

Wind turbine audibility and noise annoyance in a national U.S. survey: Individual perception and influencing factors

T. Ryan Haac,^{a)} Kenneth Kaliski, and Matthew Landis
RSG, 55 Railroad Row, White River Junction, Vermont 05001, USA

Ben Hoen and Joseph Rand
Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, California 94720, USA

Jeremy Firestone
College of Earth, Ocean, and Environment, University of Delaware, Newark, Delaware 19716, USA

Debi Elliott
Survey Research Lab, Portland State University, Portland, Oregon 97207, USA

Gundula Hübner^{b)} and Johannes Pohl^{b)}
Institute of Psychology, Martin-Luther-Universität Halle-Wittenberg, 06099 Halle, Germany

(Received 15 October 2018; revised 20 July 2019; accepted 23 July 2019; published online 14 August 2019)

With results from a nationwide survey sponsored by the U.S. Department of Energy, factors that affect outdoor audibility and noise annoyance of wind turbines were evaluated. Wind turbine and summer daytime median background sound levels were estimated for 1043 respondents. Wind turbine sound level was the most robust predictor of audibility yet only a weak, albeit significant, predictor of noise annoyance. For each 1 dB increase in wind turbine sound level (L_{1h-max}), the odds of hearing a wind turbine on one's property increased by 31% [odds ratio (OR): 1.31; 95% CI (confidence interval): 1.25–1.38] and the odds of moving to the next level of annoyance increased by 9% (OR: 1.09; 95% CI: 1.02–1.16). While audibility was overwhelmingly dependent on turbine sound level, noise annoyance was best explained by visual disapproval (OR: 11.0; 95% CI: 4.8–25.4). The final models correctly predict audibility and annoyance level for 80% and 62% of individuals, respectively. The results demonstrate that among community members not receiving personal benefits from wind projects, the Community Tolerance Level of wind turbine noise for the U.S. aligns with the international average, further supporting observations that communities are less tolerant of wind turbine noise than other common environmental noise sources at equivalent A-weighted sound levels. © 2019 Acoustical Society of America. <https://doi.org/10.1121/1.5121309>

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Pages: 1124–1141

I. INTRODUCTION

Wind turbine noise can cause annoyance (WHO, 2018), reduce social acceptance of wind energy, create conflict and negative experiences in local communities, and result in delayed or derailed wind projects (Rand and Hoen, 2017). Thus, if wind turbines continue to add to the mix of energy generation as is projected (Rogelj *et al.*, 2018), understanding the factors that lead to audibility and noise annoyance could help improve the compatibility between wind projects and their surrounding communities.

Some of the first researchers to study wind turbine noise with larger upwind wind turbines (>500 kW) were Pedersen and Persson Waye (2004), who found that noise annoyance was due not only to the sound level category of wind turbine noise, but also to subjective factors such as perception of wind turbine appearance and self-reported noise sensitivity. Since then, several other studies have investigated the association between wind turbine sound and noise annoyance

and/or audibility (Table I). While these studies used different approaches and metrics, a common theme emerged: factors specific to individuals, such as self-reported noise sensitivity, visual impressions, and concerns about physical safety, were often more highly correlated with noise annoyance than a single sound level metric's representation (numerical or categorical) of wind turbine sound levels.

Endpoints of interest in most noise-related dose-response studies are often explored through the binary lens of “Highly Annoyed” and “Not Highly Annoyed” individuals (Miedema and Vos, 1998). This classification provides a polarized categorization of reactions throughout the surrounding population (Schultz, 1978). Further, the Community Tolerance Level (CTL) provides a method for comparing community response to specific noise sources (Fidell *et al.*, 2011; Schomer *et al.*, 2012; Michaud *et al.*, 2016b). The CTL is defined as the long-term day-night sound level (DNL) at which 50% of the population is considered Highly Annoyed by a noise source. CTL has been used to propose that wind turbine noise elicits higher levels of annoyance at equivalent sound levels compared to railway, aircraft, and road traffic sources (Michaud *et al.*, 2016b).

^{a)}Electronic mail: ryan.haac@rsginc.com

^{b)}Also at: MSH Medical School, Hamburg, Germany.

TABLE I. Summary of prior studies of community response to wind turbine sound.

Study	Number of respondents	Country	Wind Turbine Sound Level Quantification	Included Measurable Variables ^a	Included Subjective Variables	Modeled Metric	Background Sound Included	Adjusted to Long Term Metric
Pedersen and Persson Waye (2004)	351	Sweden	Modeled	No	Yes	L_{eq} at 8 m/s	No	No
Pedersen and Persson Waye (2007)	754	Sweden	Modeled	Yes	Yes	L_{eq} at 8 m/s	No	No
van den Berg <i>et al.</i> (2008) and Pedersen <i>et al.</i> (2009)	725	Netherlands	Modeled	Yes	Yes	L_{eq} at 8 m/s	No but used rural classification of area in regression model	L_{den}
Janssen <i>et al.</i> (2011)	1820	Sweden, Netherlands	Modeled	Yes	Yes	L_{eq} at 8 m/s	No	L_{den}
Pawlaczyk-Luszczynska <i>et al.</i> (2015)	361	Poland	Modeled with some verification	No	Yes	L_{eq}	No	L_{den}
Kuwano <i>et al.</i> (2014)	747 nearby, 332 distant	Japan	Measurements to create a model	No	Yes	$L_{eq,in}$	Yes, but not in regression model	No
Magari <i>et al.</i> (2014)	62	U.S.	Measured	Yes	Yes	L_{eq}	No	No
Michaud <i>et al.</i> (2016a, 2016b)	1238	Canada	Modeled with some verification	Yes	Yes	L_{annual}	Yes, but not in regression model	DNL
This study	1025	U.S.	Modeled	Yes	Yes	L_{1h-max}	Yes, summer daytime L_{50}	DNL

^aModeled independent non-personal variables that can be directly observed, other than sound, such as wind turbine characteristics and participation.

Previous studies of wind turbine noise annoyance are set out in Table I. In most, wind turbine sound level was modeled. Each study used different modeling parameters and averaging times, making comparisons difficult (Old and Kaliski, 2017). Although each provided some estimate of long-term sound levels in the form of annual DNL or L_{den} (day-night-evening level), they do not appear to have been based on a full accounting of site-specific meteorology. Long-term sound levels are affected by meteorological conditions that affect sound propagation, such as wind shear (change in wind speed with height above ground), wind direction, turbulence intensity, and temperature profile (Ingard, 1953). Long-term sound levels are also affected by changes in sound emissions from the source (sound power), which for wind turbines are primarily a function of wind speed (van den Berg, 2008; Keith *et al.*, 2016b). To this end, the present study evaluated the impact of long-term meteorology with a variable representing average atmospheric stability and a sound level adjustment variable based on site-specific wind speed distribution.

Given the European Union Environmental Noise Directive (Directive 2002/49/EC), European researchers have tended to use the long-term metric, L_{den} . In contrast, this study uses L_{1h-max} as the primary metric because it is a more practical regulatory metric in the U.S. that can be accurately assessed in the field and through modeling.

In addition to sound level metrics, prior studies have not typically assessed wind turbine characteristics as predictors of wind turbine audibility or annoyance. Rotor diameter and hub height may influence feelings of encroachment, visibility, and general intrusiveness, and may also have an impact on sound characteristics, such as amplitude modulation (van Kamp and van den Berg, 2017). Blade tip speeds can affect the characteristic sound produced by a wind turbine and its sound power (Arakawa *et al.*, 2005). Wind turbines with elevated low-frequency noise emissions may be audible at greater distances than other wind turbines, potentially resulting in increased noise annoyance (Hongisto *et al.*, 2017; Møller and Pedersen, 2011). This study evaluates the effects of several wind turbine characteristics on outdoor audibility and noise annoyance.

Moreover, prior studies did not account for the theory that individuals will self-sort among communities based on their valuation of local amenities and disamenities offered by those communities (Tiebout, 1956). Applied to wind turbine development, the theory suggests that individuals who move in after the construction of a wind project are more likely to accept its auditory and visual effects than those who have lived near the project site prior to the wind turbine development (Firestone *et al.*, 2018). For respondents who lived in the area at the time of construction, experiences with project development and associated public engagement are relevant: one's prior attitude manifests expectations that may set the course of one's perception of a particular project, which is evaluated in this study.

The masking of background sound and its effect on self-reported audibility and noise annoyance have not been widely studied over a large population because a consistent approach to the estimation of background sound over a wide area is lacking in most countries. Environmental sources may mask wind turbine sound, rendering the turbines

inaudible or less audible (Nelson, 2007). Masking also changes the characteristics of the sound, for example, by reducing amplitude modulation at a receiver (RSG *et al.*, 2016). Thus, it is reasonable to hypothesize that for a given level of wind turbine sound, increasing background sound would reduce the audibility and noise annoyance of wind turbine sound.

In contrast to noise annoyance, audibility has been found to be more dependent on objective variables. Pedersen *et al.* (2009), the only study in Table I that evaluated audibility discretely, found that noticing wind turbine sound was correlated with sound pressure level, turbine visibility, and a categorical representation of whether the location was rural with a main road (as opposed to without one). Economic benefits or whether the receptor was in a built-up area were not associated with noticing wind turbine sound. Pedersen *et al.* (2009) did not extend the audibility analysis to additional independent variables; the present study addresses this gap by analyzing wind turbine audibility in the context of the range of factors mentioned above.

This study, sponsored by the U.S. Department of Energy (DOE), through the Lawrence Berkeley National Laboratory, is an analysis of how sound level, objective characteristics, and subjective measures influence wind turbine audibility and noise annoyance amongst wind turbine neighbors throughout the U.S. The research question is addressed by considering the implications of the effects of meteorology and averaging times/metrics on wind turbine sound level, turbines characteristics, residency in the area prior to the wind project, subjective factors, and background sound levels. It is based on a national mail, internet, and phone survey of wind project neighbors and part of a multi-faceted research effort.¹

II. METHODS

A. Study approach

This study utilizes survey data, modeled wind turbine sound levels, an estimate of background sound levels, and other external variables to assess the acoustic and attitudinal impact of wind turbine noise in the U.S.

The structure of the analysis presented here differs from most previous studies in that the prediction of noise annoyance is done in two parts. First, the analysis focuses on factors that affect audibility of wind turbines outside one's home. Second, for those respondents who indicated wind turbine audibility on their property, factors that contributed to the level of noise annoyance were evaluated. This approach recognizes an important distinction: those who cannot hear wind turbines will not be directly annoyed by wind turbine noise.

This study also estimates a dose-response relationship between sound pressure level category and wind turbine noise annoyance using the CTL. The CTL results are best used to compare the dose-response of these U.S. respondents to those in other countries and other environmental noise sources.

B. Sampling

A dataset of modern wind turbines installed through 2014 guided the determination of the potential homes to be

surveyed.² Turbines were considered "modern" if they were at least 111 m in total height (hub height plus rotor radius) and held a nameplate capacity of 1.5 MW or greater, which resulted in 29 848 turbines in 604 projects. From 1.29×10^6 homes in the U.S. located 8 km or less from a modern wind turbine, an initial random sample of 43 041 homes was drawn. The location of the homes was confirmed using two different geolocation services; only residences that agreed between the two sources (within 0.4 km) were retained. Geodetic distance from each residence to its nearest turbine was determined using the "Geonear" (Picard, 2010) function in Stata, which finds nearest neighbors between sets of locations by calculating the geodetic distance between pairs of X/Y coordinates using the Haversine equation on a reference ellipsoid (Vincenty, 1975). Geographical position accuracy and phone record matching decreased the sample to 15 455 addresses.

