three counties in Northern New York, 461 of which were within three miles of wind turbines. They found that two of the three counties had significant property value decreases while the third had positive indicators. For context, this study is relatively equivalent in terms of organizational respect and depth to Ms. Hinman's study from Illinois State University; credible but not from a world-class organization such as the Berkeley Lab or RICS. A significant failing of the study that makes it difficult to trust compared to other studies is the short time frame of the data for the two counties with negative impacts. Their wind farms became operational in 2008 and 2009, basically in the last year of the data set. The county with positive impacts went live in 2006, in the middle of the data set, providing a much richer analysis space. There are several other significant differences between the two counties that showed negative results and the county with positive results as well.

- The two counties with negative impacts (Franklin and Clinton) had significantly fewer transactions — 210 between them — than the county with some positive impacts (Lewis) which had 251 transactions by itself.

- The two counties with negative impacts had significantly higher resales of properties than the county with positive impacts, 75 to 65.
- The two counties with negative impacts are adjoining to one another with the third county two hours drive away, effectively in another community conversation region and making it possible for other local impacts to be masked; three completely separate or three completely co-located regions would have eliminated this oddity.
- The two counties with negative impacts had fewer wind turbines on average than the county with positive impacts (221 between them to 194 in Lewis).

This region also has a robust set of anti-wind activist groups. The 2011 anti-wind documentary, Windfall , is from upstate New York, and Lisa Linowes, a long-term anti-wind advocate with ties to astroturf-supporters such as the Heartland Institute and the Koch brothers was the sole technical advisor to the movie and has been active in the area. Despite the largest county with the longest history of wind energy and the most transactions having positive indicators for property values, the authors focused their conclusions dominantly on the negative counties. The authors state in their initial preamble, since revised, that they did not believe it possible that wind turbines didn't negatively affect property values. They found the results they expected, ignoring the significant oddities in their results. This study can only be considered of moderate reliability due to the challenges.

A German study is also worth assessing briefly. It covers 1,405 transactions near a wind farm of nine wind turbines in Germany. It found lower property values near wind farms, regardless of whether the wind turbines could be seen or not. It is weak as it does not have control values from other areas, does not assess other potential causes of hedonic impact and has a limited transaction base. At best it is an interesting outlier from the preponderance of evidence of only moderate reliability.

There are four anecdotal sets of property value appraisals by property value appraisers — McCann, Gardner, Lansink and Reardon — in Canada, the USA and Australia that are often mentioned. They variously use case studies, paired sales analysis and an apparently invented statistical method in one case. They cover a few dozen property transactions at most with little in the way of methodological rigor or control. They all show strong evidence of pre-existing bias in their statements. Given the tiny sample sizes and poor methodological rigor, they cannot be considered reliable as evidence. One Australian report by a property appraiser, Peter Reardon, follows in the footsteps of weak anecdotal assessments in Canada and the USA, looking at three sales near wind farms and pairing them with properties elsewhere. It has the typical weaknesses of poor methodology and rigor, but a statement from a purchaser of one of the two properties which apparently suffered property value impacts came into my hands via a correspondent. It's worth looking at what they say about the property that they purchased. Netting it out, it was grossly overpriced for reasons having nothing to do with the nearby wind farm, and everything to do with the property itself.

As you know the property had been on the market since September 2010 at no time did we see it advertised at $320,000. We spoke to the agent when it was priced at $299,000 which we thought was grossly over valued even for a lifestyle block let alone a grazing block, having as you stated not only one but two 330KV lines transversing the block along with the associated easement restrictions (some 50 double sided pages of conditions and and terms), it is divided by the duel carriage Hume Highway and two truck parking bays (North & South), with the associated noise and litter problems, it has no 240V power access on the block (and we know what that costs). That's the lifestyle detractions of the block. Now Grazing- the block has over 30% water logging and drainage problems, covering both sides of the highway-in fact many times we saw the agents vehicle parked on the edge of the road- presumably inspections by "foot" The block had poor boundary fencing on the southern side, the carrying capacity of the block is app. 2.5 DSE per Ha. We therefore came to the value of $205,000 (2500 per Ha.) This was allowing some $8000 for "proximity" to the Highway- having purchased her brother's property some 12 months before at app. $2400Ha.(carrying capacity of6 DSE per Ha.) (no agent involved in this transaction!) We had to increase this offer by some $20,000 to secure this deal. I think Real Estate Agents are no different in the country to their city cousins- raising unrealistic expectations of the value of property especially in a difficult market. It would seem that people want sub-division prices for undeveloped land, not allowing for development and approval costs. Having also sold the mentioned 80Ha block on the Collector Rd we know the demands of financing lifestyle blocks in recent years. This block does have 240V power available as per Council Sub-division regulation.

Summary

The anecdotes about property value loss represent real people telling the truth as they see it, which is to say, from a limited perspective in both space and time. What they are observing is accurate – lower sales prices than they expected – but their interpretation of the reasons appears to be flawed. However, decisions on policy and legislation must be made on the most robust evidence. The evidence related to property value and wind farms is clear: the only impact that wind farms have is that host properties are worth more after the wind turbines are installed. Nearby properties are unaffected.

WIND TURBINES AND HEALTH

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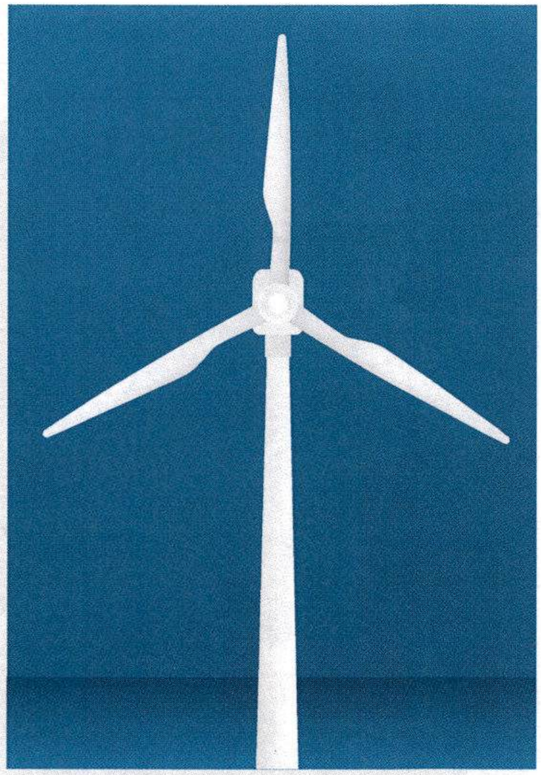


INTRODUCTION

Wind produced electricity has made an extraordinary expansion. In just over 20 years, global wind electricity generating capacity has increased almost 100 fold (6,100 megawatts (MWs) in 1996; 539,123 MW in 2017).[1]

While Asia, Europe, and North America all contain countries that lead in wind-produced electricity (China, Germany, U.S.), just 10 countries are responsible for more than 80 percent of all production.[2] Specific states within the United States are responsible for the majority of production. Iowa has 10 times the capacity of neighboring Wisconsin[i] and five times the capacity of better wind-resourced Nebraska.[3]

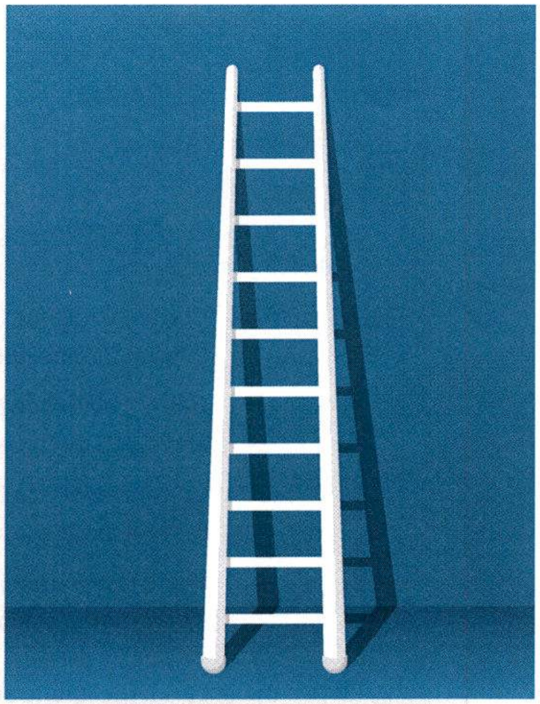
Internationally and within the United States, the availability of renewable resources (e.g., wind, solar, hydro, geothermal), the cost of renewables compared to traditional generating sources, and government policy drive the amount of renewable electricity produced. Citizen support also impacts the development of renewable energy and such support is influenced by public perceptions about the benefits and risks related to wind power, the largest source of new renewable electricity in the U.S.

This joint statement from the Environmental Health Sciences Research Center at the University of Iowa College of Public Health, Iowa Policy Project, and the Iowa Environmental Council summarizes the results of the best research available and concludes that there is little scientific evidence that sound from wind turbines represents a risk to human health among neighboring residents.

HOW TO RESEARCH HEALTH EFFECTS

Any new technology often must answer to the various effects its expansion may have on both economics and health. Frequently human and environmental health are treated as external to the economics of decisions regarding power generation. This leads to a discounting of the health impacts of fossil-fuel-based power generation that cause a substantial burden to citizens. Science can answer questions about potential harm from emerging technologies and thus help policy makers make sound decisions. Most will agree that economic progress should not introduce health problems to an area. To find if problems exist with wind electricity production, well-constructed scientific studies, rather than local conversations, should be our guide.

i Wisconsin in 2017 had 746 MW of wind power capacity while Iowa had 7,312 MW.
Wind energy produced 37 percent of Iowa's electricity, while in Wisconsin the amount was just 2.3 percent.



A basic concept from the science of public health requires that a human health risk be a true hazard and that there is exposure to that hazard. As an example, working on a ladder can be hazardous, but first one must climb the ladder. Wind turbines produce sound pressure, but if the frequency is at or below the threshold of human perception and the sound pressure level is low at area residences, there is little or no exposure to cause human health problems.

There have been a modest number of studies of wind turbines and health — some published in peer-reviewed scientific journals with strong reputations, others found on websites or published with no expert review. The source, extent of peer review, and scientific quality must determine the weight scientists and policy makers give to any study.

REPUTABLE REVIEWS OF WIND TURBINE EXPOSURES AND HAZARD POTENTIAL

Two authoritative peer-reviewed, critical reviews have been done on the topic of wind turbines and health.[ii] Perhaps the most thorough review on the subject was published in 2015 by the Council of Canadian Academies. That organization "is an independent, not-for-profit organization that supports independent, science-based, authoritative expert assessments to inform public policy development in Canada."[4] The Council review summarized here was written by an expert panel of nine university professors and an engineering firm CEO and was extensively peer reviewed.

The expert panel started by looking at a wide range of relevant peer-reviewed journal articles, web pages, legal decisions, and the grey literature (non-peer-reviewed publications such as websites) on wind turbine health effects. They compiled a list of 32 symptoms and health conditions referenced in this literature and found that the health effects most commonly blamed on turbine sound include: annoyance, sleep disturbance, and stress-related conditions.[5] The authors used this list as a starting point to assess whether there are any causal links between exposure to wind turbine noise and health impacts. Next, they reviewed the available literature to evaluate the claims.

ii Critical review articles are articles written by content experts to evaluate the state of the science and weigh the evidence regarding a particular hazard.

The expert panel's evaluation of the scientific evidence regarding various complaints led to the following overall conclusions:

- Current evidence is ***sufficient*** to establish a causal relationship between a person's exposure to wind turbine noise and feelings of **annoyance**.[iii]
- Current evidence is ***limited*** for a causal relationship between exposure to wind turbine noise and **sleep disturbance**.[iv]
- Current evidence is ***inadequate*** to determine whether there is a link between exposure to wind turbine noise and **stress or other health outcomes**.[v]
- There is ***evidence of no causal relationship*** between **hearing loss** and exposure to noise at any distance at the sound pressure levels that are associated with wind turbines.[vi]

While the expert panel found sufficient evidence the wind turbines can cause annoyance, they also noted that current evidence is not sufficient to establish whether the level of annoyance is related to the visual impact of the turbines or other factors such as personal attitudes. Studies completed so far do not measure noise independently from these factors. There is also a lack of data about baseline levels of annoyance without the turbines, the size of the annoyance effect, and how the impact changes in different wind and weather conditions.[6]

There is also a question in the scientific literature about the magnitude of citizen concern and about how that compares to energy production from alternative sources. According to one of the papers evaluated by the expert panel, noise complaints between the years 2007 and 2011 in the Province of Alberta were fewer than complaints about other energy activities such as oil and gas operations.[7]

The second critical review, published in 2014, is by Robert J. McCunney, a professor at the Massachusetts Institute of Technology (MIT) and several others.[8] The authors state that their work received funding from the Canadian Wind Energy Association but that the funder "did not take part in editorial decisions or reviews of the manuscript." MIT conducted an independent review of the work and determined there was academic independence and the work was without bias.

This review found no evidence that people residing close to wind turbines experience disease outcomes but did find that some people experienced annoyance with the turbines or turbine noise, similar to the

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iii "Sufficient" evidence of a causal relationship means that a relationship was found and that chance, bias, and confounding factors can be ruled out with reasonable confidence.

iv "Limited" evidence of a causal relationship means a causal association was considered by the Panel to be plausible, but that chance, bias, and confounding factors could not be ruled out with reasonable confidence.

v "Inadequate" evidence of a causal relationship means that the available studies lack the quality, consistency, or statistical power to lead to a conclusion about whether a causal relationship exists.

vi "Evidence of no causal relationship" means that several adequate studies covering the full range of exposure consistently show no association between exposure and effect at any level of exposure.

findings in the Council of Canadian Academies review. However, this review also found that the percent of participants expressing annoyance varied across the studies they reviewed.[9]

nocebo

[noh-**see**-boh]

noun

A detrimental effect on health produced by psychological or psychosomatic factors such as negative expectations of treatment or prognosis.

CONFOUNDING FACTORS

When people experience symptoms of compromised health, yet there is not enough evidence to find more than annoyance and no other health effects, it is reasonable to look for other explanations, including confounding factors. Confounding factors are things that can "muddy" the results of otherwise well-designed scientific studies. One such factor is the "nocebo effect." Related to the similar-sounding placebo effect, the nocebo effect comes into play, in this case, when people are predisposed to believe they will experience health consequences from wind turbines coming to their area.

Nocebo effects were investigated in both the reputable reviews used in our research. Both the McCunney review and the report of the Council of Canadian Academies cite a paper by Fiona Crichton and colleagues (2014) in the physiology literature.[10] Crichton and her team did not work in the field measuring noise levels but used students to replicate the experience of people living near wind farms. The study looked at infrasound, which is "sub-audible," or produced in a frequency range below what can be heard by humans. Proponents of negative health effects from wind turbines have often pointed to this sub-audible sound as causing problems.

The study divided 54 university students into two groups who attended a session at the listening room of the Acoustic Research Center at the University of Auckland, NZ. One group was exposed to sub-audible infrasound for 10 minutes. The other group was exposed to silence. All participants then viewed one of two short videos, one describing dangers of infrasound and the other describing benefits of wind power and the lack of health problems. A second 10-minute listening session followed. Those who had seen the provocative video, taken from material readily found on the internet, found that their symptoms and the severity of those symptoms increased, whether or not they were actually subjected to sub-audible infrasound. The conclusion of the Crichton paper should be a suggestion to policy makers deciding on the location of wind farms.

> "*If symptom expectations are at the heart of symptom expression, current proposals to address health concerns, such as increasing minimum set back distances for wind turbines from residences, may do little to alleviate health complaints and related opposition to wind farm development.*[11]"

The Crichton paper led to another by Renzo Tonin and others in Australia 2016.[12] This study was designed to replicate that of Crichton et al. The size of the study was increased to 72 participants. The study first subjected volunteers to one of two films, the first designed to heighten the perception that infrasound is harmful and the second to reduce this perception. They then asked volunteers to listen to acoustic headphones that were either producing real infrasound or no sound at all. For those subjected to infrasound, the sound pressure level and waveform were set to simulate "an environment allegedly causing residents to have experienced severe adverse health effects."[13] The investigators found that volunteers who viewed the film designed to heighten the perception that infrasound is harmful generally reported more symptoms and higher intensity of symptoms than those who viewed the film designed to reduce this perception, regardless of whether or not they had actually been exposed to infrasound. Investigators believe that this supports the hypothesis of a nocebo effect and that perception, and no direct physical effect, may influence reported symptoms.

The McCunney review shows economic benefit, or lack of benefit, is another confounding factor for the presence or absence of annoyance. The review found evidence that residents who receive compensation for living near wind turbines are less likely to report adverse health effects than those who live nearby but do not receive economic benefit. Another of the studies notes that receiving benefit is a personal choice and consequently a matter of control over one's environment.

One of the reviewers of our statement reminded us of a well-known study by Paul Slovic about how people estimate hazard and risk.[14] If people believe that they are not in control of a technology, that it is applied without their consent, and that potential risks are not shared equitably, they might perceive the technology as more of a danger. Slovic categorizes these as "dread factors." This may help explain the gap in reported impacts between people who are compensated for turbine siting and those who are not.

In addition, if a technology is not fully understood by laypersons or if potential effects are invisible to human perception, a person's estimate of the hazard may also be elevated. This is termed the "unknown factor." Technologies that combine both factors, like a wind development, may be seen as more risky and tend to draw opposition from neighbors.

To the extent that these perception factors are at work, increasing the distance of wind farms from residences might do little to reduce annoyance. However, finding ways for residents to have more control over exact location of individual turbines or be compensated for the loss of their former viewscape might have an effect.

The literature on these confounders helps explain the conclusion of an earlier report in a U.S. environmental journal in 2011.[15]

> *"To date, no peer reviewed scientific journal articles demonstrate a causal link between people living in proximity to modern wind turbines, the noise (audible, low frequency noise, or infrasound) they emit and resulting physiological health effects ... "*

The authors further concluded, "Given that annoyance appears to be more strongly related to visual cues and attitude than to noise itself, self-reported health effects of people living near wind turbines are more likely attributed to physical manifestation from an annoyed state than from infrasound. This hypothesis is supported by the peer-reviewed literature pertaining to environmental stressors and health." [16]

CONCLUSION

There is no authoritative evidence that sound from wind turbines represents a risk to human health among neighboring residents. The only causal link that can be identified is that wind turbines may pose an annoyance to some who live near them. However, annoyance is likely influenced by a person's feelings about the impacts of wind turbines on viewsheds, whether they get an economic benefit from the turbines, whether they have had a say in the siting process, and attitudes about wind power generally.

Given the evidence and confounding factors, and the well-documented negative health and environmental impacts of power produced with fossil fuels, we conclude that development of electricity from wind is a benefit to the environment. We have not seen evidence that wind turbines pose a threat to neighbors. We conclude that wind energy should result in a net positive benefit to human health.

GLOSSARY

Nocebo — a detrimental effect on health produced by psychological or psychosomatic factors such as negative expectations of treatment or prognosis.

Confounding Factor — A confounding factor in a study is a variable which is related to one or more of the variables defined in a study. A confounding factor may mask an actual association or falsely demonstrate an apparent association between the study variables where no real association between them exists. If confounding factors are not measured and considered, bias may result in the conclusion of the study.

Critical Review — Critical review articles are articles written by content experts to evaluate the state of the science and weigh the evidence regarding a particular hazard.

Viewshed — the view of an area from a specific vantage point.

Causal — relating to or acting as a cause.

Infrasound — sound waves with frequencies below the lower limit of human audibility.

1 Global Wind Energy Council. Global statistics 2017. http://gwec.net/global-figures/graphs/.

2 Ibid.

3 American Wind Energy Association. Wind Capacity by State. 2017. https://www.awea.org/wind-101/basics-of-wind-energy/wind-facts-at-a-glance/.

4 Council of Canadian Academies, 2015. *Understanding the Evidence: Wind Turbine Noise.* Ottawa (ON): The Expert Panel on Wind Turbine Noise and Human Health, Council of Canadian Academies.

5 Ibid. Page 52.

6 Ibid. Page 74.

7 Ibid. Page 59.

8 McCunney, RJ, Mundt, KA, Colby, WD, Dobie, R, Kaliski, K and Blais, M. *Wind Turbines and Health: A Critical Review of the Scientific Literature.* JOEM Vol 56, Number 11, November 2014.

9 Ibid. Page 125. Referencing Thibault, B., Angen, E., & Weis, T. (2013). *Survey of Complaints Received by Relevant Authorities Regarding Operating Wind Energy in Alberta.* Calgary (AB): The Pembina Institute.

10 Crichton, Fiona et al. Can Expectations Produce Symptoms from Infrasound Associated with Wind Turbines? Health Psychology 2014. Vol. 33, No. 4, 360-364.

11 Ibid. Page 364.

12 Tonin, Renzo; Brett, James; Colagiuri, Ben. The effect of infrasound and negative expectations to adverse pathological symptoms from wind farms. Journal of Low Frequency Noise, Vibration and Active Control 2016, Vol. 35(1) 77–90 (2016).

13 Ibid. Page 79.

14 Slovic, Paul. "Perception of Risk." Science, vol. 236, no. 4799, 1987, pp. 280–285. JSTOR, www.jstor.org/stable/1698637.

15 Knopper, LD and Ollson, AC. Health effects and wind turbines: A review of the literature. *Environmental Health* 201110:78. https://ehjournal.biomedcentral.com/track/pdf/10.1186/1476-069X-10-78.

16 Ibid. Page 8 of 10.

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Energy Research & Social Science 87 (2022) 102471

Contents lists available at ScienceDirect

Energy Research & Social Science

journal homepage: www.elsevier.com/locate/erss

In the shadow of wind energy: Predicting community exposure and annoyance to wind turbine shadow flicker in the United States

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ARTICLE INFO

Keywords:
Wind turbine
Shadow flicker
Annoyance
Acceptance
Social impacts

ABSTRACT

The moving shadows caused by wind turbines, referred to as "shadow flicker" ("SF"), are known to generate annoyance in a subset of the exposed population. However, the relationship between the level of modeled SF exposure and the population's perceived SF and SF annoyance is poorly understood. Improved understanding of SF exposure impacts could provide a basis for exposure thresholds and, in turn, potentially improve community acceptance of and experience with wind power projects.

This study modeled SF exposure at nearly 35,000 residences across 61 wind projects in the United States, 747 of which were also survey respondents. Using these results, we analyzed the factors that led to perceived SF and self-reported SF annoyance. We found that perceived SF is primarily an objective response to SF exposure, distance to the closest turbine, and whether the respondent moved in after the wind project was built. Conversely, SF annoyance was not significantly correlated with SF exposure. Rather, SF annoyance is primarily a subjective response to wind turbine aesthetics, annoyance to other anthropogenic sounds, level of education, and age of the respondent.

We also examined regulations governing SF in the sample project areas and compared them to SF exposure in the surrounding population. Additionally, we found that noise limits could serve as a proxy for SF exposure, as 90% of those exposed to wind turbine sound of no more than 45 dBA L_{1h} had SF exposure of less than 8 h per year (a prototypical EU regulatory threshold).

1. Introduction

1.1. Background

Targets to decarbonize the US electricity sector rely on increasing the installed capacity of wind energy in the United States from approximately 110 gigawatts (GW) today [1] to nearly 600 GW by 2035 [2]. Many European countries have similarly ambitious goals [3,4]. Meeting these targets could necessitate thousands of new wind projects and, therefore, many willing host communities. Several common annoyances—such as opaque planning and approval processes, and sound, visual/aesthetic, and shadow flicker (SF) impacts [5]—have been identified by community members living near existing wind projects. These annoyances affect individuals living near existing wind projects and raise questions of distributive fairness. Concerns about these impacts also influence a local community's attitudes toward newly proposed wind projects [6]—affecting wind project permitting timelines and outcomes. To balance these competing goals, some communities have opted to enact highly restrictive siting ordinances or moratoria on wind projects until such concerns and impacts are better understood (e.g., recent US examples from Kansas [7] and Indiana [8]). While overly restrictive wind energy siting ordinances have been shown to increase electricity costs and emissions [9], ignoring social impacts could also result in negative societal outcomes.

Abbreviations: AIC, **Akaike Information Criterion; CI, Confidence Interval; dBA, Sound pressure level in A-weighted decibels; GW, Gigawatt; L_{1h}, One-hour equivalent continuous sound level; LBNL, Lawrence Berkeley National Laboratory; MRLC, Multi-Resolution Land Characteristics; MW, Megawatt; NOAA, National Oceanic and Atmospheric Administration; OR, Odds Ratio; RPM, Rotations Per Minute; SF, Shadow Flicker; VIF, Variance Inflation Factor; WETO, Wind Energy Technologies Office; WSD, Weighted Shadow Duration; WT, Wind Turbine.**

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https://doi.org/10.1016/j.erss.2021.102471
Received 21 May 2021; Received in revised form 7 December 2021; Accepted 10 December 2021
Available online 15 February 2022

Careful analyses of the sound impact from turbines have been conducted by multiple parties (e.g., in the United States [10], Canada [11], Europe [12], and Japan [13]). Similarly, the visual impact of wind projects has been widely researched [14–18], as have attitudes toward and annoyances from wind project planning processes [6,19,20].

Rarely, however, have perceived SF, exposure, or annoyance levels been the focus of rigorous research. Perhaps as a result of this research void, regulations around SF in the United States and in Europe are variable and unstandardized—if they exist at all. A better understanding of the magnitude, drivers, and potential mitigation strategies of SF annoyance is needed for the wind industry, policymakers, and potential host communities to better understand this concern and be able to properly regulate it, if desired.

1.1.1. *What is shadow flicker?*

Shadow flicker, or SF, is an effect of pulsating light and shadow caused by the sun shining through rotating wind turbine blades. The intensity of SF diminishes with increasing distance from a wind turbine, which means it is typically most noticeable near the wind turbine. The area where SF occurs is largest when the sun is relatively close to the horizon, thus it is most common in the morning and evening hours to the west and east of the turbine, respectively. Similarly, the area of impact is typically larger at higher latitudes, where the sun spends more time at lower angles from the horizon (i.e., at large solar zenith angles). SF is expressed as either the maximum number of hours/year or minutes/day. It is modeled either assuming the "worst case" (e.g., turbines always operating, no intervening clouds), or what is termed "real case" that considers mitigating factors related to meteorology and project operation. A detailed discussion of these models and methods is provided in Section 2.1.3.

1.1.2. *What is annoyance?*

Lindvall et al. [21] define annoyance as "a feeling of displeasure associated with any agent or condition believed to affect adversely an individual or group." Lindvall et al. recognize that feelings of annoyance are not necessarily pathogenic and may or may not result in negative health consequences. Hübner et al. [22] go further to define "annoyance stress" by evaluating self-reported annoyance in the presence of additional stress indicators such as sleep disturbance, irritability, and coping responses. As such, there is a distinction between self-reported annoyance and annoyance stress, in that the former could be considered an attitude while the latter may lead to health impacts. In this study, we focus on self-reported annoyance on a five-point scale, with the highest annoyance category being "very annoyed." This is distinct from the highest category of annoyance stress of "strongly annoyed" [22].