To ensure a sample that was representative of the full population of individuals living near turbines in the U.S., the sample was stratified by project size (greater or less than 10 turbines) and distance to the nearest wind turbine (0–0.8, 0.8–1.6, 1.6–4.8, and 4.8–8 km). The final set of records was drawn from each project-size/distance strata to ensure adequate samples within each strata. Oversampling occurred at 15 discrete wind project sites where sound modeling was initially planned. These sites were selected to provide a diversity of turbine manufacturers, geographies, project sizes, median background sound levels, population densities, and topographies. Finally, to ensure adequate dispersion of homes across the country, four projects that included a disproportionately large fraction of the sample were deliberately under-sampled.

A total of 7845 records were ultimately loaded for phone sampling and a total of 6000 records were prepared for the mail/internet survey. The mail/internet survey included 750 phone non-responding homes and 5250 records that did not have matching phone numbers or were excluded because of locational disagreement as noted above. The mail/internet survey generally followed Dillman *et al.* (2014), with an introductory letter, which included a web address and unique web PIN, a second mailing with a paper survey, and a reminder postcard. There were no differences between the multi-modal survey instruments other than those necessitated by the mode.

C. Survey instrument

The instrument comprised a 50-question survey³ that sought information regarding the following:

- Respondents' present attitude toward the nearby project and their attitude prior to construction;
- Participation in and perceived fairness of the project's planning and siting process;
- Relationship to the local wind project (e.g., turbines on property, compensation, number of turbines visible, and ability to hear turbines from property and inside home);
- Perceptions of and reactions to the project (e.g., appearance, landscape changes, turbine sounds, shadow flicker, lighting);
- Background information (e.g., length of residence, awareness of project development, place attachment, noise sensitivity, and acute and chronic stress);

- General attitudes toward sources of electricity, climate change, and wind energy’s effectiveness at combating it; and
- Demographic information.

Portland State University’s Survey Research Lab conducted telephone surveys⁴ and administered follow-on internet and mail surveys. The phone survey occurred in March and April of 2016 with mail/internet surveys following through July of 2016. All respondents who completed the survey were entered into a drawing to win one of four \$500 gift cards. Individuals contacted were not informed that the survey would inquire into audibility and sound annoyance. Rather, they were informed of the more general purpose of the survey—that is, to “understand [the] experiences, perceptions, and opinions” of wind turbine neighbors (see footnote 4).

The research team received a total of 875 phone responses out of 3114 resolved (not to be called back because they completed the survey, asked to never be called back, or refused to take part) and 6332 eligible (resolved plus, e.g., reached voice mail or was asked to call back) phone numbers. Response rates for the phone survey were 13.8% for “eligible” numbers and 28.1% for “resolved” numbers. Nonresponse phone survey follow-up calls averaged 6.3 calls/number; residences closer to wind turbines were prioritized for follow-up calls to ensure the sample size for this cohort was adequate. The research team also received 483 web and 347 mail responses out of a total of 4637 eligible addresses (accounting for undeliverable mail, etc.), resulting in a response rate for the mail/web survey of 17.9%. All mail/web respondents received two mail invitations

in addition to the actual mail survey. In general, response rates were consistently higher for residences closer to the turbines, potentially indicating greater interest in the survey. The maximum response rate (25%) was observed from the mail/web survey for residences within 0.8 km of the nearest turbine.⁵ A total of 1705 responses were obtained from near 250 wind projects.

Of the 1705 responses, 621 responses were located within 0.8 km of a wind turbine and another 500 responses were between 0.8 and 1.6 km. In the context of projects operating in the U.S. at the time, responses were well distributed across the country, with the majority located in the midwestern U.S. (Fig. 1). For this study, sound levels were predicted for 1043 respondents living in the vicinity of 61 projects (435 within 0.8 km of a wind turbine and 293 between 0.8 and 1.6 km).

D. Response interpretation

1. Assessment of wind turbine audibility

Respondents were asked, “Have you ever heard sound from the wind project,” to which they could respond “Yes,” “No,” or “Don’t know.” If they answered yes, they were then asked, “Can you hear sound from the wind project when you are on your property, but outside your home?” Finally, respondents answering in the affirmative were asked if they could hear the turbines, “...in your home?” Using these responses, a respondent’s wind turbine audibility is characterized as “Cannot Hear,” “On Property,” or “In Home.” Outdoor audibility on the respondent’s property was

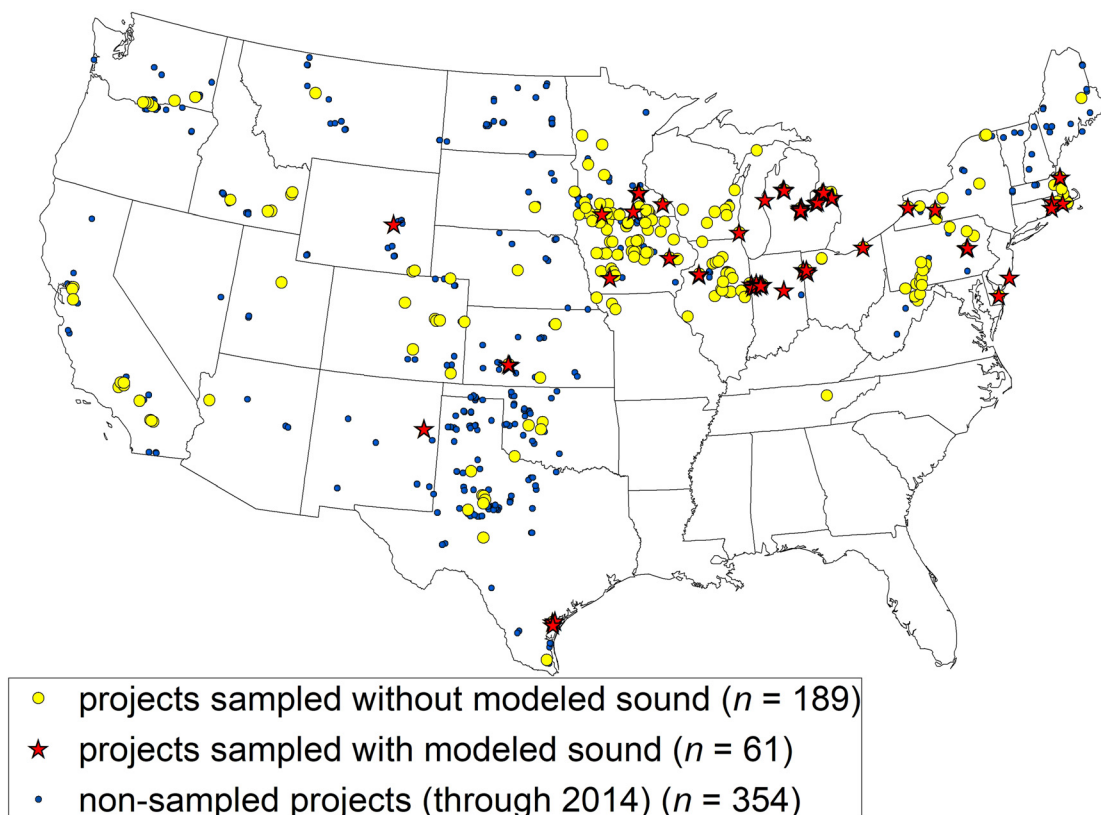


FIG. 1. (Color online) Wind power projects in the U.S., highlighting those surveyed and modeled for this study. Sound was modeled at 24% of the sampled projects, representing 61% of respondents.

chosen as the first endpoint tested because only outdoor sound level was modeled.

2. Assessment of respondent noise annoyance

Prior to inquiring about annoyance, the survey prefaced respondents with the following statement: “The next set of questions asks about any effects the local wind project has had on you. For these questions, think about the experiences you have had over the past year.” Then, respondents were asked, “To what extent do you feel annoyed by each of the following effects of the local wind project?” Four effects were listed: “Change to the landscape,” “Wind turbine lighting,” “Shadow flicker,” and “Sound of the wind project.” For each effect, the possible responses were 1 = “Not at all,” 2 = “Slightly,” 3 = “Somewhat,” 4 = “Moderately,” and 5 = “Very.” This study only considered the indicated annoyance to “Sound of the wind project,” i.e., noise annoyance. For analysis as a dependent variable, the three middle reactions, Slightly, Somewhat, and Moderately, were combined into one category (“Mildly”) to represent respondents who elicited a mild negative reaction to wind turbine noise. This resulted in three annoyance categories: “Not at all,” “Mildly,” and “Very.” Reported noise annoyance was only considered valid in this study for respondents who also reported hearing wind turbines on their property (see Sec. IV C for further discussion).

3. Formulation of additional variables from survey responses

A single three-level categorical variable was formulated to describe a respondent’s participation in (or relationship with) their local project. By convention, project participants are compensated in some way for the project, e.g., lease payments for hosting a turbine. This study compares respondents who did not participate in their local project (non-participants), respondents who were compensated for hosting a turbine on their property (host and compensated), and respondents who were compensated but did not host a turbine (compensated). Wind project neighbors receiving compensation without hosting a wind turbine may have granted the wind project easements for project infrastructure (e.g., roads, powerlines), leased land to the developer (e.g., substations), or consented to a “good neighbor agreement” (NYSERDA, 2017). Monetary compensation levels for wind turbine hosts were considerably higher than for non-hosts.⁶

Additional survey responses were formed into variables describing the respondent and some personal attributes. The variable “move-in” distinguishes those who moved in after construction and respondents who lived in the area prior to the wind project. A respondent’s “prior attitude” toward the local wind project prior to construction was included with a positive, negative, and neutral group. Note that in the presence of subjective variables, prior attitude subsumes the move-in variable, as these variables contain mutually exclusive groups of respondents. Noise sensitivity was assessed as a five-level ordered categorical variable based on the survey responses (i.e., Not at all, Slightly, Somewhat, Moderately, and Very), with “Not at all noise sensitive” as the omitted

reference level. Last, a “like look” variable was assigned to respondents based on whether or not they liked the appearance of the local wind project or were neutral.

4. Assessment of CTL (dose-response analysis)

Although the survey instrument deviated from ISO/TS 15666 (2003), which is discussed in Sec. IV C, respondents who indicated they were “Very Annoyed” were regarded as being Highly Annoyed.⁷ The percentage of Highly Annoyed respondents by sound level category was calculated for two groups: all respondents and only non-participants, resulting in two distinct CTLs.

E. Additional data collection

Survey responses were supplemented with additional attributes, which included wind turbine data, sound levels, meteorology, and site characteristics.

1. Wind turbine data

Wind turbine data were obtained via the U.S. Wind Turbine Database (Hoen *et al.*, 2018), including coordinates, model, maximum power output, hub height, rotor diameter, and tip speed (Table II). Attributes for the wind turbine nearest to each respondent were assigned for the regression analysis.

Apparent sound power levels for wind turbines in this study were collected by octave band to the extent they were available. For wind turbines without available spectral data, spectra were estimated based on the reported overall A-weighted level as proposed by Keith *et al.* (2016a). These estimates were used for 5% of the turbines included in the sound propagation models, representing about 15% of respondents. Additionally, the C-to-A ratio of the turbine closest to each respondent was assigned to that respondent, which is the overall C-weighted sound power level of the wind turbine minus the overall A-weighted sound power level. The greater the C-to-A ratio, the greater the proportion of low-frequency sound generated by the wind turbine relative to the full spectrum. The C-to-A ratio is reported with an asterisk (“*”) in this work due to the lack of data below the 63 Hz octave band.⁸

2. Wind turbine sound levels

The level of wind turbine sound is one of the most important variables in the study. The authors chose to model wind turbine sound using the L_{1h-max} metric: the maximum

TABLE II. Descriptive statistics of distinct wind turbines included in the sound propagation models ($n = 38$ unique turbines).

	Minimum	Maximum	Mean	SD
Hub Height (m)	70	100	85.9	9.1
Rotor Diameter (m)	77	117	90.8	8.9
Turbine Capacity (MW)	1.5	2.5	1.8	0.3
Rotor Tip Speed (m/s)	61.8	87.4	75.7	7.1
Turbine Sound Power (dBA)	103.1	109.1	105.2	1.5
C-to-A Sound Power Ratio*	7.5	14.9	10.3	2.2

A-weighted 1 h equivalent continuous average wind turbine sound level at each receptor that is reasonably expected under normal operating conditions. The L_{1h-max} is a common regulatory metric in the U.S. (Fowler *et al.*, 2013). Since long-term averages are also useful for understanding ongoing exposure to wind turbine sound, this study includes annualized sound power correction and mean inverse Obukhov length (as a proxy for temperature profile) (Kaliski *et al.*, 2018a) as factors that influence long-term sound emissions and propagation effects, respectively.

Sound propagation modeling was performed according to ISO 9613-2 (ISO, 1996) as implemented in CadnaA version 4.6 (Datakustik[®], 2016) software to predict L_{1h-max} at each respondent's home. All wind turbines within 8 km of each receiver were considered to be operating at maximum sound output with no noise-reduced operations (NROs). Sound levels were calculated at 4 m above ground level. To account for atmospheric absorption (ISO 9613-1, 1993), the temperature and humidity were set at 10 °C and 70%, respectively. The ground type was represented as half hard/half porous ($G = 0.5$), except for large bodies of water ($G = 0$). Buildings and foliage attenuation were not included. Two decibels were added to the model results to account for remaining manufacturer sound power and propagation uncertainty (Bowdler *et al.*, 2009, RSG *et al.*, 2016, Kaliski *et al.*, 2018b).

Sound propagation modeling was undertaken at 30 wind projects to generate a large sample size and provide a broad diversity of projects. To account for other nearby wind projects that could affect the sound levels at respondent homes, each sound propagation model included any wind project within 8 km of a respondent. Respondents living within 8 km of the additional projects were also added to the sound propagation models, if applicable. This way, 61 distinct wind projects, totaling 3267 turbines (26 different makes and models) were modeled for 1043 respondent homes, 1025 of which indicated whether they could hear or not hear wind turbines on their property.

3. Annualized sound levels

While L_{1h-max} is the representation of equivalent wind turbine sound levels used in the regression models,⁹ the effect of long-term wind turbine sound power emissions is also included through a variable called "DNL correction" (DNL^* minus L_{1h-max} , calculated for each respondent). Hourly simulations of turbine sound power output were generated using project-level hub-height wind speed obtained from the NREL Wind Toolkit (NREL, 2018) in conjunction with turbine sound power output curves and project-level capacity factors. Hourly data from 2007 to 2012 were processed for locations geographically central to each included wind project. DNL was calculated by applying a 10-dB penalty during the night (22:00 to 07:00) (ANSI, 2013). The approximate day-night level ("DNL*") was on average 3.6 dB [standard deviation (SD) = 1.2] higher than L_{1h-max} . The average annual equivalent sound level was 3.5 dB (SD = 1.4) less than L_{1h-max} . The asterisk (*) in DNL^* denotes that the sound level metric is not a true DNL, in that

it does not account for conditions when atmospheric stability and wind direction are less favorable for sound propagation, or any NROs at the modeled projects. As a result, the DNL^* is the upper bound of the *actual* DNL for long-term outdoor wind turbine sound.

4. Background sound levels

Estimated background sound levels were obtained from the U.S. National Park Service (NPS) mapping of A-weighted median ambient daytime summer sound levels (L_{50}) of the U.S. (National Park Service, 2014). The maps were generated using statistical relationships between ambient sound level and biogenic, geospatial, and anthropogenic surface characteristics (Mennitt *et al.*, 2014). The L_{50} is calculated by the NPS in a 270-m grid across the U.S. The median deviation of measured versus modeled sound levels was reported to be 3.1 dB at natural sites and 1.7 dB at urban sites (Mennitt *et al.*, 2014). Note that there are many measures that can be made to quantify background sound, including different seasons, times of day, and sound level metrics. Presently, only summer daytime L_{50} is available from the NPS as a comprehensive representation of overall background sound. This background L_{50} provides a consistent and *relative* measure of background sound amongst the study participants.

F. Data analysis techniques

1. Regression models

This analysis differentiates a respondent's experience with and response to wind turbine noise through sound levels and other covariates using two sets of models. First, the factors contributing to wind turbine audibility outdoors were assessed ($n = 749$). Adding variables in succession, three models are presented, with each building on the previous: a Basic model (sound levels, project participation, demographic variables, and stratification variables); an Observable model (adding variables than can be directly measured); and a Subjective model (adding variables describing respondent personal experience). Then, wind turbine noise annoyance *among respondents who could hear the wind turbines on their property* was tested following the same procedure with the same covariates ($n = 407$).

Although respondents out to 8 km were sampled and included in the sound propagation models, only respondents located within 5 km of the nearest turbine were included in the regression models due to few respondents being able to hear the wind turbines beyond 5 km. Only three respondents out of 132 living farther than 5 km from a turbine indicated turbine audibility or noise annoyance on their property, nearly resulting in a singular condition for this distance bin. Moreover, given that maximum short-term wind turbine sound levels were modeled well below 20 dB at 5 km from the nearest wind turbine, including respondents from distances greater than 5 km would not have been useful in predicting noise annoyance. Respondents without resolved survey responses forming the independent variables (i.e., missing values) were excluded from the regression analysis.

No data weighting was applied to the regression models but controlling variables were included to account for unequal probability of selection given sampling strategy/strata and to address differential response rates by gender, age, and education.¹⁰ To test the robustness of the unweighted regression approach, a weighted¹¹ regression, in which the sample was weighted to account for census tract demographics and survey stratification, was run for comparison. Although there were some minor differences in the significance of some variables with the weighted model, there were no substantive differences in the conclusions.

Covariates were selected based on those that were necessitated by sampling (demographics, sample stratification), factors that previous research has shown to be significant (wind turbine related or not), wind turbine characteristics, simulated long-term equivalent wind turbine sound power level correction (with DNL nighttime penalty), and long-term atmospheric stability. Selected variables were not eliminated from the model on the basis of insignificance, as systematically removing non-significant variables biases p -values and standard errors low and coefficients high (Heinze and Dunkler, 2017; Harrell, 2001). The fact that a specific variable is not significant in the presence of covariates may, in itself, be a result to be interpreted. Variables were only eliminated from the model if multicollinearity was found or for lack of data.¹² If multicollinearity was found, the authors sought to replace the variable with a similar representation or drop it altogether.

In Table III, descriptive statistics of all variables in the models, grouped into functional classification groups, are provided for the survey sample ($n = 1705$) and the subsample of respondents with modeled sound ($n = 1025$).

2. Statistical methodology

a. Regression model formulation. The audibility models used binary logistic regression to estimate the probability that a respondent hears the turbines on their property, while the noise annoyance models applied an ordinal logistic model for three response levels (Not at all Annoyed < Mildly Annoyed < Very Annoyed). The regression analyses were implemented using the R software environment (R Core Team, 2018; Harrell, 2018).

For ease of interpretation, the regression model coefficients are presented as odds ratios (ORs), calculated as $\exp(\beta)$, where β represents the coefficient of interest. ORs, a measure of effect size, are a common form of reporting logistic regression coefficients and indicate the effect of a one-unit increase in a continuous covariate or a change in levels of a categorical covariate on the odds of experiencing the dependent variable in question. For instance, an OR of 1.15 indicates that for a one-unit increase in sound levels, a respondent would have a 15% increase in the odds of being able to hear the wind turbines. Unity is the no-effect value and values less than 1 indicate that the odds decrease with increasing values of the covariate. In ordinal logistic regression, the interpretation of the OR is similar: it is the change in the odds of having a higher value of the response variable.

Variance inflation factors (VIFs) test for collinearity in the models (James et al., 2017). A VIF of 1.0 indicates that

there is no correlation. Typically, a VIF above 4 deserves a closer look. This study employs a conservative maximum VIF of 2.5 for independent variable inclusion.

b. Variable importance. The relative importance of each variable is characterized using change in Akaike Information Criteria (Δ AIC; Harrell, 2018). This represents the effect on the model fit when that variable is removed from the regression. Higher Δ AIC values signify stronger predictors. For categorical variables, the Δ AIC measure is particularly useful in that it shows the strength of the whole variable as opposed to the individual model coefficients.

c. Model accuracy. The overall fit of the model is measured with several indicators: leave-one-out cross-validation (LOOCV), area under the receiver operating curve (AUC), and Nagelkerke's R^2 (R_N^2). These are described below.

In LOOCV, the regression model is estimated repeatedly leaving out one case (i.e., respondent; Geisser, 1993). Then, the predicted outcome for the omitted case is compared to the actual outcome for that respondent. The goal is to see if the model correctly predicts the case that was "left out." The results of the validation are expressed as the proportion of outcomes that are correctly predicted for each level of the response variable. In addition to the proportion of correct predictions, the LOOCV can also be summarized by the multiclass area under the receiver operating characteristic curve (Hand and Till, 2001), which is a measure of model fit obtained by comparing the LOOCV predicted responses to the observed responses (Robin et al., 2011). The AUC ranges from 0.5 for a model with no predictive ability to a maximum of 1.0 for a model with perfect predictive ability (Fawcett, 2006).

Nagelkerke's R^2 is a "pseudo- R^2 " and is used as an index of overall model quality (Nagelkerke, 1991). It is calculated as a measure of the improvement of the log-likelihood of the model compared to that of a null model and is designated here as R_N^2 .

3. CTL (dose-response analysis)

Responses were weighted and grouped into 5 dB categories using DNL*. Proportions of Highly Annoyed respondents were calculated for each sound level category for respondents with resolved audibility and noise annoyance ($n = 1023$) and for the subset of respondents who were not compensated for the project ($n = 818$). The percentage of Highly Annoyed responses in each sound level category was then fit to a dose-response relationship, as shown in Eq. (1) (Fidell et al., 2011),

$$\text{Percent Highly Annoyed} = 100e^{-\left[1/(10^{(\text{DNL}-\text{CTL}+5.306)/10})^{0.3}\right]}, \quad (1)$$

where the CTL represents the DNL at which half of the population is considered Highly Annoyed. The key difference between an analysis of Highly Annoyed individuals for calculating of the CTL and the Very Annoyed endpoint tested in the regression models is that the CTL dose-response

TABLE III. Distribution of modeled variables among subsets of survey response data by count and descriptive statistics: mean, mean and SD, or distribution of responses (%). The modeled sound level dataset is very similar in proportions and means to the full survey sample.