1.1.3. *Wind neighbor survey background*

Lawrence Berkeley National Laboratory's National Survey of Attitudes of Wind Power Project Neighbors ("LBNL Neighbor Survey") was conducted by many of the same authors as this paper [6,10,22,23]. This survey collected data in 2016.

Hübner et al. [22] demonstrated that self-reported annoyance to SF, although lower than that of turbine noise, was similar to annoyance to traffic and more prevalent than annoyance to agricultural machinery, turbine lighting, or landscape changes.[1] From this same survey data, we found that of those who could experience the effects, though, SF emoted a high negative reaction. Twenty percent of the 1705 respondents indicated they noticed SF *on their property*, and 7% reported being very annoyed by it. However, of those that experienced SF *in their residence*, approximately one-third reported being very annoyed. Further, wind project developers often rank SF as one of the top concerns of communities.[2] However, the role of SF in the experience of neighbors of wind projects has not been well studied in the United States or abroad.

Statutorily, there is no US national SF regulation, and regulatory limits on SF in states, counties, and towns vary or are often nonexistent [24,25]. Several countries have guidelines or standards, most of which use the same thresholds as or reference the German national guidelines for the evaluation of SF [24,26] (as will be discussed in Section 1.3 and Section 3.4.2). However, there are currently no international standards for how to model SF exposure levels around turbines.

To examine how SF exposure affects perception and annoyance, we conducted a mixed-methodology (both quantitative and qualitative) study using surveys of people living around US wind turbines and combined this data with SF modeling. We modeled SF for 61 unique wind projects across 17 states and 50 counties. These sites included approximately 750 survey respondents and more than 34,000 additional homes (non-survey respondents) from the surrounding population within 2 km of a wind turbine, making this the largest SF dataset analyzed for perceived SF and annoyance that we are aware of. From respondents, we collected survey data on whether they perceived SF in their home and the degree to which they were annoyed by it. We also collected a suite of demographic characteristics and attitudes toward the nearby project.

1.2. *Research objectives*

The present analyses of modeled SF exposure and survey-reported annoyance were intended to investigate the following research objectives:

1. Quantify SF exposure across a large and geographically diverse sample of residences to develop a general understanding of SF experienced in populations living near wind turbines.
2. Use a mixed-method approach to examine the correlation between modeled SF exposure and individuals' reported levels of perceived SF and annoyance to help inform regulations in the United States and abroad.
3. Create a model to predict individual perceived SF and SF annoyance to better understand the magnitude, drivers, and potential mitigation strategies for SF impacts.

1.3. *Previous shadow flicker research*

As early as 1984, SF from turbines was recognized for its potential to be an adverse community impact. Verkuijlen and Westra [27] found that to avoid nuisance, the SF frequency should remain below 2.5 Hertz (Hz) (50 rotations per minute [RPM] for a three-bladed wind turbine). These conclusions were primarily based on previous research related to the onset of epileptic, nausea, and dizziness symptoms [28]. However, the authors conceded that the prior literature was not specific to wind turbines, and that further study was needed. In a later study specific to wind turbines, Harding et al. confirmed that to protect against epileptic impacts, wind turbines should not exceed 60 RPM [28]. For context, modern utility-scale wind turbines rotate at less than one-third of this rate; the fleetwide simple average for US turbines from 1998 to 2019 is 17.4 RPM.[3]

In 1999, Pohl et al. [29] conducted a survey of 223 residents in Germany who lived around wind projects, to determine the impacts of SF and to examine whether the proposed regional SF limit was reasonable with respect to impacts. They found that SF exposure alone did not explain SF

[1] However, with respect to Annoyance Stress, 0.2% were strongly annoyed by SF compared with 1.1% to noise, 1.2% to lighting, and 1.5% to landscape change in the US sample.

[2] Collected via conversations with various developers.

[3] Derived from an internal Lawrence Berkeley National Laboratory database (not capacity weighted).

annoyance. However, when adding in weighing to account for SF sensitivity of different types of rooms and SF exposure of those rooms in individual homes, they found a clear linear relationship between this weighted shadow duration and SF annoyance. They also found that certain residents with high levels of exposure "spent less time in the shaded living spaces and in open spaces around the house and felt…activities indoors and outdoors as well as in their leisure time were severely disturbed as compared to people who were not exposed to shadows" (translation). They concluded that the proposed limit of 30 h of SF per year was likely to prevent most cases of substantially annoyed individuals. The hours estimate was based on a model of purely astronomical shading duration ("worst case"), which gives an upper limit to the duration of periodic shading to which a dwelling is exposed. This model can then be adjusted down by meteorological and turbine operation corrections to mimic actual operating conditions ("real case"). Germany later adopted the 30 h/year (and 30 min/day) worst case and an 8 h/year real case limits for its guidelines for wind projects [26].

Koppen et al. summarized US and EU SF standards in 2017 and found that when SF limits existed, the 30 h/year (and 30 min/day) limit was consistently applied [24]. Many of these in the EU were expressed as a worst case. They observed real case limits in some jurisdictions as well (e.g., Germany, Australia, Belgium, Denmark, and Sweden), with maximums of either 8 or 10 h/year (and 8 to 10 min/day). This suggests a worst-to-real-case relationship of roughly 3 to 1 and a rough equivalent between hours/year and maximum minutes/day. The metric in the three US examples cited did not differentiate between real or worst-case metrics.

In one of the largest and most comprehensive studies of its kind to date, Health Canada surveyed 1,238 people living between 0.25 km and 11.22 km from existing wind turbines in two Canadian provinces [30]. Among other important findings, the researchers found that SF exposure, expressed in maximum minutes per day, improved the ability to estimate high annoyance from wind turbines when combined with other factors such as noise, concern with physical safety, and noise sensitivity. For the lowest level of wind turbine SF exposure (0 to 10 min/day worst case), 3.8% of the population was highly annoyed by SF, while of those experiencing the highest level of exposure (>30 min/day worst case), 21.1% were highly annoyed by SF. However, when modeling SF without additional observable and subjective variables, the predictive strength of the model was weak (R^2 of 0.1). The authors concluded, "In addition to addressing some of the aforementioned shortcomings, future research may also benefit by considering variables that were not addressed in the current study. These may include, but not be limited to, personality traits, attitudes toward WTs [wind turbines], and the level of community engagement between WT developers and the community." This research addresses some of these variables.

Frieberg et al. [31] conducted a systematic literature review on the influence of wind turbine visibility, including indirect effects such as SF, on health. They recommended that additional high-quality research be conducted on the subject, including, "the combined impact of visual and audible aspects of wind turbines on residents' health, and the complex interdependency with other variables (e.g., attitude toward wind energy, economic benefit) should be taken into consideration." This research attempts to address some of these areas of study.

2. Data and methods

2.1. Data

A wide range of data were collected and generated for this research effort. The following sections describe these data in additional detail. One of the key variables was modeled duration of SF exposure at each home (Section 2.1.3). The inputs for those models included the following:

- Wind turbine and project data (Section 2.1.1).
- Residence (i.e., receiver) locations (Section 2.1.2).
- Topography and land cover (Section 2.1.3).
- Meteorology, including wind speed, wind direction, and cloud cover (Section 2.1.3).

Those modeled SF data were, in turn, key inputs to both the perceived SF and SF annoyance models (Section 2.2.2). The models required survey response data such as demographics, self-reported perceived SF and SF annoyance levels, and other response data (Section 2.1.4). Finally, we collected data on SF ordinances (whether they existed, and if so, the relevant limit) for all 50 counties represented in our analysis (Section 2.1.5).

2.1.1. Wind turbine and project data

The 61 wind projects used for modeling encompassed 2,982 wind turbines spread across 17 US states and 50 counties (Fig. 1). Data on each of these wind turbines were obtained from the US Wind Turbine Database (USWTDB) [1,32]. These data included turbine location (i.e., latitude/longitude), rated capacity, hub height, rotor diameter, manufacturer, model, total height, total project capacity, and number of turbines in the project. Table 1 shows summary statistics on the wind turbines.

Additional turbine data that are not available from the USWTDB—such as power curves for operational profiles—were applied from data built into the SF modeling software described in Section 2.1.3.

The wind projects included in this analysis ranged from a 1.5-megawatt (MW) wind project with a single wind turbine to a 515 MW project with 222 turbines. The median project capacity and number of turbines were 180 MW and 87, respectively.

2.1.2. Receiver (residence) data

The residence location data were obtained from CoreLogic.[4] Data comprised all single-family homes, condominiums, duplexes, and apartments with complete addresses located within 2 km of one of the 61 wind projects. Initially, this yielded a sample of 46,175 receivers (i.e., residences).

A variety of quality control measures were used to verify the receiver location data, including removing duplicate location records, validating via an alternative source of location data, and visually inspecting using aerial imagery.[5] Of the total sample, we found 34,117 unique locations and 12,058 duplicates. Some of these duplicates were multi-family housing units, but most were determined to be inaccurately geocoded and grouped into centroids of subdivisions or blocks. The duplicated locations were evaluated for geospatial accuracy. We visually examined all locations with >100 receivers using satellite imagery ($n = 9$), as well as a random sample of 25 additional duplicate sites, and the 100 locations with the highest modeled SF using satellite imagery. We matched each receiver location to the nearest "building" location from Microsoft's open-source building footprint data [33], flagging any locations found to be more than 40 m from the nearest structure. If the flagged location was a survey receptor, it was visually inspected with satellite imagery and then relocated ($n = 157$). The remaining (non-survey respondent) receiver locations were removed from the analysis. We additionally removed excess duplicate receivers for locations with 10 or more records (keeping any survey respondents, if applicable). This process resulted in a final set of 34,940 receivers, which included the 747 survey respondents.

2.1.3. Modeled shadow flicker data

In this study, two aspects of SF were quantified—the annual number of SF hours (and daily SF minutes) at each home and their distributions

[4] See https://www.corelogic.com/find/property-data-solutions/ for more info on their data products.

[5] All survey respondents' residence locations were manually verified with aerial photography.

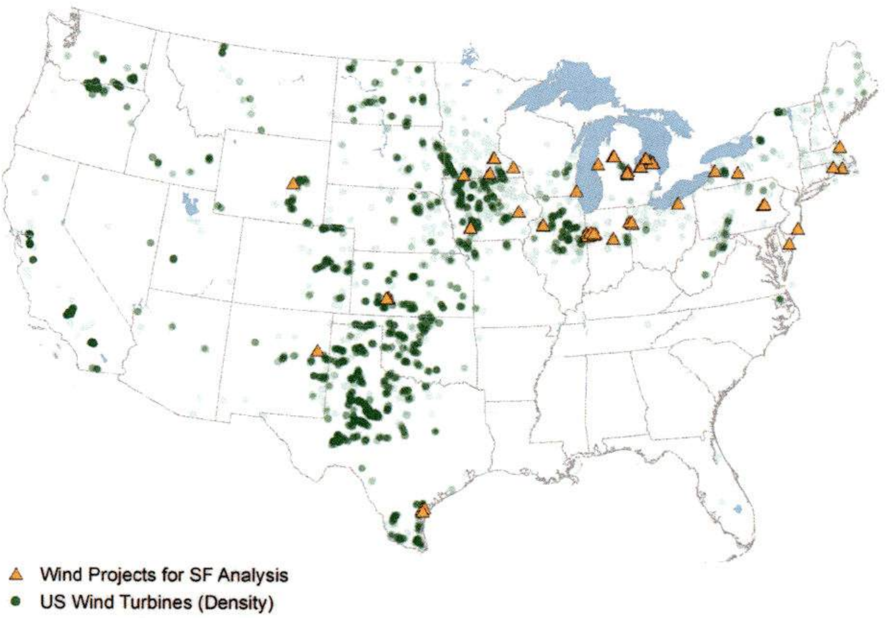


Fig. 1. Map of wind projects used for SF analysis.

Table 1
Descriptive statistics of all wind turbines included in the SF models ($n = 2982$ across 61 projects, not capacity weighted).

Metric	Minimum	Median	Maximum	Mean	Standard deviation
Hub height (m)	70	80	100	85.3	8.5
Rotor diameter (m)	77	83	117	89.3	10.1
Turbine capacity (MW)	1.5	1.65	2.5	1.8	0.3
# of turbines in project	1	87	222	48.9	52.1
Project size (MW)	1.5	180	515	87.0	96.3

by time of day and over the year. These were modeled using the SHADOW module in windPRO Version 3.3.

Predicting SF at residences surrounding a wind project is achieved through calculations of sun angles at different times of day and periods of a year at a given latitude; this is done while accounting for turbines' heights and intervening topography. This enables estimates of the maximum cumulative number of hours in a year (or hours per day) that a home will experience SF. SF can be modeled (and, for that matter, regulated) in terms of "real" or "worst" case. Worst case modeling is the astronomical maximum SF, assuming turbines are always operating (i.e., rotating) and there is no cloud cover. Real case modeling includes meteorology (e.g., cloud cover [34]), turbine operational factors (e.g., downtime), wind speed and direction [35], and potentially land cover [34], each of which can reduce worst-case levels. Real case modeling, therefore, results in fewer hours of calculated SF, all else being equal. We posit the real case model is a better approximation of actual conditions experienced by wind project neighbors, and therefore it is the metric we primarily use in the analysis.

The model outputs the periods of every SF event for each residence. Using these data, we estimated other parameters like maximum number of SF minutes in any day, as well as seasonality and time-of-day impacts.

The most SF occurs close to a wind turbine and (in the northern hemisphere) primarily to the northeast and northwest of a turbine, and to a lesser extent, to the north (Fig. 2A). When multiple turbines are between the sun and a home, a combination of SF from those turbines is possible (Fig. 2B). The farther one moves away from a turbine, the greater the decrease in SF intensity. At 15 rotor diameters from a wind turbine (roughly 1.3 km for the median turbine in this analysis) the SF intensity is diffuse enough that little observable light flicker occurs. Therefore, for this study, SF beyond that limit was not modeled.