Group	Variable Name	Type ^a	Variable Description (Units or Reference Level ^b and Order)	Full Sample			
				All Respondents (<i>n</i> = 1705)		Modeled Sound (<i>n</i> = 1025)	
				<i>n</i>	Mean (SD)	<i>n</i>	Mean (SD)
Dependent	Annoyance ^c	O	[Cannot Hear] < Not at all Annoyed < Mildly Annoyed < Very Annoyed	[53] / 21 / 17 / 9		[52] / 22 / 17 / 9	
	Audibility	B	0 = Cannot hear turbine on property, 1 = Can hear turbine on property	1682	0.46	1025	0.48
Demographic	Female	B	0 = not female, 1 = female	1686	0.53	1016	0.55
	Age	C	Respondent age, years	1667	58 (15)	1004	58 (15)
	College	B	0 = no college degree, 1 = college degree	1686	0.48	1014	0.48
	White	B	0 = not white, 1 = white	1678	0.9	1010	0.89
	Income	C	Median income of survey selected census categories (×\$10 000)	1479	7.4 (5.2)	893	7.2 (5.1)
Stratification	Dominant	B	0 = not under-sampled, 1 = under-sampled due to population distribution	1705	0.07	1025	0.09
	Discrete	B	0 = not over-sampled, 1 = over-sampled for initial sound modeling	1705	0.33	1025	0.53
	Project size ^d	B	0 = small project (10 turbines or less), 1 = large project (>10 turbines)	1705	0.64	1025	0.6
	# of turbines	C	Number of turbines in local project	1705	49 (52)	1025	50 (57)
Relationship	Project participation ^c	Ca	Non-participant /Compensated (not host)/Host and Compensated	1661	81 / 12 / 5	998	80 / 12 / 5
Sound Level	Wind turbine	C	Wind turbine sound level (L _{1h-max})			1025	36.7 (10.5)
	Background L ₅₀	C	Median summer daytime sound level (L ₅₀) (dBA)	1687	40.9 (5)	1025	41.9 (5.1)
Site Conditions	Atm. Stability	C	Atmospheric stability (mean long-term inverse Obukhov Length)			1025	0.004 (0.015)
	DNL correction	C	Adjustment to DNL using long-term wind turbine sound power emission			1025	3.47 (1.2)
Turbine Specifications	C-to-A ratio*	C	Turbine sound power C-to-A ratio (no data below 63 Hz octave band) (dB)			1025	10.1 (1.8)
	Rotor diameter	C	Rotor diameter (m)	1693	88.4 (9)	1020	89.5 (9.2)
	Hub height	C	Hub height (m)	1693	84 (8.5)	1020	85 (9.2)
	Tip speed	C	Rotor tip speed at full output capacity (m/s)			1025	77 (6.3)
Individual	Turbine view	B	0 = Cannot see turbine, 1 = Can see turbine	1647	0.8	995	0.8
	Move-in	B	0 = Resident prior to project, 1 = Move-in after project was built	1639	0.23	988	0.22
Subjective	Prior attitude ^c	Ca	Neutral / Negative / Positive / Move-in after	1639	41 / 10 / 26 / 23	988	42 / 9 / 28 / 22
	Noise sensitive	O	Not at all < Slightly < Somewhat < Moderately < Very	1694	23 / 31 / 22 / 15 / 8	1020	25 / 32 / 21 / 14 / 8
	Like look (visual) ^c	Ca	Neutral / No / Yes	1646	14 / 25 / 61	990	14 / 24 / 63

^aVariable type: C = continuous, B = binary, Ca = categorical, O = ordinal.

^bReference level in bold.

^cPercentages may not add to 100 due to rounding; Prior attitude combines with the mutually exclusive move-in variable for 100%.

^dNot included in regression models due to multicollinearity with variables of interest (mostly background sound level); actual number of turbines in a project was used in its place.

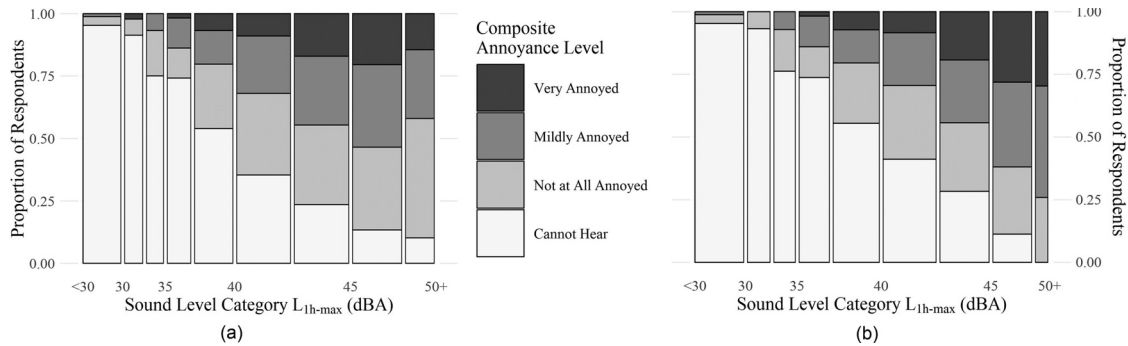


FIG. 2. Composite annoyance: distribution of outdoor audibility and annoyance level by sound level category for (a) all respondents ($n = 747$; two respondents who indicated wind turbine audibility but did not provide an annoyance level are excluded from the plot) and (b) for only non-participants ($n = 591$; two respondents who indicated wind turbine audibility but did not provide an annoyance level are excluded from the plot). Bar widths are proportional to the number of respondents in each exposure category. Each bar represents a grouping of 2.5 dBA, except for the top sound level category, which includes respondents with modeled sound levels greater than or equal to 47.5 dBA.

analysis includes all respondents with resolved audibility, while the Very Annoyed regression analysis tested noise annoyance only among respondents for whom wind turbines were audible on their property.

III. RESULTS

A. Sound levels and survey results

The composite distribution of wind turbine audibility and noise annoyance among respondents is presented together in Fig. 2. Figure 2 shows that wind turbine audibility and noise annoyance both increase with sound level category. Below 40 dBA L_{1h-max} , over half of the respondents indicated that they were unable to hear the turbines on their property and less than 20% expressed some noise annoyance, i.e., they were Mildly or Very Annoyed. At 45 dBA and above, about half of the respondents reported that they were annoyed by wind turbine noise. A comparison of Figs. 2(a) and 2(b) reveals that in wind turbine noise categories above 45 dBA, project participants reported less audibility and annoyance than non-participants. Furthermore, all non-participants with a modeled wind turbine sound level of 47.5 dBA L_{1h-max} or greater reported hearing wind turbine noise on their property.

Table IV expands on the distribution of responses and sample characteristics by sound level category. It reveals the following:

- Larger projects (more turbines) were associated with higher sound level categories (Spearman's $\rho = 0.47$).
- Average background sound levels tended to be lower in higher wind turbine sound level categories.¹³
- College education, whether a respondent identified as white, and income were strongly associated with audibility but less so with noise annoyance.
- About 90% of respondents within 5 km could see wind turbines from their property.
- Higher sound level categories were significantly associated with higher rates of negative visual perceptions (except above 50 dBA).¹⁴
- More than 2/3 of respondents with wind turbine sound levels above 40 dB could hear the turbines on their property.

Of these, about 2/3 also reported hearing turbines in their home.

- Among respondents who reported hearing wind turbines on their property, the annoyance level was statistically significant with respect to sound level category only when project participants were excluded from the analysis.

Further analysis reveals that there was a significant association between noise annoyance level and hearing wind turbines inside the home (Chi-squared test, $p < 0.001$). However the directionality of the association is important: while respondents who reported hearing wind turbine noise in their home were not necessarily Very Annoyed by the noise (27% of respondents who reported hearing wind turbine noise in their home found it very annoying), nearly all respondents who were Very Annoyed by the noise also reported hearing wind turbine noise in their home (72 out of 73 Very Annoyed responses).

B. Regression model results

Three successive models are presented for testing the multivariable relationships between respondent audibility and noise annoyance: the Basic variables model, the Observable variables model, and the Subjective variables model. Each model includes the variables contained in the preceding iteration.

1. Audibility

Wind turbine sound level was the strongest predictor of wind turbine audibility (Table V). Background sound levels also had a significant effect, albeit in the opposite direction. With project participation, sound levels, and controlling variables accounted for, wind turbine audibility outdoors was predicted correctly 80% of the time. Adding in observable quantities was found to improve the R_N^2 from 0.54 to 0.58. Although age, atmospheric stability, DNL correction, rotor tip speed, turbine view from property, and move-in after construction of the local project were significant, the overall ability of the model to correctly predict audibility remained unchanged (i.e., 80% of responses predicted correctly). Finally, adding in the subjective variables did not improve audibility predictions; no subjective variables were significant. Thus, wind turbine sound level is the most important

TABLE IV. Sample characteristics as a function of wind turbine sound level category. Each variable was assessed for significant variability across sound level categories. Categorical (and binary) variables were assessed with Pearson’s chi-squared test and continuous variables were assessed with one-way ANOVA. The distribution of characteristics across exposure categories is shown for the audibility dataset ($n = 749$). Only overall values (and p -values) are included for each variable in the context of the annoyance dataset ($n = 407$). Lastly, noise annoyance is assessed across sound level categories for all respondents and only non-participants.

Variable Name	Statistic	Sound Level Category						Audibility		Annoyance	
		<30	[30–35]	[35–40]	[40–45]	[45–50]	[50 +]	Overall	p -value	Overall	p -value
Sample size	n	82	90	143	244	177	13	749		407	
Distance (km)	Mean (SD)	2.9 (1.1)	2 (0.9)	1.3 (0.5)	0.8 (0.3)	0.5 (0.2)	0.2 (0.1)	1.2 (0.9)	<0.001	0.8 (0.4)	<0.001
	Min–Max	1.2–4.8	0.9–4.6	0.5–3.2	0.3–1.6	0.2–1.1	0.1–0.4	0.1–4.8		0.1–4.2	
Female	%	41	54	56	59	51	38	54	0.067	54	0.445
Age	Mean (SD)	61 (15)	60 (15)	57 (14)	58 (14)	58 (15)	61 (17)	59 (15)	0.433	57 (14)	0.349
College	%	68	50	56	37	45	31	47	<0.001	45	0.146
White	%	82	87	90	92	97	100	91	<0.001	96	0.017
Median income ^a	n : Mean (SD)	71: 8.5 (5.2)	82: 7.5 (5)	130: 6.7 (4.8)	220: 6.5 (4.6)	156: 8.3 (5.6)	11: 10.8 (6.6)	672: 7.4 (5.1)	<0.001	365: 7.6 (5.1)	0.022
Dominant project	%	12	14	15	9	3	0	10	0.002	4	0.318
Discrete project	%	41	41	42	56	60	54	51	0.002	54	0.023
# of Turbines	Mean (SD)	15.7 (34.1)	31.3 (45.7)	40.3 (51.7)	59.6 (57.4)	87.6 (60)	104.3 (84.2)	55 (59)	<0.001	70 (59)	<0.001
	Min–Max	1–152	1–152	1–193	1–222	1–222	1–222	1–222		1–222	
Project Participation No/Comp./Host comp.	% ^b	100/0/0	97/3/0	94/6/0	77/20/4	55/30/15	31/15/54	79/15/6	<0.001	68/25/7	<0.001
Background L ₅₀ (dBA)	Mean (SD)	45.2 (5.2)	44 (5)	42.2 (4.9)	41.3 (4.1)	40.5 (2.6)	40.6 (2.6)	42 (4.5)	<0.001	40.4 (3.1)	<0.001
	Min–Max	32.9–52.2	33.3–52.2	33.3–52.2	32.3–52.2	36.5–52.2	38.5–46	32.3–52.2		32.9–52.2	
Turbine view	%	56	79	87	96	99	100	89	<0.001	98	0.132
Move-in after	%	30	23	22	20	19	8	21	0.23	16	0.757
Prior attitude: Neutral /Neg./Pos./ Move-in after	% ^b	41/4/24/30	48/6/23/23	48/7/23/22	39/10/32/20	32/13/36/19	31/0/62/8	40/9/30/21	0.006	39/13/32/16	0.304
Noise sensitive: Not at all to Very	% ^b	30/28/18/13/10	17/38/23/14/8	25/37/17/11/9	23/32/22/14/9	37/26/21/11/5	15/46/15/15/8	27/32/20/12/8	0.249	26/31/22/13/8	0.399
Like look of wind project: Neutral / No / Yes	% ^b	17/1/72	14/18/68	19/20/61	13/27/61	6/32/61	8/8/85	13/24/63	<0.001	11/32/57	0.088
Hear on property	%	4	17	38	69	88	92	54	<0.001	100	
Hear in home	%	2	8	20	41	64	69	35	<0.001	64	0.019
Annoyance sample	n	3	15	54	169	154	12			407	0.577
Annoyance levels ^c	% ^b	67/33/0	73/20/7	54/33/13	46/36/19	44/36/21	58/33/8			47/35/18	
Annoyance sample (non-participants only)	n	3	14	49	120	88	4			278	0.011
Annoyance levels ^c	% ^b	67/33/0	79/21/0	51/35/14	45/34/21	28/40/32	25/75/0			42/36/22	

^aMedian income of survey selected census categories ($\times \$10\,000$).

^bPercentages may not add to 100 due to rounding.

^cDependent variable tested in Noise Annoyance model. Noise Annoyance levels = Not at all Annoyed/Mildly Annoyed/Very Annoyed.

TABLE V. Audibility model results. For each variable included in each model, the OR, its 95% CI, and Δ AIC value are provided. ORs that are bolded and underlined denote statistical significance ($p < 0.05$).

$(n = 749)$									
	BASIC			OBSERVABLE			SUBJECTIVE		
Nagelkerke R^2	0.54			0.58			0.60		
AUC	0.80			0.79			0.80		
Maximum VIF	1.72			2.36			2.30		
Proportion Predicted Correctly									
	Cannot Hear	0.74		0.73		0.74			
	Hear on Prop.	0.86		0.86		0.86			
Total Proportion Correct	0.80			0.80			0.80		
Variable	OR	(95% CI)	Δ AIC	OR	(95% CI)	Δ AIC	OR	(95% CI)	Δ AIC
Female	1.01	(0.68, 1.49)	-2	1.00	(0.66, 1.49)	-2	0.95	(0.63, 1.45)	-2
Respondent age	0.99	(0.98, 1.01)	0	0.99	(0.97, 1 ^a)	2	0.99	(0.97, 1.001)	1
College	1.52	(1.001, 2.29)	2	1.46	(0.95, 2.23)	1	1.37	(0.88, 2.12)	0
White	1.41	(0.63, 3.17)	-1	1.62	(0.67, 3.92)	-1	1.52	(0.63, 3.69)	-1
Dominant project	0.42	(0.18, 0.98)	2	0.40	(0.16, 0.96)	2	0.39	(0.16, 0.98)	2
Discrete project	0.77	(0.5, 1.19)	-1	0.61	(0.37, 0.99)	2	0.60	(0.37, 0.996)	2
Number of turbines in project	1.00	(0.99, 1.002)	-1	1.00	(0.995, 1.003)	-2	1.00	(0.995, 1.003)	-2
Project participation (Non-participant ^b)			19			19			16
– Compensated: not a host	2.01	(1.01, 4.01)		1.73	(0.85, 3.55)		2.14	(1.03, 4.43)	
– Compensated: turbine host	0.20	(0.09, 0.45)		0.17	(0.07, 0.38)		0.22	(0.09, 0.52)	
Wind turbine sound level (L_{1h-max})	1.32	(1.26, 1.38)	131	1.31	(1.25, 1.38)	111	1.31	(1.25, 1.38)	103
Summer daytime background L_{50}	0.88	(0.83, 0.94)	13	0.91	(0.85, 0.98)	5	0.93	(0.86, 0.99)	3
Atmospheric stability ^c				1.02	(1.002, 1.04)	3	1.02	(1.003, 1.04)	3
DNL correction				1.35	(1.07, 1.71)	4	1.38	(1.09, 1.75)	5
Sound power C-to-A ratio*				0.96	(0.82, 1.12)	-2	0.96	(0.82, 1.13)	-2
Rotor diameter				0.98	(0.96, 1.01)	0	0.98	(0.96, 1.01)	0
Turbine hub height				0.99	(0.96, 1.02)	-1	0.99	(0.96, 1.02)	-1
Rotor tip speed				1.08	(1.03, 1.14)	9	1.08	(1.03, 1.13)	8
View of turbine from property				3.87	(1.52, 9.85)	6	4.27	(1.66, 10.94)	7
Move-in after construction				0.56	(0.34, 0.94)	3			
Prior attitude (Neutral) ^b									2
– Negative							2.10	(0.83, 5.35)	
– Positive							0.85	(0.5, 1.44)	
– Move-in after construction							0.57	(0.32, 1)	
Noise sensitive (Not at all) ^b									-4
– Slightly							1.27	(0.74, 2.19)	
– Somewhat							1.71	(0.92, 3.16)	
– Moderately							1.34	(0.65, 2.78)	
– Very							2.14	(0.88, 5.18)	
Like look of wind project (Neutral) ^b									2
– No							1.34	(0.65, 2.78)	
– Yes							2.14	(0.88, 5.18)	

^aValue rounds to 1 at 3 significant digits yet is indeed less than 1 (p -value = 0.04).

^bCompared to reference level; Δ AIC represents importance of the variable as a whole.

^cAtmospheric stability (mean inverse Obukhov length) is scaled by 1000 in the model to improve interpretation of results.

predictor of audibility, with a Δ AIC score almost an order of magnitude higher than the next highest covariate: a 1 dB increase in wind turbine sound level is associated with an increase in the odds of hearing the local wind project by 31% [OR 1.31; 95% Confidence Interval (CI): 1.25–1.38]. For additional context, a 3 dB increase in wind turbine sound level translates to an increase in the odds of hearing the local wind project by a factor of 2.3 (95% CI: 2.14–2.38).

Project participation was the second most important factor for predicting audibility. The odds of hearing wind turbines were 2.1 (95% CI: 1.03–4.43) times higher for those who were compensated without hosting a turbine than for non-participants

(Table V). However, turbine hosts had lower odds (OR: 0.22; 95% CI: 0.09–0.52) than non-participants of hearing wind turbines on their property. The lower audibility among wind turbine hosts is counterintuitive and is discussed in Sec. IV B.

Although much less important than sound levels and project participation, several other independent variables were significant factors in determining wind turbine audibility. Faster tip speeds were associated with increased audibility: the OR indicates that an increase of 1 m/s in tip speed is associated with an increase in the odds of hearing the local wind project by 8% (OR: 1.08; 95% CI: 1.03–1.13). Increases in long-term wind turbine sound power emissions

relative to the maximum reported sound power level (DNL correction) and atmospheric stability, as well as being able to see the turbine from one's property, were significantly associated with increased odds of hearing the local wind project on one's property. Higher background sound levels were significantly associated with decreased odds of hearing wind turbines on one's property (OR: 0.93; 95% CI: 0.86–0.99).

2. Noise annoyance

While significant in all three Noise Annoyance models, sound levels were not the dominant predictor of the response variable (Table VI). In the Basic Noise Annoyance model, wind

turbine sound level, background L_{50} , and project participation were significant. Project participation was the most important variable, decreasing the odds of being annoyed by wind turbine noise by 86% if hosting (OR: 0.14; 95% CI: 0.06–0.35) and 58% if not hosting (OR: 0.42; 95% CI: 0.27–0.68). However, the R_N^2 of this first model was just 0.12, with no Very Annoyed responses predicted by the cross-validation procedure.

In the Observable model, rotor diameter (OR: 1.03; 95% CI: 1.004–1.06) and move-in after construction (OR: 0.37; 95% CI: 0.21–0.66) became significant in addition to the previous variables, which resulted in a modest increase in R_N^2 to 0.17. The Observable model was still only able to

TABLE VI. Noise Annoyance model results. For each variable included in each model, the OR, its 95% CI, and Δ AIC value are provided. ORs that are bolded and underlined denote statistical significance ($p < 0.05$).

<i>(n = 407)</i>		BASIC			OBSERVABLE			SUBJECTIVE		
Nagelkerke R^2		0.12			0.17			0.56		
AUC		0.61			0.61			0.78		
Maximum VIF		1.35			2.02			2.23		
Proportion Predicted Correctly										
		Not at all	0.75		0.64		0.83			
		Mildly	0.38		0.40		0.38			
		Very	0.00		0.04		0.52			
Total Proportion Correct		0.48			0.45			0.62		
Variable	OR	(95% CI)	Δ AIC	OR	(95% CI)	Δ AIC	OR	(95% CI)	Δ AIC	
Female	0.90	(0.61, 1.32)	-1	0.87	(0.59, 1.29)	-1	<u>0.60</u>	(0.39, 0.94)	3	
Respondent age	1.00	(0.98, 1.01)	-2	0.99	(0.98, 1.01)	-1	0.99	(0.97, 1.003)	1	
College	1.00	(0.67, 1.49)	-2	1.10	(0.73, 1.64)	-2	0.96	(0.6, 1.51)	-2	
White	2.52	(0.74, 8.53)	-1	2.98	(0.77, 11.52)	0	1.52	(0.37, 6.34)	-2	
Dominant project	2.62	(0.89, 7.72)	1	<u>3.46</u>	(1.12, 10.71)	2	3.39	(0.95, 12.1)	2	
Discrete project	0.92	(0.6, 1.39)	-2	0.94	(0.59, 1.48)	-2	1.11	(0.65, 1.89)	-2	
Number of turbines in project	1.00	(0.997, 1.005)	-2	1.00	(0.997, 1.004)	-2	1.00	(0.99, 1.003)	-2	
Project participation (Non-participant ^a)			22			21			-1	
– Compensated: not a host	<u>0.42</u>	(0.27, 0.68)		<u>0.43</u>	(0.27, 0.7)		0.90	(0.52, 1.57)		
– Compensated: turbine host	<u>0.14</u>	(0.06, 0.35)		<u>0.14</u>	(0.06, 0.36)		0.42	(0.15, 1.19)		
Wind turbine sound level (L_{1h-max})	<u>1.08</u>	(1.03, 1.14)	10	<u>1.08</u>	(1.02, 1.14)	8	<u>1.09</u>	(1.02, 1.16)	5	
Summer daytime background L_{50}	<u>0.90</u>	(0.84, 0.97)	7	<u>0.89</u>	(0.82, 0.97)	6	0.92	(0.84, 1.01)	1	
Atmospheric stability ^b				0.99	(0.97, 1.01)	-1	0.98	(0.96, 1.01)	0	
DNL correction				0.94	(0.75, 1.19)	-2	1.25	(0.95, 1.65)	1	
Sound power C-to-A ratio*				1.01	(0.88, 1.15)	-2	0.96	(0.83, 1.11)	-2	
Rotor diameter				<u>1.03</u>	(1.004, 1.06)	3	<u>1.04</u>	(1.01, 1.07)	5	
Turbine hub height				1.02	(0.99, 1.04)	-1	0.99	(0.96, 1.02)	-2	
Rotor tip speed				0.98	(0.94, 1.02)	0	1.00	(0.95, 1.05)	-2	
View of turbine from property				0.46	(0.1, 2.15)	-1	0.44	(0.08, 2.39)	-1	
Move-in after construction				<u>0.37</u>	(0.21, 0.66)	10				
Prior attitude (Neutral) ^a									13	
– Negative							0.97	(0.48, 1.96)		
– Positive							<u>0.45</u>	(0.25, 0.8)		
– Move-in after construction							<u>0.24</u>	(0.12, 0.48)		
Noise sensitive (Not at all) ^a									14	
– Slightly							<u>2.24</u>	(1.19, 4.2)		
– Somewhat							<u>2.57</u>	(1.3, 5.08)		
– Moderately							<u>2.98</u>	(1.33, 6.66)		
– Very							<u>8.49</u>	(3.33, 21.6)		
Like look of wind project (Neutral) ^a									81	
– No							<u>11.0</u>	(4.8, 25.4)		
– Yes							0.49	(0.23, 1.05)		