Physical obstructions from structures and land cover such as trees or other vegetation were not included in the SF models. Although these objects can significantly reduce SF at a shadow receiver, reliable high-resolution data were not consistently available across the full set of modeling areas. To test the potential model impacts of land cover, though, six of the study's modeling areas—those which had survey respondent shadow receivers receiving high amounts of annual SF hours—were modeled again with the 30-m gridded 2011 National Land Cover [34] included. Most receivers were unaffected: 94% of receivers with modeled SF had the same annual SF hours for the land-cover and no-land-cover scenarios. Because we found most receivers were unaffected by land cover's inclusion, and because of the relatively coarse grid of obstructions, we did not otherwise include the effect of land cover in this study.

2.1.4. *Survey data*

Survey data were obtained from the LBNL Neighbor Survey [20]. This survey asked respondents 50 questions about their experience living in proximity to existing utility-scale wind energy projects. Details on that survey's methods, including sample selection, the survey instrument, and multimodal (phone, mail, internet) data collection, are reported at length elsewhere [6,10,22,23], and therefore are only briefly discussed here.

The survey frame encompassed all US residences within 8 km of any utility-scale wind turbine ($\geq$1.5 MW in nameplate capacity) constructed through the end of 2015. This resulted in a population of 1.29 million residences around 604 wind projects, comprising 29,848 individual turbines. To ensure an adequate sample of residents most likely to experience SF and other impacts, the sample was stratified and some oversampling was conducted—most notably among residences closest to turbines (<1.6 km). Oversampling also occurred at 15 wind project sites (representing a diversity of turbine models, geographies, project sizes, population densities, and topographies) where sound modeling was initially planned; these sites also formed the basis for the present SF analysis. After data collection, we selected 15 additional wind project sites for a total of 30 sites, that included 61 wind projects, which were used for the corresponding sound modeling analysis [10] and this SF analysis.

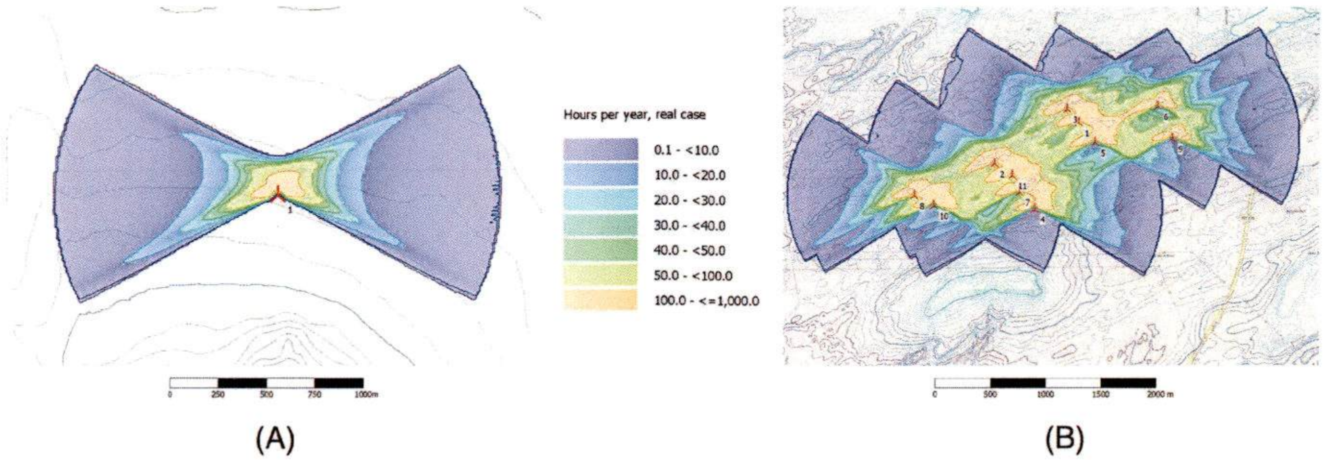


Fig. 2. Example of annual SF hours around (A) a single wind turbine and (B) a string of wind turbines.

Survey data collection occurred in 2016. Ultimately, a total of 1705 valid responses were received from residents living within 8 km of 250 US wind projects, with the majority (1121) of respondents living within 1.6 km of a turbine. For this study, SF exposure was modeled for a total of 747 survey respondents living within 2 km of 61 wind projects.

The survey data provided basic demographic data (e.g., age, sex, education level) and data about respondents' potential relationship with the local wind project (e.g., whether they received compensation), and self-reported data on perceived SF and level of SF annoyance.

For perceived SF, respondents were asked if "the blades of a wind turbine ever cast a shadow on your property, outside your home?" An affirmative answer to this question triggered the follow-up of "Do the blades of a wind turbine ever cast a shadow in your home?" We use the latter response as our dependent variable, for several reasons. First, SF is regulated at homes. Second, a home is a single point rather than a large area. Finally, most human exposure is in or around a home.

To determine SF annoyance, respondents were asked: "To what extent do you feel annoyed by the following effects of the local wind project?" Where "shadow flicker" was listed as an option, they could respond "Not at all," "Slightly," "Somewhat," "Moderately," "Very," or "Don't Know."

2.1.5. *Shadow flicker ordinance data*

Wind energy siting ordinances were collected and reviewed for all 50 US counties represented in this analysis. From these ordinances, we collected data on whether SF exposure was regulated, and if so, what the SF limit was, what metric was used (i.e., real or worst case, hours per year or minutes per day), and what location(s) the limit applied to (e.g., "non-participating dwelling"). These data were used to contextualize our discussion around SF exposure.

2.2. *Analysis methods*

This section describes the analysis methods. We briefly discuss the perceived SF and SF annoyance (dependent variable) response categories and the regression models used to validate and predict them with a variety of covariates (i.e., controlling variables).

2.2.1. *Dependent variable categories*

Two dependent variables are considered in the regression model analysis: perceived SF and SF annoyance.[6] These were created by combining responses from the survey (Section 2.1.4) and modeled annual real-case SF exposure (Section 2.1.3) to represent a dose-response relationship of perceived SF and SF annoyance. The response groups for perceived SF include "no perceived SF in home" and "perceived SF in home." The former includes two survey response levels: "no perceived SF" and "perceived SF on property but not in home." For SF annoyance, the respondents were categorized as "not," "mildly," or "very" annoyed. "Mildly" annoyed includes the three survey response levels: "slightly," "somewhat," and "moderately."

2.2.2. *Regression models*

To examine the relationships between various covariates and the dependent variable (perceived SF and SF annoyance, with perceived SF ["PSF"] used in this example), we assume the following relationship:

$$PSF_i = f(\text{modeled SF, respondent characteristics, wind project characteristics}) \tag{1}$$

Specifically, we estimate the following basic logistic regression model.[7]

$$PSF_i = \alpha + \beta_1(MSF_i) + \sum_a \beta_2(R_i) + \sum_a \beta_3(WP_i) + \varepsilon_i \tag{2}$$

where:

PSF_i represents perceived SF in the home for respondent I (binary yes/no).

α is the constant or intercept across the full sample.

MSF_i is the modeled SF for respondent i, (hours/year real case).

R_i is a vector of characteristics for respondent i, including their age, gender, if they attended college, and if they received compensation from the wind project.

WP_i is a vector of characteristics of the nearby wind project for respondent i, including the size of the project, the distance the nearest turbine was from the respondent, and if it was oversampled for the survey or not.[8]

ε_i is a random disturbance term for respondent i.

[6] For a survey respondent to be included in both models, their homes must have had at least 1 min per year of worst case (astronomical) SF. In addition, for the annoyance model, only those who reported observing SF in their home were included.

[7] R: A language and environment for statistical computing (Version 4.0.2) was used for the statistical analysis herein. https://www.R-project.org/.

[8] The two categories of oversampling are dominant or discrete. The former refers to under-sampling because the project was located in a high population area, while the latter refers to oversampling because it was the focus of additional detailed analyses (like this study).

Table 2
Regression model variable summary.

Group	Variable	Model*	Data type†	Sample mean or percentage** (SD)			Description, including categories (where applicable)††
				Survey sample (n = 717)‡	Perceived SF model (n = 328)	SF annoyance model (n = 283)	
Dependent variables	Perceived SF	B, O, S	C	65/31/4	44/56	16/84	No SF in home/SF in home/Unknown (where applicable)
	SF annoyance	B, O, S	C	15/13/10/62	27/23/17/33	41/34/25	Not at all/Mildly/Very/Unknown or Other (where applicable)
Stratification	Distance bin	B, O, S	C	57/39/5‡‡	77/23	88/12	Distance from nearest turbine: **0–0.8 km**/0.8–1.6 km/1.6 to 4.8 km‡‡
	Large project	B, O, S	B	61%	76%	78%	**<10 turbines (0)**, >10 turbines (1)
Controlling	College	B, O, S	B	44%	41%	42%	**No college degree (0)**, College degree (1)
	Female	B, O, S	B	56%	56%	54%	**Not female (0)**, Female (1)
	Age	B, O, S	N	56 (14.9)	57.7 (15.2)	57.8 (13.7)	Respondent age (years)
Relationship	Project participation	B, O, S	C	74/16/6/4	64/25/10	56/30/13	**Non-participant**/Compensated (not host)/Host and Compensated
Stimulus	SF	B, O, S	N	6.1 (9.9)	11.1 (11.3)	13.0 (12.1)	Real-case SF hours per year
Turbine	Rotor diameter	O, S	N	90.3 (8.7)	92 (8.8)	91.9 (8.5)	Nearest turbine rotor diameter (meters)
	Hub height	O, S	N	86.6 (9.2)	88.4 (9.5)	89.1 (9.5)	Nearest turbine hub height (meters)
	Tip speed	O, S	N	76.5 (6.5)	77.2 (6.7)	76.9 (6.8)	Velocity of tip of wind turbine blade at rated RPM (m/s)
	Project age	O, S	N	5.2 (1.7)	4.8 (1.3)	4.8 (1.3)	Project age in years at time of survey (2016)***
Individual	Turbines in view	O, S	N	19.3 (39.4)	26.5 (42.8)	28.3 (42.3)	Number of turbines in view from residence and property
	Move in after project	O, S	B	20%	20%	15%	**No (0)**, Yes (1)
Personal	Like look (visual)	S	C	12/24/60/3	11/29/60	10/34/56	**Neutral**/No/Yes/Unknown (where applicable)
	General annoyance	S	N	0.55 (0.72)	0.47 (0.66)	0.45 (0.64)	Average annoyance to typical community stressors†††

* Models in which variables are included: "B" = Basic, "O" = Observable, "S" = Subjective.
† Data Types: "B" = Binary, "C" = Categorical, "N" = Numerical.
‡ Not all survey sample variables have 717 valid responses, but missing entries are de minimus to the means presented.
** Distribution (%) of each response category is provided for each categorical ("C") variable, or percent "Yes" for binary variables. Standard deviation ("SD") provided in parentheses following the mean, where applicable.
†† Bolded values indicate the omitted reference level to which other categories are compared. Some categories are populated in one sample (e.g., survey) and not in others (e.g., annoyance model), therefore percentages are only shown where applicable.
‡‡ Distance bin of 1.6 to 4.8 km not represented in the regression models.
*** Newest project in sample was built in 2012, and thus minimum age is 4 years.
††† "Not at all annoyed" (0) to "Very annoyed" (4) by "Motor vehicle traffic, including cars and trucks," "Street lights," "Agricultural machinery," and "Lawnmowers, snow or leaf blowers."

The model is then repeated using SF annoyance (i.e., SFA_i) as the dependent variable. In either case, the vector of parameter estimates β_1, β_2, and β_3 are used to determine the odds ratio of each variable, calculated as e^{β}. The odds ratio signifies that a one-unit change in a covariate will lead to a decrease (values between 0 and <1) or an increase (values > 1) in the likelihood that a respondent will move to the next response level. For example, for perceived SF, it might indicate a change from not perceiving SF in their home to perceiving SF in their home, or for SF annoyance, from being "not" to "mildly" annoyed or "mildly" to "very" annoyed. When the range of the odds ratio's 95% confidence interval (CI) is completely less than one (representing lower odds of moving to the next response level) or completely greater than one (representing higher odds of moving to the next response level), the variable is considered a significant predictor; this is equivalent to the standard method of assigning variable significance for variables with a p-value of <0.05.

Because the units of the various covariates differ, we analyze the strength of the correlations via the Akaike information criterion (AIC). The AIC represents the impact on the model fit when it is removed from the regression. A higher AIC value indicates a stronger relationship between the covariate and the dependent variable.

The overall fit of the model is measured using Nagelkerke's R^2 ($R_N{}^2$), which is a "pseudo-R^2" used as an index of overall model quality [36]. It is calculated as a measure of the improvement of the log likelihood of the model compared to that of a null model. To ensure the independence of the variables included in each model, multi-collinearity is assessed with the variance inflation factor (VIF) [37]; the maximum VIF for each model is reported with the results in Section 3.3. Typically, a VIF above four warrants further investigation into the collinearity among model variables.

To indicate the efficacy of each model in predicting responses, the proportion of responses that the regression model correctly predicts is determined using a "leave-one-out cross validation" procedure. For each sample, the regression model is calculated without one respondent. Then, using the model's results, we predict the missing response (either PSF_i or SFA_i), repeating for each respondent, and compare those predicted results to those of the respondents.