^aCompared to reference level; Δ AIC represents importance of the variable as a whole.

^bAtmospheric stability (mean inverse Obukhov length) is scaled by 1000 in the model to improve interpretation of result.

predict 4% of Very Annoyed respondents, with 45% of responses correctly predicted overall. In the Subjective model, the addition of subjective variables resulted in a considerable increase in model performance ($R_N^2 = 0.56$). The Subjective model was able to correctly predict 52% of the Very Annoyed responses (total proportion correct of 0.62). All newly added variables (i.e., prior attitude, noise sensitive and like the look) were statistically significant and had the highest ΔAIC values. Although project participation was the most important variable in the Basic and Observable and Noise Annoyance models, accounting for subjective variables rendered project participation status insignificant. Background L_{50} also lost significance once subjective variables were added.

The strongest correlates with noise annoyance were subjective factors (including self-reported noise sensitivity). Visual impression (like the look) was the most important factor (OR: 11; 95% CI: 4.8–25.4) in predicting noise annoyance with an ΔAIC of 81 compared to 14 for the next most important variable (noise sensitive). Respondents who reported the highest level of noise sensitivity had 8.5 times higher odds of moving to the next level of annoyance compared to respondents who reported no noise sensitivity (OR 8.49, 95% CI: 3.33–21.6) and about 3 times the odds of moving to the next level of annoyance compared to the middle three levels of self-reported noise sensitivity. While having prior positive attitude was important in the model, having had a negative attitude was not significantly different from the reference (neutral) group (OR: 0.97; 95% CI: 0.48–1.96). This may be due to the strong association between negative attitude and negative visual impressions: 73% of respondents with negative prior attitudes toward the project also reported that they did not like the look. In the absence of like the look, all levels of prior attitude, including negative attitude, were significant (results not shown).

The addition of the subjective variables had a notable effect on the importance of project participation in the Noise Annoyance models. Wind project participation was the strongest predictor ($\Delta AIC > 20$) until subjective variables were included in the regression. No wind turbine hosts reported being Very Annoyed by wind turbine noise. In contrast, 13 out of 113 respondents who were compensated without hosting a turbine reported being Very Annoyed by wind turbine noise. Survey responses revealed strong relationships between project participation and perceptions of the wind project,¹⁵ which may explain the change in importance of project participation upon the addition of the subjective variables.

Alongside subjective variables, wind turbine sound levels, turbine rotor diameter, identifying as female, and move-in after were significant in the final Noise Annoyance model. A 1 dB increase in wind turbine sound level was found to be associated with an increase in the odds of moving to the next level of annoyance by 9% (OR: 1.09; 95% CI: 1.02–1.16). For context, a 3 dB increase in wind turbine sound level translates to a 28% increase in the odds of moving to the next annoyance level (95% CI: 1.20–1.36). Increased wind turbine rotor diameters were associated with greater noise annoyance: for each 1 m increase in rotor diameter, the odds

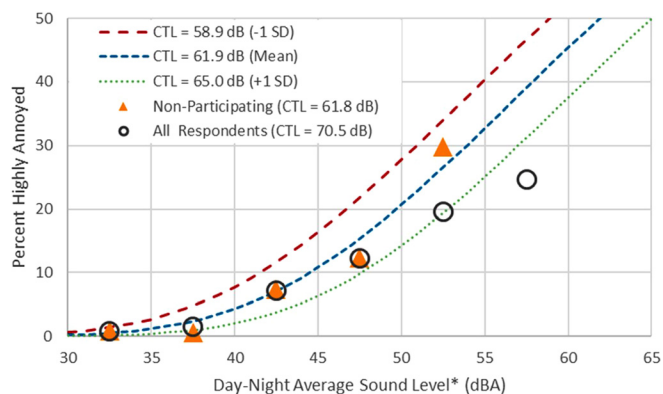


FIG. 3. (Color online) The percent Highly Annoyed for each sound level category represents the response of the population living near wind turbines in the U.S. (the data are weighted). Results are binned in 5 dB DNL* increments. The points for non-participating respondents exclude respondents who were compensated or hosted wind turbines on their property; the datasets diverge above the 45 to 50 dB sound level category. CTL curves for 58.9 and 65 dB are the ± 1 SD exposure response for wind turbine noise as reported in Michaud *et al.* (2016b).

of moving to the next level of noise annoyance increased by 4% (OR: 1.04; 95% CI: 1.01–1.07). Also, females had lower odds of moving to the next annoyance level than males (OR: 0.60; 95% CI: 0.39–0.94), signifying that when subjective factors were accounted for, females had lower odds of moving to the next level of noise annoyance than males.

C. Dose-response analysis

Figure 3 depicts the percent Highly Annoyed by sound level category for the entire study sample and for those who were not project participants. The data are plotted alongside the ranges of wind turbine CTL calculated by Michaud *et al.* (2016b). When project participants were included, the rate of increase of the percentage of Highly Annoyed individuals decreased above 50 dBA (DNL*) and no longer followed the third-order polynomial trend. From this study, the CTL was estimated to be 61.8 dB when project participants were excluded from the calculation and 70.5 dB when project participants were included (CTLs for unweighted data are similar: 60.8 dB for non-project participants and 68.0 dB for all respondents). The mean CTL among six studies in Europe and Canada was 61.9 dB (Michaud *et al.*, 2016b), so the value calculated in the U.S. (for non-participants) falls near the international average.

IV. DISCUSSION

A. Dependent variable design

Separating the prediction of audibility from that of noise annoyance distinguishes the various factors that contribute to reaction to wind turbine noise. Audibility is largely a function of wind turbine sound level, while alternatively, noise annoyance from audible sound is largely a function of subjective factors (though wind turbine sound level is also a significant factor). Residents who are unable to perceive a community noise source and those that notice a community noise—but express no annoyance toward the sound—represent two separate groups of individuals with distinct

experiences; they should not be treated as one. Regardless, the range of R_N^2 and the predictive characteristics of the models (i.e., poor prediction of noise annoyance without subjective variables) presented in this work show good agreement with prior literature performing similar analyses, albeit with slightly different response variables (e.g., [Michaud et al., 2016b](#)).

B. Factors influencing wind turbine audibility and noise annoyance

The long-term average sound level is useful for comparing to other dose-response studies and for considering long-term exposure to wind turbine sound, but many jurisdictions often use short-term sound levels to set standards ([Fowler et al., 2013](#)). This study helps bridge that gap by using the L_{1h-max} as the primary sound level metric in regressions yet also calculating a long-term sound level metric (i.e., DNL) to compare to other studies. The dose-response analysis reveals that wind turbine noise annoyance in the U.S. (among the population not receiving personal benefits from the local project) is comparable to the international average CTL calculated by [Michaud et al. \(2016b\)](#) and thus supports the assertion that wind turbines are more annoying than other community noise sources at similar long-term sound pressure levels. When project participants were included in the dose-response relationship, the community became more tolerant of wind turbine noise, particularly at higher sound levels, which parallels results found by [van den Berg et al. \(2008\)](#).

This study showed that background sound levels affected the audibility of wind turbines, which is most likely due to the masking of wind turbine sound by other sources ([Nelson, 2007](#)). Using partially masked loudness ([Zwicker and Fastl, 2007](#)) to calculate the “residual” loudness of wind turbine noise in contrasting ambient soundscapes, Nelson showed that perceived loudness of wind turbine noise is a function of the character of the existing background sound. Background sources can include natural sounds (e.g., wind, water, foliage, and insects) and anthropogenic sounds (e.g., transportation, agriculture, and industry) that vary considerably with time and place. Therefore, the masking provided by background sound and its impact on wind turbine audibility is often difficult to accurately quantify in absolute terms ([Hathaway and Kaliski, 2006](#)). Thus, caution is in order for using this research as the basis to create regulatory limits relative to background sound levels.

Atmospheric conditions can produce substantial changes in sound levels experienced from a given community noise sources at a given location ([Kaliski et al., 2018a](#)). Projects sited in areas with more stable atmospheric conditions (on average) and higher long-term wind turbine sound emissions (relative to short-term levels) were significantly associated with increased audibility. However, these factors had no influence on noise annoyance, which suggests that the L_{1h-max} is just as suitable for predicting noise annoyance as long-term averages. Modeling the L_{1h-max} using simple parameters eliminates the problems of comparing results between researchers that use different methodologies to calculate

long-term averages and avoids the larger uncertainties related to modeling sound levels over a typical year for every unique respondent.

Although the C-A ratio is a good indicator of the relative low-frequency content present in a sound, the results of this study indicate that the relative low-frequency dominance of nearby wind turbines did not have a significant effect on either audibility or noise annoyance. That is, with overall sound levels accounted for, wind turbines with higher C-A ratios did not significantly result in higher audibility or noise annoyance in the regression models. This finding supports the observation by [Leventhall \(2003\)](#) that the C-A ratio is not a suitable predictor for annoyance. However, in this study, the caveat remains that the C-A ratio was only tested with data down to the 63 Hz octave band due to poor availability of low-frequency spectral data on turbines sound powers tested prior to 2012.

In the presence of the covariates assessed, project size was found to have no significant effect on either audibility or noise annoyance. However, a significant trend of increasing project size with increasing sound level category existed in the sample, which the authors believe to be related to the expansive footprint of larger projects in rural areas where respondents may receive sound from multiple nearby turbines. Project size is not significant in the regression models perhaps because the variability accounted for by project size is better explained by wind turbine sound levels. That is, according to the [Baron and Kenny \(1986\)](#) criteria, wind turbine sound level is the “mediator” variable through which the effect of project size is realized.