Three parallel models for each dependent variable are estimated, each with progressively more covariates: Basic, Observable, and Subjective. These covariates are shown in Table 2, and are grouped into functional classification groups. Column 3 denotes which of the three models the covariates are used in. The Basic model ("B") contains all stratification, controlling, relationship, and stimulus variables. The Observable model ("O") adds wind turbine and project characteristics covariates specific to each individual respondent (i.e., objective variables). The Subjective model ("S") expands the scope of covariates to personal variables, including the degree to which respondents liked the look of the nearby wind project, and their general annoyance to community nuisances. In addition to the model and covariate distribution, Table 2 also contains summary statistics for the covariates, means for continuous variables, and percentages for categorical variables.

3. Results and discussion

3.1. Population exposure to shadow flicker

This research utilized a large population with modeled SF and a robust sample of those that perceive SF across a wide range of modeled SF hours.

3.1.1. Full sample population

Fig. 3 shows the number of receivers (homes) in our sample with (dark grey) and without (orange) modeled SF as a function of distance to the nearest wind turbine. The total number of residences in the sample increases with increasing distance from the nearest turbine. The total *number* of residences with any modeled SF (grey bars) peaks near 1000 m to the nearest turbine because modeled SF fades considerably beyond that distance.[9] The proportion of the sample population with modeled SF (green line) is highest at distances closest to the turbine. Greater than 50% of the sample residences within 550 m of the nearest turbine have some modeled SF hours.

3.1.2. Sample with modeled shadow flicker

Fig. 4 includes only those receivers with modeled SF. It shows the different levels of modeled SF hours per year by distance from the nearest turbine producing SF. (Note that this may differ from the "nearest turbine" as used in Fig. 3). It also includes the percentage of the sample that has >8 h/year real-case SF (blue line)—a maximum limit used in some SF standards (see discussion in Section 1.3). A majority of residences within 750 m were modeled with real case SF exposure above 8 h per year. Within 500 m, 90% have more than 8 h of modeled real case annual SF.

3.2. Survey respondent shadow flicker summary

This section presents survey responses used to build perceived SF and SF annoyance categories and compares them to modeled annual SF exposure.

3.2.1. Perceived shadow flicker

Fig. 5 presents the distribution of perceived SF among survey respondents. Each bar represents the proportion of respondents in each response group and modeled SF exposure category. The width of each bar is proportional to the sample size in that category.

Fig. 5A provides the full survey sample of SF receivers, while Fig. 5B presents only those with some modeled SF exposure. Both include three respondent categories: perceived SF in home, perceived SF on property, and no perceived SF. The proportion of respondents that notice SF in their homes increases as the number of annual hours increase. This is expected, as the more SF a home is modeled to have, the more likely it is that the resident will report perceiving SF in their home. For individuals with some modeled SF (>0) at their home, roughly 15% report that they can perceive SF only on their property but not in their home (shown in Fig. 5 as "On Property"). This percentage is consistent regardless of SF exposure levels.

Of those that have modeled SF in the range of 4 to 8 h/year real case, only about half (52%) reported perceiving SF in their home. We believe that this disparity is due to other factors that are not considered in this study that mitigate SF exposure, particularly land cover, the use of rooms that may be exposed to the SF, whether windows face the wind turbines, draperies and other window covers, and whether the occupants are home during the SF events.

3.2.2. Shadow flicker annoyance

Fig. 6 presents parallel results for reported annoyance to SF. Fig. 6A appears to indicate that the distribution of SF annoyance increases with SF exposure across all respondents. However, it is notable that roughly half of the respondents in the figure had no modeled SF exposure (and thus cannot be annoyed by SF in their home). When limited to only respondents with some modeled SF (Fig. 6B), the distributions between annoyance levels do not vary appreciably across exposure levels. This suggests two things: 1) the apparent increase in SF annoyance for all respondents is driven by the inclusion of the do-not-perceive-SF-in-their-home category; and 2) there is an insignificant relationship between modeled SF and SF annoyance in the sample once they are excluded. This was tested directly and is described in Section 3.3.

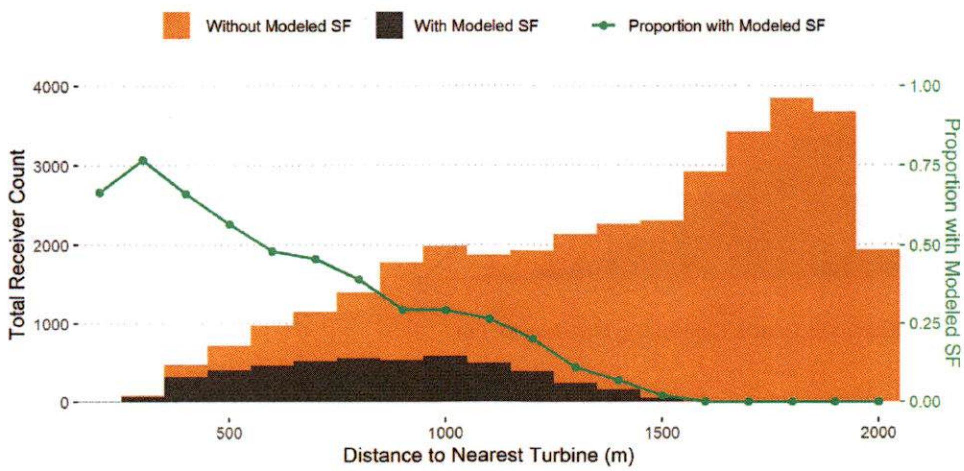


Fig. 3. Distribution of modeled SF by distance[a] within the full population sample ($n = 34,940$). The green line indicates the proportion of the sample population with modeled SF for each distance group. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
[a]Receivers are binned into 100 m groups, centered on the interval (e.g., the 500 m bin is 450 m to 550 m).

3.2.3. Distribution of responses, by exposure

To directly compare SF exposure to perceived SF and SF annoyance, Fig. 7 shows box plots representing all survey respondents. The "box" provides the 75th, 50th (median [dark line]), and 25th percentile of the

[9] The decrease in "without modeled SF" beyond 1,900 m for Figs. 3 and 4 is a result of not modeling SF beyond distances 15 times total turbine height (see Section 2.1.3).

distribution of the sample. The "tails" on the boxes represent the range of 95% of the data. The plot reaffirms that the prevalence of perceived SF in one's home increases with modeled SF exposure. However, the number of modeled SF hours alone is insufficient to explain reported SF annoyance among survey respondents.

3.3. Regression results

The results from the three (Basic, Observable, and Subjective) logistic regression (logit) models for perceived SF and SF annoyance, as described in Section 2.2.2 and Table 2, are presented in Table 3 and Table 4.[10]

3.3.1. Perceived shadow flicker

The basic perceived SF model (Table 3) correctly predicted perceived SF for 68% (see "Total Proportion Correct") of respondents, with an R_N^2 of 0.32. With the Observable model, the predictive power of the model improves, with 71% of responses correctly predicted and an increase of R_N^2 to 0.38. Although adding subjective variables slightly improved the R_N^2 to 0.41, the predictive power of the model decreased (though insignificantly) to 70%. This suggests that perceived SF prediction is not significantly improved over the Observable model by adding subjective variables. All models correctly predicted at least 75% of the respondents that perceived SF in their home (see the green bordered portions of the bar graphs at the top of Table 3) and about 60% of respondents that did not perceive SF in their home.

Turning to the regression results, the real-case annual SF hours is the strongest predictor of perceived SF, with an AIC about four times greater than the next covariate (22.6 vs. 7.6). Across all three models, a one-hour increase in annual real-case wind turbine SF is associated with an increase in the odds of perceiving SF in the home by 12% to 13%. Logically, quantifiable SF exposure should be a good predictor of whether a respondent perceives SF or not. The model indicates that, indeed, a significant dose-response relationship is present. Further, respondents farther than 800 m (~0.5 miles) from the nearest wind turbine had 65% to 66% lower odds of perceiving SF than respondents within 800 m (see the Distance Bin variable in Table 3). The odds of perceiving SF in one's home were at least 75% lower for those who moved into the area after the project was built compared with those who lived in the area prior to the project's construction (see the move-in-after variable in Table 3). Project participation did not significantly contribute to the prediction of perceived SF in one's home.

3.3.2. Shadow flicker annoyance

The SF annoyance results (Table 4) differ substantially from those of perceived SF. For SF annoyance, the Basic and Observable models are relatively weak predictive models, with $R_N^2 < 0.27$ and less than 49% of the total responses correctly predicted. Adding subjective variables considerably increases the model's effectiveness, increasing R_N^2 to 0.58 and correctly predicting 65% of the responses overall.

In the Basic SF annoyance model, respondent participation in the project is the most influential predictor (AIC = 25.1); participants had about 81% lower odds of being annoyed by SF than non-participants. Annoyance was comparable among project participants that hosted wind turbines on their properties and those that were compensated without hosting a turbine, relative to non-participants. After project participation, a respondent's college education (AIC = 6.6) was the strongest predictor of SF annoyance; respondents who had completed college had 57% lower odds of moving to a higher annoyance level than those that did not attend college. Modeled SF exposure was the third-strongest correlate: a one-hour annual increase in real case SF was associated with a 4% increase in the odds of SF annoyance. Age (AIC = 6.0) was the fourth-strongest predictor in the Basic model, with decreased odds of SF annoyance among older respondents.

Adding objective variables did not increase predictive strength of the model (see "Observable" model). In fact, none of the observable vari-

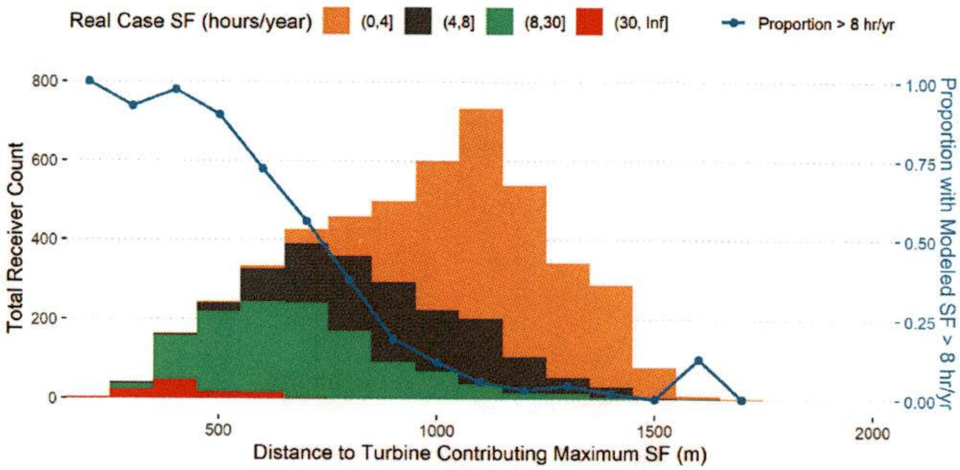


Fig. 4. Modeled real-case SF hours per year bins,[a] by distance[b] from the nearest flicker-producing turbine for receivers with some modeled SF ($n = 4825$). The blue line indicates the proportion over 8 h/year.[c] (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
[a]SF ranges are open ("(") on the left and closed ("]") on the right, i.e., (4, 8] is $4 < x \leq 8$.
[b]Receivers are binned into 100 m groups, centered on the interval (e.g., the 500 m bin is 450 m to 550 m).
[c]The decrease in "without modeled SF" beyond 1,900 meters is a result of not modeling SF beyond distances 15 times total turbine height (see Section 2.1.3). The small increase in SF level for respondents at 1,600 m is due to a small sample size (n = 8); one of these receivers had three distinct wind turbines contributing SF annually. Of the three wind turbines, the farthest turbine at 1,620 meters contributed the most SF; the other two turbines contributing SF were within 800 meters of the receiver.

[10] Although we present multivariate correlation results in the regression tables, we did examine univariate correlations as well. Contact the authors for more information on those.

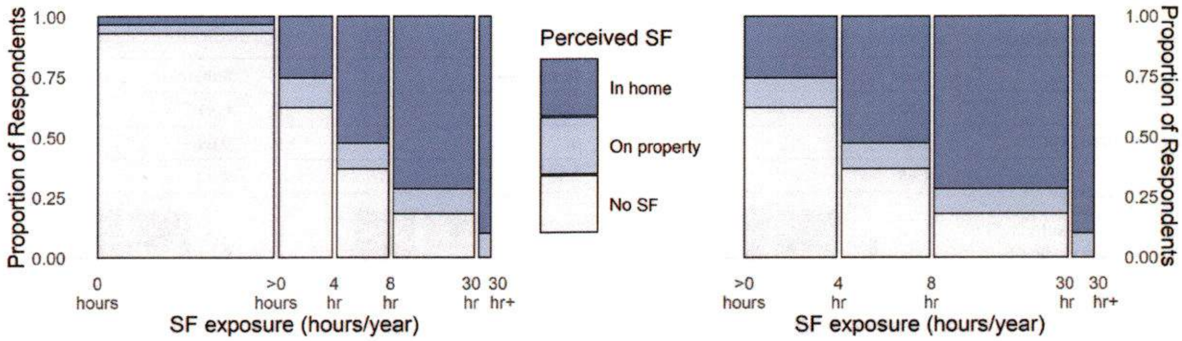


Fig. 5. Distribution of perceived flicker by real-case SF for (A) all respondents ($n = 717$) and (B) only respondents with modeled SF ($n = 393$).

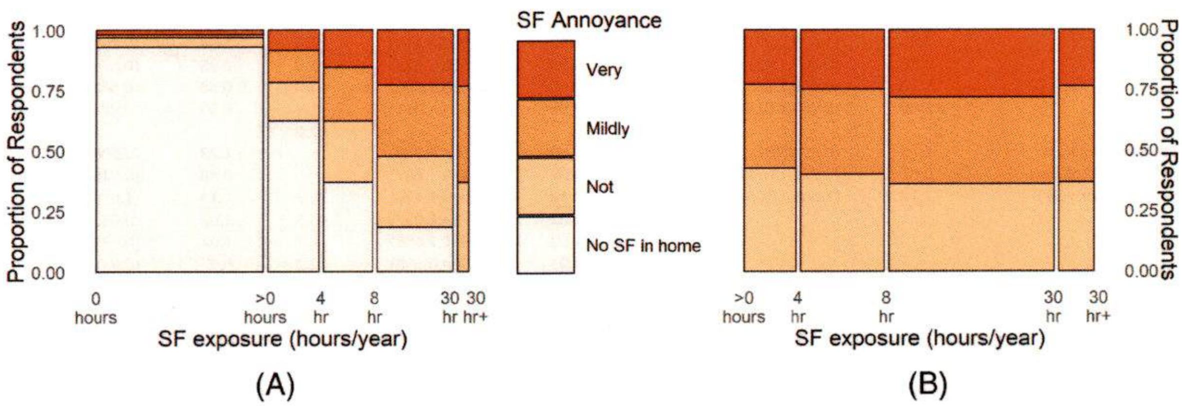


Fig. 6. Distribution of SF annoyance by Real Case SF for (A) all respondents ($n = 717$) and (B) only respondents with modeled SF ($n = 260$).

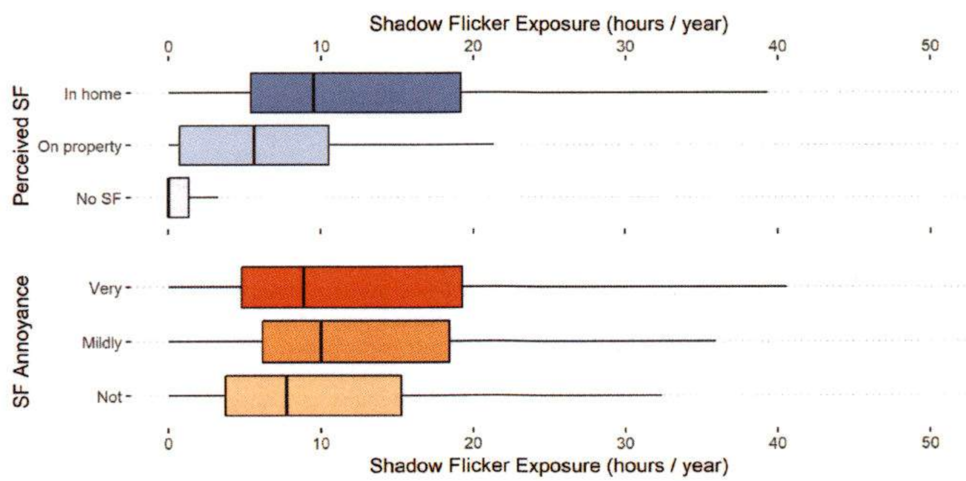
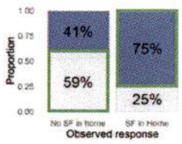
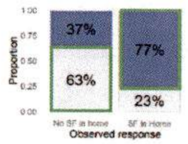
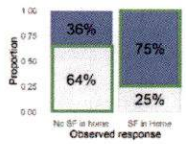


Fig. 7. Box plots of SF exposure by respondent reported perceived SF and SF annoyance (perceived SF: n = 717; SF annoyance: n = 260).

ables were significant in predicting SF annoyance. In contrast, all Subjective model variables were significant in predicting the SF annoyance outcomes. The respondents' stated attitudes toward the aesthetics of the

Table 3
Perceived SF regression results.

($n = 328$)	Basic			Observable			Subjective		
Nagelkerke R^2	0.32			0.38			0.41		
Area under the curve (AUC)	0.67			0.7			0.69		
Maximum VIF	1.85			2.13			2.92		
Leave-one-out Cross validation results Proportion correctly predicted SF in Home No SF in home									
Total proportion correct	0.68			0.71			0.70		
Variable	OR[†]	(95% CI)	ΔAIC	OR[†]	(95% CI)	ΔAIC	OR[†]	(95% CI)	ΔAIC
Distance bin	**0.35**	(0.178,0.678)	7.6	**0.35**	(0.171,0.699)	6.7	**0.34**	(0.167,0.699)	6.6
Large project	2.30	(1.039,5.07)	2.2	2.22	(0.907,5.414)	1.1	1.98	(0.795,4.93)	0.2
College	0.86	(0.507,1.47)	−1.7	0.93	(0.533,1.629)	−1.9	0.95	(0.536,1.667)	−2.0
Female	1.10	(0.655,1.848)	−1.9	1.05	(0.605,1.806)	−2.0	0.98	(0.563,1.716)	−2.0
Age	1.00	(0.983,1.018)	−2.0	0.99	(0.974,1.011)	−1.4	0.99	(0.974,1.012)	−1.5
Project participation[*],[a]			−3.0			−3.0			−3.5
- Compensated: not a host	1.12	(0.59,2.13)		0.99	(0.501,1.962)		1.23	(0.606,2.501)	
- Compensated: turbine host	0.67	(0.271,1.671)		0.62	(0.235,1.627)		0.88	(0.318,2.409)	
SF (real case, hours per year)	**1.12**	(1.068,1.165)	22.6	**1.13**	(1.078,1.179)	25.7	**1.13**	(1.076,1.18)	23.9
Rotor diameter				1.02	(0.984,1.057)	−0.8	1.02	(0.985,1.061)	−0.7
Hub height				1.02	(0.991,1.056)	−0.1	1.02	(0.984,1.049)	−1.1
Tip speed				0.95	(0.904,0.998)	2.2	0.95	(0.9,0.998)	2.1
Project age				1.19	(0.901,1.569)	−0.5	1.21	(0.906,1.608)	−0.4
# of turbines in view				1.00	(0.996,1.012)	−1.0	1.00	(0.995,1.011)	−1.5
Move in after				**0.23**	(0.106,0.51)	11.2	**0.25**	(0.112,0.563)	9.3
Like look of wind project (neutral)[a]									4.6
- No							2.65	(0.944,7.417)	
- Yes							0.99	(0.388,2.511)	
General annoyance							0.93	(0.618,1.404)	−1.9

[*] Compared to those that are not hosting nor being compensated.
[a] ΔAIC represents the importance of the variable as a whole.
[†] Odds ratio (OR). Bolded and underlined values indicate a significance at $p < 0.05$.

local wind project (i.e., if they did or did not like the look of it vs. a neutral response) was by far the strongest correlate (AIC = 62.3).[11] The respondents' general annoyance to environmental nuisances (AIC = 9.7), if they attended college (AIC = 9.2), their age (AIC = 6.9), the age of the nearest wind project (AIC = 4.3), and if the respondent was compensated but not a host were all statistically significant. With subjective variables considered, modeled SF exposure was not a statistically significant predictor of SF annoyance. The Subjective model correctly predicted 65% of annoyance levels overall, 73% of the very annoyed responses, and 79% of not-at-all-annoyed responses.

Moving in after the project was built was found to be a strong predictor of perceived SF in this study and in previous literature for: attitudes toward wind projects [23]; perceptions of the planning process [6]; and both the audibility of wind turbine noise in the home and wind turbine noise annoyance [10]. However, we found moving in after a project was built was not significantly correlated with SF annoyance.

In summary, although this study found a strong relationship between modeled SF exposure and perceived SF reported by survey respondents, the relationship between SF exposure and SF annoyance is much weaker, indicating other factors are likely at play that cause annoyance.[12]

3.4. Exposure to shadow flicker compared with existing guidelines and sound levels

The combined survey data, SF exposure data, and data on US county-level SF exposure limits allow us to examine other relationships. We first calculate a ratio between worst and real-case SF estimates and compare that to the 3:1 ratio commonly used in EU SF standards (see Section 1.3). We then assess modeled exposure against the most commonly enforced SF limits in our sample (see Section 2.1.5) and examine them relative to project participation. Finally, we look at the relationship between SF exposure and sound exposure by comparing SF exposure categories and modeled sound-level categories.

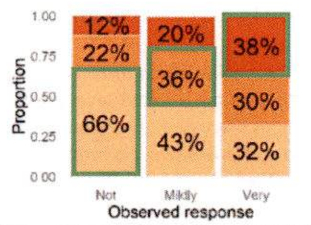
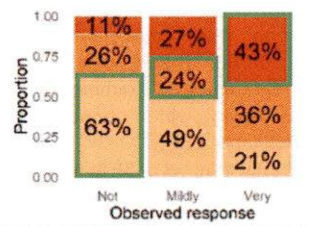
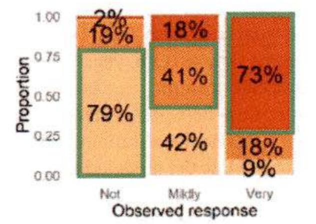
3.4.1. US state- and county-level shadow flicker ordinances

The data from wind energy siting ordinances for all 50 US counties represented in this analysis were revealing: most counties in this analysis (62%) do not enforce any limit on SF exposure. Two states (New York and Ohio) have enacted statewide SF limits (30 h/year), and only 13 other county-level ordinances were identified (10 at 30 h/year, 2 at 0 h/year, and 1 at 40 h/year). Of the 15 authorities that do specify any limit on SF exposure, 30 h/year was by far the most common limit.

[11] Although not discussed here in detail, liking the look of the turbines was nuanced among respondents. Those who did like the look did not believe the turbines were "attractive" but did feel they represented "progress." Alternatively, those that did not like the look believed they "did not fit" with the landscape and were "unattractive".

[12] One reviewer pointed out that perceptions of the planning process have been found to be a strong predictor of wind turbine annoyance [6] and strongly annoyed individuals [21]. As noted later in the document, this might be a useful variable to study in future analyses.

Table 4
SF annoyance regression results.

(n = 220)	Basic			Observable			Subjective		
Nagelkerke R^2	0.23			0.27			0.58		
Area under the curve (AUC)	0.63			0.66			0.8		
Maximum VIF	1.85			2.07			2.73		
Leave-one-out Cross validation results Proportion correctly predicted 									
Total Proportion Correct	0.49			0.45			0.65		
Variable	**OR**†	**(95% CI)**	**ΔAIC**	**OR**†	**(95% CI)**	**ΔAIC**	**OR**†	**(95% CI)**	**ΔAIC**
Distance bin	0.51	(0.214,1.235)	0.2	0.57	(0.227,1.45)	−0.6	0.39	(0.14,1.091)	1.2
Large project	1.26	(0.54,2.946)	−1.7	1.29	(0.519,3.207)	−1.7	0.95	(0.329,2.767)	−2.0
College	**0.43**	(0.245,0.755)	6.6	**0.42**	(0.232,0.745)	6.7	**0.33**	(0.171,0.632)	9.2
Female	1.55	(0.906,2.648)	0.6	1.56	(0.899,2.72)	0.5	1.58	(0.853,2.92)	0.1
Age	**0.97**	(0.951,0.991)	6.0	**0.97**	(0.945,0.988)	7.4	**0.96**	(0.939,0.987)	6.9
Project participation (non-part.)*, a			25.1			23			1.4
- Compensated: not a host	**0.19**	(0.097,0.374)		**0.19**	(0.093,0.377)		**0.39**	(0.177,0.869)	
- Compensated: turbine host	**0.18**	(0.073,0.42)		**0.17**	(0.067,0.425)		0.55	(0.196,1.565)	
SF (real case, hours per year)	**1.04**	(1.011,1.062)	6.2	**1.04**	(1.009,1.062)	5.0	1.03	(0.995,1.055)	0.5
Rotor diameter				0.98	(0.944,1.018)	−1.0	0.99	(0.943,1.03)	−1.4
Hub height				1.02	(0.986,1.051)	−0.8	0.99	(0.953,1.024)	−1.6
Tip speed				0.98	(0.936,1.029)	−1.4	0.96	(0.907,1.017)	−0.3
Project age				0.78	(0.585,1.038)	0.9	**0.65**	(0.467,0.916)	4.3
# of turbines in view				1.00	(0.995,1.008)	−1.8	1.00	(0.997,1.011)	−0.8
Move in after				0.53	(0.24,1.189)	0.4	0.60	(0.239,1.524)	−0.9
Like look of wind project (neutral)a									62.3
- No							**10.88**	(3.273,36.158)	
- Yes							**0.32**	(0.108,0.953)	
General annoyance							**2.39**	(1.45,3.945)	9.7

* Compared to those that are not hosting nor being compensated.
[a] ΔAIC represents the importance of the variable as a whole.
† Odds Ratio (OR). Bolded and underlined values indicate a significance at $p < 0.05$.

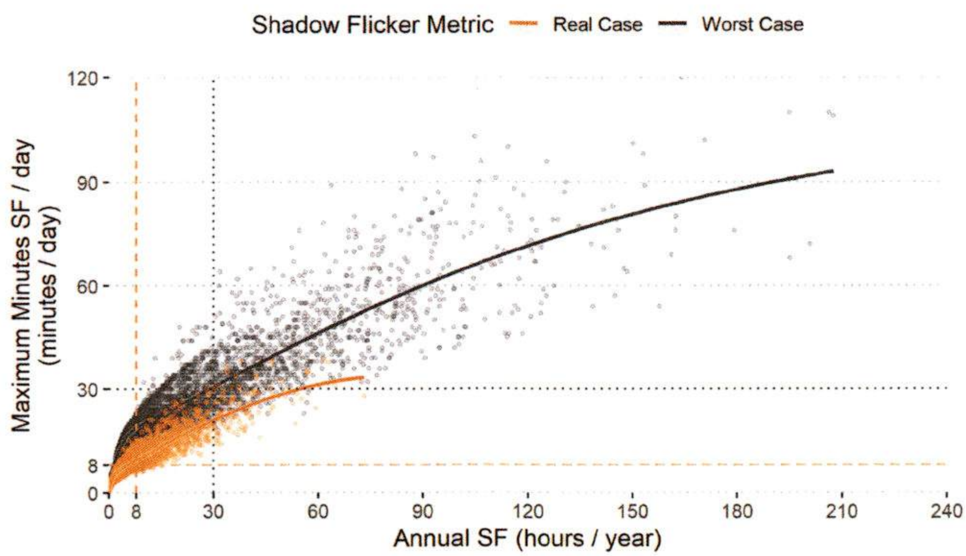


Fig. 8. Comparison of modeled SF exposure metrics for the sample population with modeled SF (n = 4,825).