Whether a turbine can be viewed from a property has been found in other studies to affect noise annoyance ([Pedersen and Pernilla, 2008](#); [van den Berg et al., 2008](#)). In this study, turbine visibility is a significant variable in the Audibility model: the odds of hearing wind turbines were 4.3 (95% CI: 1.66–10.9) times higher for respondents who could see a turbine from their property. However, as in [Michaud et al. \(2016b\)](#), this study found that the effect on noise annoyance was not significant.

The regression models showed that those who move in after a wind project is constructed had 44% lower odds of hearing the wind turbines (Table V) and 63% lower odds of being annoyed by their sound compared to prior residents (Table VI). In general, those who moved in after wind development were less annoyed by wind turbine noise than those who lived in the area prior to the project being built. This aligns with [Tiebout’s \(1956\)](#) original theory that suggests that “sorting” will encourage more supportive (and therefore, less-negative) individuals to move into the community. As we did not sample those individuals who moved out, we cannot say whether or not they voted with their feet due to audibility and noise annoyance. [Firestone et al. \(2018\)](#) suggest that existing residents may have been more likely to express negative attitudes toward a project than those who moved in afterward because some of them may have been negatively affected by the process leading to permitting, had negative experiences with the developer, or perceived a negative change in the landscape. However, [Firestone et al. \(2018\)](#) also found that the opposite was true if residents perceived

the development process to be open, transparent, and inclusive. In this study, compared to respondents who were neutral toward the project prior to construction, a positive prior attitude significantly decreased the odds of noise annoyance; negative prior attitudes were significantly associated with increased noise annoyance, but only when visual impressions were excluded from the model.

Previous studies on wind turbine noise have identified subjective factors as important drivers of noise annoyance. Self-reported noise sensitivity and whether a respondent feels that the wind turbines mar the landscape have been found to increase noise annoyance from wind turbines (Pawlaczyk-Łuszczynska *et al.*, 2014; Pedersen and Persson Waye, 2004; Michaud *et al.*, 2016b). Consistent with those findings, the Noise Annoyance model including subjective variables in this study shows that both variables have a significant effect on noise annoyance, with visual effect (appearance) as the most important for noise annoyance. However, the direction of causation for this effect is not known: it is not possible to determine whether someone is more likely to be annoyed by wind turbine noise because they object to wind turbines visually or whether noise annoyance has led them to have a negative association with the visual aspects of the wind turbines. In other words, one cannot determine whether these effects are re-enforcing, or whether they are endogenous—that is, jointly determined.

This study categorized respondents who received personal benefits from their local wind project as those hosting a wind turbine on their property and those who were not. The regression model results demonstrate that these two groups of project participants are significantly different. In regard to wind turbine audibility, the Audibility model established that non-hosting participants had the highest odds of hearing wind turbines on their property, while wind turbine hosts had the lowest odds. The lower odds of audibility among wind turbine hosts is a nonintuitive result, given that hosts, on average, had the highest wind turbine sound levels in the sample.¹⁶ The unexpected result could be due to the relatively small sample size of hosts ($n = 43$), but outliers that could have disproportionately affected the results were not apparent. Alternatively, the authors speculate that as the oldest¹⁷ group of the “project participation” variable, age-induced hearing loss may have contributed to the lower odds of wind turbine audibility among hosts.¹⁸ In regard to noise annoyance, in the absence of subjective variables, wind turbine hosts had lower odds of moving to the next level annoyance than both non-participants and participants not hosting wind turbines.

Among project participants in this study, participants not hosting wind turbines on their property generally held more negative attitudes and perceptions toward the project than wind turbine hosts. Negative impressions among non-hosts may be due to compensation itself as a validation of a specific negative impact of the project or a missed opportunity for additional revenue from the project. Neighbor agreements (compensation for impacts, such as noise) and variances (monetary waivers for deviations from land-use regulations) are formal admissions of local impacts (NYSERDA, 2017). Also, since hosting a turbine was more lucrative than not hosting one (see footnote 6),

non-hosts may have been disappointed that they missed out on an income opportunity, if, for example, the final wind turbine array layout did not include a wind turbine on their property.

C. Study limitations

Although the degree of regularity of audibility was not established by the survey instrument, the audibility of wind turbine noise tested in this study was formulated based on questions implying a present stimulus (“Can you...hear,” i.e., “Are you able to...hear”) and thus relies on the respondent’s interpretation of the question. Moreover, the survey did not assess if a respondent had normal hearing.

The survey did not explicitly inquire about the location where respondents experienced the reported noise annoyance (i.e., at home or elsewhere in the community). To provide confidence in assessing noise annoyance at one’s residence, the less than 3% of respondents who were unable to hear wind turbines on their property that reported at being at least Slightly Annoyed by wind turbine noise were excluded from the Noise Annoyance model in this study. These respondents may have been exposed to wind turbine noise at a location that did not correspond to their residence or they may have indicated noise annoyance without any exposure. Limiting the tested noise annoyance response to those who reported hearing wind turbines on their property increased the likelihood of predicting annoyance for the location where sound was modeled.

The survey instrument’s method of assessing annoyance level deviated from the ISO/TS 15666 (2003), “Acoustics—Assessment of noise annoyance by means of social and socio-acoustic surveys,” because noise annoyance was not the only research effort involved (see footnote 1) and consistency in the response scale throughout the multipurpose survey was of greater importance. The result is that the assignment of Highly Annoyed was based on the authors’ interpretation of the survey responses.

While the overall response rate was higher for respondents living closer to wind turbines, selection bias was not found (see footnote 5). Moreover, given that the study focused on modeled sound level rather than distance *per se*, individuals living closest (i.e., within 1.6 km) were most valuable to this study. Selection bias, if found, would be concerning if those who lived closer to wind turbines responded at lower rates than those who lived farther away.

Field measurements to validate the sound propagation modeling were not performed due to budgetary constraints and impracticality. Meaningful measurements would have required wind turbine operational data to inform the expected sound power level as well as precise meteorological data to understand the propagation conditions. Likewise, field measurements would have required cooperation from wind turbine project operators to shut down wind turbines so that background sound could be assessed and subtracted from the measurements.

V. CONCLUDING REMARKS

The factors that affect wind turbine audibility and noise annoyance are distinct: wind turbine sound level is the

strongest predictor of audibility while more experiential and psychological variables, such as visual perception, self-reported noise sensitivity, and prior attitude/move-in after, were the strongest predictors of noise annoyance in this study. The results suggest that wind turbine noise annoyance is mostly an expression of personal experience and visual perceptions rather than an objective response to wind turbine sound level. Increasing summer daytime median background sound levels were significantly associated with decreased audibility and noise annoyance, but the effect was relatively small (and insignificant for noise annoyance once subjective variables were considered). For respondents not receiving personal benefits from their local wind project, the estimated CTL for wind turbine noise in this study (60.8 dB) is consistent with research results from other countries, validating the notion that communities are less tolerant of wind turbines than other environmental noise sources at the same long-term A-weighted sound level.

Several avenues of future research could help further explain wind turbine audibility and noise annoyance:

- The simulation of long-term sound level emissions in this study considered neither the frequency of unstable atmospheric conditions nor the percent of time a respondent is downwind from the local project (the amount of time downwind from a source is known to affect sound levels received from wind turbines; *RSG et al., 2016*). Fully accounting for these would produce a more accurate estimation of site-specific DNL. Most dose-response studies do not simulate the effect of changing sound propagation conditions throughout a year, using only a fixed constant to go from a single modeled (or monitored) sound level to a long-term average. This is a drawback that should be addressed in future studies using long-term sound metrics.
- In the regression model, inverse Obukhov length and long-term wind turbine sound power emissions relative to the maximum reported sound power level were significant predictors of audibility. Thus, several sound level-related metrics, as opposed to a single sound level, may provide a better understanding of objective wind turbine sound exposure. Further research on wind turbine audibility could consider additional variables such as wind shear and turbulence, which have been postulated to affect the level of amplitude modulation from wind turbines (*Renewable UK, 2013*).
- The authors encourage, where possible, a more holistic definition of annoyance response to be considered that includes perception (i.e., audibility), personal evaluation of the noise (i.e., self-reported annoyance), and symptoms (stress indicators, health effects, sleep impacts). See *Pohl et al. (2018)* and *Michaud et al. (2016c)*.
- The survey results indicated that most Very Annoyed individuals could hear the wind turbine in their home. Further research is needed to understand the mechanisms that permit hearing sound in one's home (e.g., home construction or window type) and whether improvements to sound insulation or sound masking can consistently be used to reduce wind turbine audibility and noise annoyance, and if they supersede the correlations with subjective variables found in this study.

- The effects of physical wind turbine characteristics should be further investigated. Increases in wind turbine rotor diameter correspond to an increase in tip speed absent a decrease in rotor speed. Therefore, as wind turbines get larger, higher levels of audibility and noise annoyance may occur.

ACKNOWLEDGMENTS

The authors wish to acknowledge Seongeun Jeong and Dev Millstein of the Lawrence Berkeley National Laboratory for assistance in amassing the NREL meteorological data used in this study. The authors would also like to thank Patrick Gilman, Maggie Yancey, Valerie Reed, and Jocelyn Brown-Saracino of the U.S. DOE, and Jose Zayas, formerly with the DOE, for their support. This work was funded by the Wind Energy Technologies Office within the Office of Energy Efficiency and Renewable Energy of the DOE, under Contract No. DE-AC02-05CH11231.

¹A summary of the overall project can be found at <https://emp.lbl.gov/projects/wind-neighbor-survey>.

²U.S. Wind Turbine Data accessible here: <https://eerscmap.usgs.gov/uswtdb/>.

³See supplementary material at <https://doi.org/10.1121/1.5121309> for mail-based survey instrument.

⁴Introductory telephone script: "Hello, my name is <fill in name> and I'm calling from Portland State University on behalf of the U.S. DOE. We're conducting a survey of people living near wind power projects throughout the United States to better understand their experiences, perceptions, and opinions. The survey is completely voluntary and confidential. It should take about 15 to 20 minutes and you can skip any item you don't want to answer or stop the survey at any time. Is now a good time to do the survey?"

⁵Nonresponse bias was examined through the influence of the two dependent variables (wind turbine audibility and noise annoyance) by comparing the responses of "late responders"—those who responded only after being contacted by telephone and not responding and then being contacted by mail and offered the opportunity to respond by mail or online—to those who responded to a single mode of contact. In each case, whether the data were unweighted, weighted but not with regard to distance, or fully weighted, the means between the two populations were not statistically significantly different from one another. Likewise, bias from response type was not found: the response modes (mail/phone/internet) were tested as an independent variable in the regression models and never approached significance. As a result, response type was excluded from the regression analysis.

⁶Responses from the survey indicate that wind turbine hosts, on average, were compensated at levels 3 to 4 times that of non-hosts. Some respondents hosted multiple turbines on their property (37% hosted one turbine, 54% hosted two to four turbines, with the remaining 9% hosting more than four). The maximum number of turbines hosted by a single landowner was 12. All but one host indicated that they received annual payments, while 33% of hosts also received an initial lump sum payment. Eighty-five percent of respondents who were compensated without hosting received annual payments, 25% of whom also received a lump sum; the other 15% were provided a lump sum payment only.

⁷The second highest response category in the survey, "Moderately Annoyed," does not elicit a clear language interpretation as Highly Annoyed. The approach taken here appears to be consistent with Schultz's interpretation of a 1975 Swedish survey (*Rylander et al., 1976*) that associated Highly Annoyed only with the Very Annoyed responses.