Notably, only two of those regions specify a modeling metric (real or worst). In the authors' experience, where there is ambiguity as to the metric, in most circumstances the 30 h/year limit is modeled during permitting as real case.

3.4.2. *Real vs. worst-case ratio and modeled exposure*

As described in Section 1.3, Koppen et al. [24], document a common three-to-one ratio between worst and real case SF guidelines. That is, a 30 h/year real-case limit would allow about three times more SF exposure than a 30 h/year worst-case limit. In this section, we test if those relationships were borne out in our data and also examine the relationship between hours/year and minutes/day, which are sometimes apparently used interchangeably in regulations [24].

Fig. 8 plots the modeled maximum number of minutes of SF in a day against the annual SF hours for each respondent with any modeled SF in our sample population ($n = 4825$). Both the real case (orange) and worst case (dark grey) modeled values are provided, and a trendline fitted to the data is superimposed over the scattered data. Horizontal dotted lines denote 30 and 8 min/day, and, separately, vertical lines denote 30 and 8 h/year. These dotted lines nearly intersect on the solid trendlines of the scattered worst and real case modeled SF values. This indicates that a ratio of 30 worst case hours/year is roughly equivalent in our data to the 30 worst case minutes/day, as is 8 real case hours/year and 8 min/day. Further, the ratio in our data of worst to real case is roughly three to one ($r^2 = 0.93$), which is equivalent to the German guidelines and others outlined by Koppen et al. [24].

The data from Fig. 8 also indicate that approximately 7% of all modeled residences in the sample population (including both survey respondents and non-respondents) exceed either 30 h/year worst case or 8 h/year real case (the "30/8 limit"). Although we do not show distance in the figure, the data indicate that 21% of residences within 1 km of *any turbine* exceed the 30/8 limit. As discussed in Section 3.4.1, the majority of counties in our sample do not apply SF exposure limits, and those that do fail to specify whether those limits are real or worst case limits. Fig. 8 elucidates that if those limits were in force, compliance would not be achieved at many residences. However, we found that only 2.3% of those with modeled SF exceeded 30 h/year real case. This supports our interpretation that real case is used with 30 h/year standards where the metric is ambiguous.

3.4.3. *Survey respondent exposure summary*

Considering the sample of survey respondents ($n = 717$), 27% exceed the 30/8 limits. This percentage is above the 7% of the full sample population discussed in Section 3.4.2 because the respondents are, by design, closer to turbines than the general population and have a higher preponderance of exceeding the limits. Considering the 404 survey respondents with *any* modeled SF, 50% exceeded either of the 30/8 limits, with 37% exceeding both.

Individuals living closest to wind turbines are also likely to host a turbine or are otherwise being compensated, which could accommodate higher levels of SF as part of that agreement. Table 5 shows that at least 70% of the turbine hosts experience SF above either limit, 55% or more of the compensated neighbors exceed the limits, and at least 34% of the non-participants have modeled SF that are above both limits.

Importantly, in line with the findings above, the group that exceeds the 30/8 limits is no more likely to be annoyed by SF than respondents who are under the limit.

Table 5
SF exposure in the United States above the "30/8 limit" with respect to project participation for survey respondents with modeled SF.

Project participation	Above 8 hours per year real case	Above 30 hours per year worst case	*n*
Non-participants	37%	34%	249
Compensated	60%	55%	92
Turbine host	73%	71%	41

3.4.4. *Combined wind turbine noise and shadow flicker exposure*

We examine if sound-level limits can be used as a proxy for SF limits, which, as discussed in Section 3.4.1, are rarely applied. Noise exposure, for our purposes here, is modeled as a one-hour equivalent continuous A-weighted sound level (L_{1h}).[13] In the US jurisdictions we reviewed, 45 dBA and 50 dBA are commonly applied noise limits (or greater for participating homes), although metrics and averaging times vary considerably.

Fig. 9 shows the proportion of the population in real-case SF categories with respect to wind turbine sound-level categories. For homes with modeled wind turbine sound level 40 dBA or below, 98% do not exceed the 8-hour real-case SF limit, while between 40 and 45 dBA, 90% do not exceed the limit. Alternatively, for those between 45 and 50 dBA or greater than 50 dBA, only 40% and 25% are below the 8-hour real-case SF limit, respectively. These results indicate that a sound limit of 45 dBA is a decent proxy for meeting a SF limit of 8 h/year real case. Paradoxically, low SF exposure limits are not a good a predictor of low noise exposure, as very low (or no) SF occurs across all sound-level categories.

The relationships are different for SF annoyance. Fig. 10 shows the distribution of respondent SF annoyance by turbine sound-level category. Fig. 10A appears to show a relationship between SF annoyance and sound level. Higher proportions of respondents exposed to sound at progressively higher sound levels reported some level of SF annoyance at higher rates. However, as outlined in Section 2.1.4, only those experiencing SF in their home can be annoyed by it in their home. Considering that cohort, we find the absence of a correlation between sound level and SF annoyance: SF annoyance levels are roughly equally distributed across sound-level categories (Fig. 10B). The survey data also indicate that noise and SF annoyance are similar among survey respondents: 71% of those very annoyed by SF ($n = 72$) indicated that they are also very annoyed by noise from the wind turbines (data not shown).

4. Conclusions

Although SF has been identified in multiple national surveys as a potential source of annoyance among wind project neighbors, the magnitude of SF exposure and drivers of SF annoyance have remained significantly understudied, leaving both developers and communities in need of science-based guidance. To help fill that research gap, this study modeled SF exposure at nearly 35,000 residences, 747 of which were also survey respondents, and developed models to predict the respondents' stated perceived SF and SF annoyance. In so doing, we provide information not only on the levels and extent of SF exposure around US wind projects, but also identify variables that do (and, of equal importance, do not) predict perception and annoyance to SF. The research also reports on findings about SF modeling and metrics, including the relationship between noise, SF exposure, and SF annoyance.

[13] Specifically, A-weighted decibels (dBA) are the level of sound weighted to mimic the perception of the human ear. In this study, we estimate the maximum expected equivalent continuous sound level over one-hour (L_{1h}), using the ISO 9613-2 sound propagation standard with mixed ground porosity ($G = 0.5$), four-meter receptor heights, and + 2 dB (dB) uncertainty (see [10] for explanation of these terms and more details).

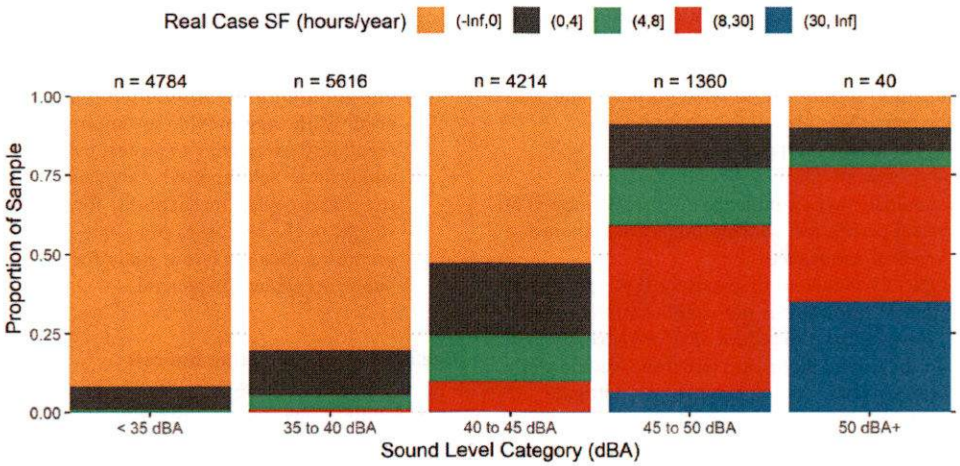


Fig. 9. Comparison of combined exposure of population to SF and wind turbine noise (by sound-level category) based on modeled real case SF (n = 16,077).[a]
[a]For sound-level categories, "*a* to *b*" means a < x ≤ b.

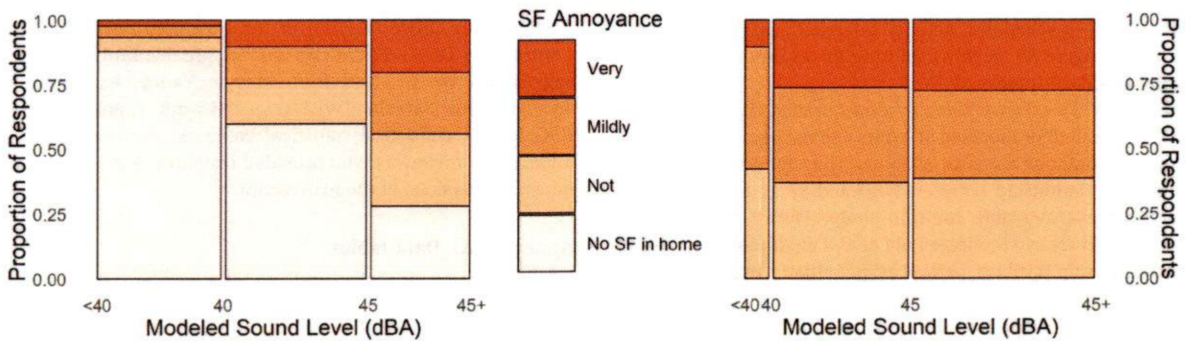


Fig. 10. Distribution of SF annoyance by modeled wind turbine sound-level category for (A) all respondents (n = 717) and (B) only respondents with modeled SF (n = 260).[a]
[a]For sound-level categories, "*a* to *b*" means a < x ≤ b.

Perceived SF is found to be largely influenced by observable characteristics, including SF exposure, distance to the nearest turbine, and whether a respondent moved in after the project was built. Notably, only about half of those with SF exposure in the range of 4 to 8 h per year real case reported perceiving SF in their home. When applied to a predictive model of an individual's perceived SF in their home, up to 71% of the perceived SF regression model predictions were correct.

Of respondents with modeled SF at their home, 17% reported being highly annoyed. SF annoyance is found to be correlated with one's subjective response to the look of the wind turbines, general annoyance to other anthropogenic sounds, level of education, and age. With subjective factors included, an individual's annoyance to SF was correctly predicted 65% of the time, with 73% of the "very annoyed" responses predicted correctly by the model. Importantly, when individual subjective factors were considered, modeled SF exposure was not significantly correlated with SF annoyance.

In summary, we find modeled SF levels predict one's perceived SF, but once perceived, higher levels of SF are not a predictor of higher levels of self-reported annoyance. These concepts are similar to findings we previously observed for wind turbine noise—that modeled wind turbine sound level was a robust predictor of wind turbine audibility but not annoyance to wind turbine noise [10,22].

SF exposure is regulated in relatively few jurisdictions across the US analysis area. The most commonly enforced limit across the United States in the project areas evaluated in our study is 30 h/year, similar in value to German worst-case guidelines and other standards found in the EU. However, in the United States, the metric is rarely defined as real or worst case, and, in our experience, is most often interpreted during the application process as real case. Of the full sample population, 7% exceed 30 h worst case or 8 h real case. Of the 404 survey respondents with any modeled SF, 50% exceeded the 30/8 worst-case/real-case limits, though a majority are project participants, and 2.3% exceeded 30 h/year real-case. Respondents exceeding those limits were no more likely to be very annoyed by SF than other respondents.

Regulated SF exposure limits are designed to mitigate annoyance, yet we find no clear dose-response relationship between SF exposure and self-reported annoyance when subjective variables are considered.

However, several of our findings can be helpful to inform SF regulatory standards. Overall, we found that an average relationship of worst to real case of roughly 3 to 1, following the relationship enforced in many EU jurisdictions. Including land-cover data in the analysis, has little effect on modeled levels for most residences, but could be used to obtain more realistic estimates of SF at individual locations, especially if high-resolution ground cover data are available. Finally, more than 90% of homes exposed to wind turbine sound levels below a typical limit of 45 dBA L_{1h} also received less than 8 h/year real-case SF. These results imply that sound-level limits might act as a decent proxy for SF limits.

This paper looks at self-reported annoyance, which is more of an attitudinal variable than annoyance stress. Accordingly, SF emissions could reduce the community acceptance of wind turbines and thus should be reduced to the extent feasible.

We offer several suggestions for future research:

(1) Future research should further examine the interactive impacts of SF, sound, and visual perception on wind project neighbors and their perceived levels of annoyance.
(2) Although SF is typically regulated by exposure (i.e., minutes or hours), we find that SF exposure is not significantly correlated with annoyance. If a goal is set to reduce SF annoyance, though, future research, in the United States and in Europe, should study other approaches, metrics, or standards to mitigate SF annoyance.
(3) Wind energy is rapidly expanding on a global scale, yet, to our knowledge, in-depth studies of SF exposure and annoyance have been conducted in few regions. Researchers should seek to replicate these types of analyses in more regions where wind energy is deployed. Additional survey questions could reveal more factors leading to annoyance such as time-of-day impacts, work and sleep schedules, activity interruptions, and measures taken to mitigate SF, such as shutting down the wind turbines during periods of intense SF.[14]
(4) Pohl et al. [29] used a weighted shadow duration (WSD) variable, which accounted for modeled SF hours and the number of shaded rooms and outdoor areas in a home. They found a consistent significant relationship between WSD and SF annoyance; these data were not available for this study. Future case studies, though, could seek to replicate Pohl et al.'s methodology to test if that relationship is robust, as well as, potentially, exploring other variables that might modify modeled SF. These variables include: the prevalent time-of-day SF is experienced, the intensity of the SF based on the turbine's distance and the number of turbines creating the SF.
(5) The annoyance stress scale (AS-scale) as developed by Hübner et al. [22], may provide an improved metric from a policy or regulatory perspective to protect public health over self-reported annoyance. Self-reported annoyance (without accounting for stress and coping mechanisms, for example) may miss the full weight of the responses of unique individuals. Indeed, this is a promising area for future study for wind turbine SF, noise, and public acceptance in general.

Declaration of competing interest

The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.

Acknowledgements

This work has been completed with the support of the Wind Energy Technologies Office (WETO) of the US Department of Energy under Contract No. DE-AC02-05CH11231. We are thankful for the support and suggestions we received from Maggie Yancy, Patrick Gilman, and Jocelyn Brown-Saracino (WETO) for this work. Thanks to Matt Landis of RSG for his consistent statistical compass. We also thank the three anonymous reviewers who provided insightful and valuable comments on earlier versions of the manuscript.

Appendix A. Data tables

Table A1
Count and percentage data for Fig. 5A.

	Count			Percentage		
	No SF	On property	In home	No SF	On property	In home
0 h	301	12	11	93%	4%	3%
>0 & ≤4 h	66	13	27	62%	12%	25%
>4 & ≤8 h	38	11	54	37%	11%	52%
>8 & ≤30 h	28	16	110	18%	10%	71%
>30 h	0	3	27	0%	10%	90%

Table A2
Count and percentage data for Fig. 5B.

	Count			Percentage		
	No SF	On property	In home	No SF	On property	In home
>0 & ≤4 h	66	13	27	62%	12%	25%
>4 & ≤8 h	38	11	54	37%	11%	52%
>8 & ≤30 h	28	16	110	18%	10%	71%
>30 h	0	3	27	0%	10%	90%

[14] Shutting down the turbines was suggested by a reviewer who is familiar with a German requirement to limit SF hours below a certain threshold.

Table A3
Count and percentage data for Fig. 6A.

	Count				Percentage			
	No SF in home	Not	Mildly	Very	No SF in home	Not	Mildly	Very
0 h	301	13	4	6	93%	4%	1%	2%
>0 & ≤4 h	66	17	14	9	62%	16%	13%	8%
>4 & ≤8 h	38	26	23	16	37%	25%	22%	16%
>8 & ≤30 h	28	45	45	35	18%	29%	29%	23%
>30 h	0	11	12	7	0%	37%	40%	23%

Table A4
Count and percentage data for Fig. 6B.

	Count			Percentage		
	Not	Mildly	Very	Not	Mildly	Very
>0 & ≤4 h	17	14	9	43%	35%	23%
>4 & ≤8 h	26	23	16	40%	35%	25%
>8 & ≤30 h	45	45	35	36%	36%	28%
>30 h	11	12	7	37%	40%	23%

Table A5
Count and percentage data for Fig. 10A.

	Count				Percentage			
	No SF in home	Not	Mildly	Very	No SF in home	Not	Mildly	Very
<40 dBA	212	13	11	5	88%	5%	5%	2%
>40 & ≤45 dBA	166	44	40	28	60%	16%	14%	10%
>45 dBA	55	55	47	40	28%	28%	24%	20%

Table A6
Count and percentage data for Fig. 10B.

	Count			Percentage		
	Not	Mildly	Very	Not	Mildly	Very
<40 dBA	8	9	2	42%	47%	11%
>40 & ≤45 dBA	38	38	27	37%	37%	26%
>45 dBA	53	47	38	38%	34%	28%

References

[1] B. Hoen, J. Diffendorfer, J. Rand, L. Kramer, C. Garrity, H. Hunt, United states wind turbine database, in: U.S. Geological Survey, American Clean Power Association, and Lawrence Berkeley National Laboratory data release, v 3.3, 2021. https://doi.org/10.5066/F7TX3DN0.

[2] A. Phadke, D. Wooley, N. Abhyankar, U. Paliwal, B. Paulos, The 2035 Report: Plummeting Solar, Wind, and Battery Costs Can Accelerate Our Clean Electricity Future, UC Berkley, Goldman School of Public Policy, Berkeley, 2020.

[3] C. Gerbaulet, C. von Hirschhausen, C. Kemfert, C. Lorenz, P. Oei, European electricity sector decarbonization under different levels of foresight, Renew. Energy 141 (2019) 973–987, https://doi.org/10.1016/j.renene.2019.02.099.

[4] J. Brodny, M. Tutak, Analyzing similarities between the European Union countries in terms of the structure and volume of energy production from renewable energy sources, Energies. 13 (4) (2020) 913, https://doi.org/10.3390/en13040913.

[5] J. Rand, B. Hoen, Thirty years of north American wind energy acceptance research: what have we learned? Energy Res. Soc. Sci. 29 (2017) 135–148, https://doi.org/10.1016/j.erss.2017.05.019.

[6] J. Firestone, B. Hoen, J. Rand, D. Elliott, G. Hübner, J. Pohl, Reconsidering barriers to wind power projects: community engagement, developer transparency and place, J. Environ. Policy Plan. 20 (3) (2018) 370–386, https://doi.org/10.1080/1523908X.2017.1418656.

[7] J. Tomich, Proposed rules threaten to derail Kan, in: Wind Industry, EE News, 24 March 2021. https://www.eenews.net/stories/1063728315/. (Accessed 13 May 2021).

[8] L. Gibson, S. Bowman, 34 Indiana counties restrict wind, solar projects, in: Lawmakers Are Pushing a Bill to Override Them, Indianapolis Star, 10 March 2021. https://www.indystar.com/story/news/environment/2021/03/10/indiana-general-assembly-wind-solar-efforts-standardize-solar-wind-projects-called-overreach/4541897001/. (Accessed 13 May 2021).

[9] T. Mai, A. Lopez, E. Lantz, M. Mowers, Interactions of wind energy project siting, wind resource potential, and the evolution of the U.S. power system, Energy. 223 (15) (2021), e119998, https://doi.org/10.1016/j.energy.2021.119998.

[10] T. Haac, K. Kaliski, M. Landis, B. Hoen, J. Rand, D. Elliott, G. Hübner, J. Pohl, Wind turbine audibility and noise annoyance in a national U.S. survey: individual perception and influencing factors, J. Acoust. Soc. Am. 146 (2) (2019) 1124–1141, https://doi.org/10.1121/1.5121309.

[11] D. Michaud, S. Keith, K. Feder, S. Voicescu, L. Marro, J. Than, M. Guay, T. Bower, A. Denning, E. Lavigne, C. Whelan, S. Janssen, T. Leroux, F. van den Berg, Personal and situational variables associated with wind turbine noise annoyance, J. Acoust. Soc. Am. 139 (3) (2016) 1455–1466, https://doi.org/10.1121/1.4942390.

[12] S. Janssen, H. Vos, A. Eisses, E. Pedersen, A comparison between exposure-response relationships for wind turbine annoyance and annoyance due to other noise sources, J. Acoust. Soc. Am. 130 (6) (2011) 3746–3753, https://doi.org/10.1121/1.3653984.

[13] S. Kuwano, T. Yano, T. Kageyama, S. Sueoka, H. Tachibana, Social survey on wind turbine noise in Japan, Noise Control Eng. J. 62 (6) (2014) 503–520, https://doi.org/10.3397/1/376246.

[14] M. Pasqualetti, Opposing wind energy landscapes: a search for common cause, Annals of the Assoc. of Am. Geogr. 101 (4) (2011) 907–917, https://doi.org/10.1080/00045608.2011.568879.

[15] P. Groothius, J. Groothius, J. Whitehead, Green vs. Green: measuring the compensation required to site electrical generation windmills in a viewshed, Energy Policy 36 (4) (2008) 1545–1550, https://doi.org/10.1016/j.enpol.2008.01.018.

[16] R. Ioannidis, D. Koutsoyiannis, A review of land use, visibility and public perception of renewable energy in the context of landscape impact, Appl. Energy 276 (2020), e115367, https://doi.org/10.1016/j.apenergy.2020.115367.

[17] K. Molnarova, P. Sklenicka, J. Stiborek, K. Svobodova, M. Salek, E. Brabec, Visual preferences for wind turbines: location, numbers and respondent characteristics, Appl. Energy 92 (2012) 269–278, https://doi.org/10.1016/j.apenergy.2011.11.001.

[18] J. Pohl, G. Hübner, A. Mohs, Acceptance and stress effects of aircraft obstruction markings of wind turbines, Energy Policy 50 (2012) 592–600, https://doi.org/10.1016/j.enpol.2012.07.062.

[19] J. Firestone, C. Hirt, D. Bidwell, M. Gardner, Faring well in offshore wind power siting? Trust, engagement and process fairness in the United States, Energy Res. Soc. Sci. 62 (2020), e101393, https://doi.org/10.1016/j.erss.2019.101393.

[20] C. Walker, J. Baxter, Procedural justice in Canadian wind energy development: a comparison of community-based and technocratic siting processes, Energy Res. Soc. Sci. 29 (2017) 160–169, https://doi.org/10.1016/j.erss.2017.05.016.

[21] T. Lindvall, E. Radford, Measurement of annoyance due to exposure to environmental factors, Environ. Res. 6 (1973) 1–36, https://doi.org/10.1016/0013-9351(73)90014-5.

[22] G. Hübner, J. Pohl, B. Hoen, J. Firestone, J. Rand, D. Elliott, R. Haac, Monitoring annoyance and stress effects of wind turbines on nearby residents: a comparison of U.S. and European samples, Environ. Int. 132 (2019), e105090, https://doi.org/10.1016/j.envint.2019.105090.

[23] B. Hoen, J. Firestone, J. Rand, D. Elliot, G. Hübner, J. Pohl, R. Wiser, E. Lantz, R. Haac, K. Kaliski, Attitudes of U.S. wind turbine neighbors: analysis of a nationwide survey, Energy Policy 134 (2019), e110981, https://doi.org/10.1016/j.enpol.2019.110981.

[24] E. Koppen, M. Gunnuru, A. Chester, International Legislation and Regulations for Wind Turbine Shadow Flicker Impact, in 7th Int, Conf. on Wind Turbine Noise, Rotterdam, 2017.

[25] F. Oteri, An Overview of Existing Wind Energy Ordinances, National Renewable Energy Laboratory, United States, 2008, https://doi.org/10.2172/944889.

[26] Federal/State Working Group for Immission Control (LAI), Notes on the determination and evaluation of optical immissions from wind turbines – update 2019, WKA-Schattenwurf-Hinweise, 2020, https://www.lai-immissionsschutz.de/documents/wka_schattenwurfhinweise_stand_23_1588595757.01. (Accessed 23 January 2020).

[27] E. Verkuijlen, C. Westra, Shadow hindrance by wind turbines, in: Proc. of Eur. Wind Energy Assoc. Conf., 1984, p. 356.

[28] G. Harding, P. Harding, A. Wilkins, Wind turbines, flicker, and photosensitive epilepsy: characterizing the flashing that may precipitate seizures and optimizing guidelines to prevent them, Epilepsia 49 (6) (2008) 1095–1098, https://doi.org/10.1111/j.1528-1167.2008.01563.x.

[29] J. Pohl, F. Faul, R. Mausfeld, Annoyance Caused by Periodic Shadow Casting from Wind Turbines, Institute of Psychology at the Christian-Albrechts-University in Kiel, Kiel Germany, 1999.

[30] S. Voicescu, D. Michaud, K. Feder, L. Marro, J. Than, M. Guay, A. Denning, T. Bower, F. van den Berg, N. Broner, E. Lavigne, Estimating annoyance to calculated wind turbine shadow flicker is improved when variables associated with wind turbine noise exposure are considered, J. Acoust. Soc. Am. 139 (3) (2016) 1480–1492, https://doi.org/10.1121/1.4942403.

[31] A. Freiberg, C. Schefter, J. Hegewald, A. Seidler, The influence of wind turbine visibility on the health of local residents: a systematic review, Intl, Archives of Occupational and Environmental Health. 92 (2019) 609–628, https://doi.org/10.1007/s00420-019-01403-w.

[32] J. Rand, L. Kramer, C. Garrity, B. Hoen, J. Diffendorfer, H. Hunt, M. Spears, A continuously updated, geospatially rectified database of utility-scale wind turbines in the United States, Sci. Data. 7 (15) (2020), https://doi.org/10.1038/s41597-020-0353-6.

[33] Microsoft, Microsoft US Building Footprints. https://github.com/Microsoft/USBuildingFootprints, 2020. (Accessed 6 October 2020).

[34] United States Geological Survey (USGS), NLCD 2011 Land Cover (CONUS), Multi-Resolution Land Characteristics (MRLC) Consortium, 2011. https://s3-us-west-2.amazonaws.com/mrlc/NLCD_2011_Land_Cover_L48_20190424.zip. (Accessed 1 May 2020).

[35] National Oceanic and Atmospheric Administration (NOAA), Comparative Climatic Data, National Centers for Environmental Information. https://www1.ncdc.noaa.gov/pub/data/ccd-data/pctpos18.dat, 2020. (Accessed 1 May 2020).

[36] N.J.D. Nagelkerke, A note on a general definition of the coefficient of determination, Biometrika. 78 (3) (1991) 691–692, https://doi.org/10.1093/biomet/78.3.691.

[37] G. James, D. Witten, T. Hastie, R. Tibshirani, An Introduction to Statistical Learning, eighth ed., Springer Science+Business Media, New York, 2017.