⁸Turbine sound power data were only consistently available down to the 63 Hz octave band. Sound power below this frequency is scarce because in the 2002 version of IEC 61400-11, the standard for measuring wind turbine, sound power did not require testing at the 31.5 Hz octave band or below. In the revised IEC 61400-11 (2012) standard, the procedure requires testing down to the 20 Hz 1/3 octave band.

⁹Short-term (L_{1h-max}) and long-term (DNL) sound level metrics produced nearly identical results in the regression models (results not shown).

¹⁰Sampling stratification for oversampling close to turbines (distance bin) and categorical project size were not included in the models due to multicollinearity with variables of interest (mostly wind turbine sound levels and background L_{50} , respectively). However, these sample strata are represented in the models through independent variables (modeled sound level, as a proxy for distance; the number of turbines in a project replaced categorical project size). Model results and conclusions were similar when using the prescribed sample strata, but variances were higher for affected variables ($VIF > 3$).

¹¹As described in Firestone *et al.* (2018), the weighting followed the method known as “iterative raking” or “sample balancing” (Battaglia *et al.*, 2009; Deming, 1943). Sample weights were prepared for over- and under-sampling based on differential response rates by gender, age, and education using American Community Survey (2014) census tract level household and demographic data. Unlike the weights used by Firestone *et al.* (2018), the weighting here did not correct for over- and under-sampling based on the respondents’ distance to the nearest turbine because modeled wind turbine sound pressure level is overwhelmingly related to distance from a wind turbine (Pearson’s $r = -0.84$) and is thereby accounted for in the models.

¹²Respondent income was not included in the regression models due to missing data (>10% of final sample). This approach was tested by running the same models presented here with the addition of the respondent income variable. Although there were some minor differences in the significance of some variables, respondent income was never statistically significant and the conclusions derived from the model were practically identical.

¹³Background sound level is a corollary of the rural character of an area and is thus strongly related to population density (Pearson’s $r = 0.69$, $p < 0.001$). There is a significant relationship between the number of turbines in a project and background sound level (Pearson’s $r = -0.45$, $p < 0.001$), as well as the number of turbines and wind turbine sound level (Pearson’s $r = 0.41$, $p < 0.001$). This suggests a general trend that for larger projects, which are often sited in more rural areas, higher wind turbine sound levels are common with lower background sound levels.

¹⁴Thirteen respondents had modeled wind turbine sound levels above 50 dBA. Of these 13 respondents, 69% were turbine hosts or otherwise compensated. The highest modeled L_{1h-max} was 55.2 dBA at a turbine host’s residence; the lowest was 40.2 dBA.

¹⁵Fifteen percent of project participants had a negative visual perception of the local project, of which approximately 90% were compensated without hosting a turbine. A similar relationship was found between project participants and prior project attitudes: five percent of project participants had negative prior attitudes toward the project, over 90% of which was expressed by project participants that did not host a turbine.

¹⁶In this study, the average (and SD of) modeled wind turbine sound pressure level are as follows: non-participants ($n = 591$): 38.3 dBA (7); compensated without hosting ($n = 113$): 44.2 dBA (3.8); compensated and hosting a turbine ($n = 43$): 47.5 dBA (3.1).

¹⁷Respondents who hosted a wind turbine were the oldest group, with a mean age of 63.1 years. On average, wind turbine hosts were 6.2 years older than respondents who were compensated without hosting a turbine and 4.6 years older than non-participants.

¹⁸For wind turbine hosts, increasing age was significantly associated with decreased wind turbine audibility [one-way analysis of variance (ANOVA), $p = 0.02$], while wind turbine sound level was not significantly associated with audibility (one-way ANOVA, $p = 0.27$). The significant univariate association between age and audibility did not hold for respondents who were compensated without hosting a wind turbine nor for non-participants. However, wind turbine sound level was significantly correlated with audibility for non-participants (one-way ANOVA, $p < 0.001$) and project participants not hosting a turbine (one-way ANOVA, $p = 0.002$), as expected.

ANSI (2013). ANSI/ASA S1.1-2013, *Acoustical Terminology* (American National Standards Institute, New York).

Arakawa, C., Fleig, O., Iida, M., and Shimooka, M. (2005). “Numerical approach for noise reduction of wind turbine blade tip with Earth simulator,” *J. Earth Simulator* 2, 11–33, available at <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.494.9766&rep=rep1&type=pdf>.

Baron, R., and Kenny, D. (1986). “The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations,” *J. Person. Soc. Psychol.* 51(6), 1173–1182.

Battaglia, M. P., Izrael, D., Hoaglin, D. C., and Frankel, M. R. (2009). “Practical considerations in raking survey data,” *Survey Practice* 2, 1–10.

Bowdler, D., Bullmore, A., Davis, B., Hayes, M., Jiggins, M., Leventhall, G., and McKenzie, A. (2009). “Prediction and assessment of wind turbine noise,” *Acoust. Bull.* 34(2), 35–37.

DataKustik® GmbH (2016). “CadnaA version 4.6,” software for emission protection, available at www.datakustik.com (Last viewed October 1, 2018).

Deming, W. E. (1943). *Statistical Adjustment of Data* (Wiley, New York, NY).

Dillman, D. A., Smyth, J. D., and Christian, L. M. (2014). *Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method* (John Wiley & Sons, Hoboken, NJ).

Fawcett, T. (2006). “An introduction to ROC analysis,” *Pattern Recog. Lett.* 27, 861–874.

Fidell, S., Mestre, V., Schomer, P., Berry, B., Gjestland, T., Vallet, M., and Reid, T. (2011). “A first-principles model for estimating the prevalence of annoyance with aircraft noise exposure,” *J. Acoust. Soc. Am.* 130, 791–806.

Firestone, J., Hoen, B., Rand, J., Elliott, D., Hübner, G., and Pohl, J. (2018). “Reconsidering barriers to wind power projects: Community engagement, developer transparency and place,” *J. Environ. Policy Plan.* 20, 370–386.

Fowler, K., Koppen, E., and Matthis, K. (2013). “International legislation and regulations for wind turbine noise,” in *Proceedings of the Fifth International Meeting on Wind Turbine Noise, INCE Europe*, Denver, CO.

Geisser, S. (1993). *Predictive Inference* (Chapman and Hall, New York, NY).

Hand, D., and Till, R. (2001). “A simple generalization of the area under the ROC curve for multiple class classification problems,” *Mach. Learn.* 45, 171–186.

Harrell, F. E., Jr. (2001). *Regression Modeling Strategies: With Applications to Linear Models, Logistic Regression, and Survival Analysis*, 1st ed. (Springer-Verlag, New York).

Harrell, F. E., Jr. (2018). “rms: Regression modeling strategies,” R package version 5.1-2, available at <https://CRAN.R-project.org/package=rms> (Last viewed October 11, 2018).

Hathaway, K., and Kaliski, K. (2006). “Assessing wind turbines against relative noise standards,” in *Proceedings of InterNoise2006*, Honolulu, HI.

Heinze, G., and Dunkler, D. (2017). “Five myths about variable selection,” *Transplant Int.* 30: 6–10.

Hoen, B. D., Diffendorfer, J. E., Rand, J. T., Kramer, L. A., Garrity, C. P., and Hunt, H. E. (2018). United States wind turbine database. U.S. geological survey, American Wind Energy Association, and Lawrence Berkeley National Laboratory data release: USWTDB V1.2, available at <https://eerscmapp.usgs.gov/uswtdb> (Last viewed October 1, 2018).

Hongisto, V., Oliva, D., and Keränen, J. (2017). “Indoor noise annoyance due to 3–5 megawatt wind turbines—An exposure-response relationship,” *J. Acoust. Soc. Am.* 142, 2185–2196.

IEC 61400-11 Ed. 2.0 (2002). “Wind turbine generator systems— Part 11: Acoustic noise measurement techniques” (International Electrotechnical Commission, Geneva, Switzerland). Withdrawn November 2012.

IEC 61400-11 Ed. 3.0 (2012). “Wind turbine generator systems—Part 11: Acoustic noise measurement techniques” (International Electrotechnical Commission, Geneva, Switzerland).

Ingard, U. (1953). “A review of the influence of meteorological conditions on sound propagation,” *J. Acoust. Soc. Am.* 25, 405–411.

ISO 9613-1 (1993). “Acoustics. Attenuation of sound during propagation outdoors. Part 1: Calculation of the absorption of sound by the atmosphere” (International Organization for Standardization, Geneva, Switzerland).

ISO 9613-2 (1996). “Acoustics. Attenuation of sound during propagation outdoors. Part 2: General method of calculation” (International Organization for Standardization, Geneva, Switzerland).

ISO/TS-15666 (2003). “Acoustics—Assessment of noise annoyance by means of social and socio-acoustic surveys” (International Organization for Standardization, Geneva, Switzerland).

James, G., Witten, D., Hastie, T., and Tibshirani, R. (2017). *An Introduction to Statistical Learning*, 8th ed. (Springer Science+Business Media, New York).

- Janssen, S. A., Vos, H., Eissess, A. R., and Pedersen, E. (2011). "A comparison between exposure-response relationships for wind turbine annoyance and annoyance due to other noise sources," *J. Acoust. Soc. Am.* **130**, 3746–3753.
- Kaliski, K., Bastasch, M., and O'Neal, R. (2018b). "Regulating and predicting wind turbine sound in the U.S.," in *Proceedings of InterNoise 2018*, Institute of Noise Control Engineering, Chicago, IL.
- Kaliski, K., Haac, T. R., Brese, D., Duncan, E., Reiter, D., Williamson, R., Pratt, G., Salomons, E., Wayson, R., McDonald, J., Zimmerman, J., Snyder, J., and Hastings, A. (2018a). NCHRP Research Report 882: How Weather Affects the Noise You Hear from Highways. TRB, National Research Council, Washington, DC.
- Keith, S. E., Feder, K., Voicescu, S. A., and Soukhovtsev, V. (2016a). "Wind turbine sound power measurements," *J. Acoust. Soc. Am.* **139**, 1431–1435.
- Keith, S. E., Feder, K., Voicescu, S. A., and Soukhovtsev, V. (2016b). "Wind turbine sound pressure level calculations at dwellings," *J. Acoust. Soc. Am.* **139**, 1436–1442.
- Kuwano, S., Yano, T., Kageyama, T., Sueoka, S., and Tachibana, H. (2014). "Social survey on wind turbine noise in Japan," *Noise Control Engr. J.* **62**, 503–520.
- Leventhall, Geoff. (2003). "A review of published research on low frequency noise and its effects," Department for Environment, Food and Rural Affairs (United Kingdom).
- Magari, S., Smith, C. E., Shciff, M., and Rohr, A. C. (2014). "Evaluation of community response to wind turbine-related noise in Western New York State," *Noise Health.* **16**, 228–239.
- Mennitt, D., Sherrill, K., and Fristrup, K. (2014). "A geospatial model of ambient sound pressure levels in the contiguous United States," *J. Acoust. Soc. Am.* **135**, 2746–2764.
- Michaud, D. S., Feder, K., Keith, S. E., Voicescu, S. A., Marro, L., Than, J., Guay, M., Denning, A., Bower, T., Villeneuve, P. J., Russel, E., Koren, G., and van den Breg, F. (2016c). "Self-reported and measured stress related responses associated with exposure to wind turbine noise," *J. Acoust. Soc. Am.* **139**, 1467–1479.
- Michaud, D. S., Feder, K., Keith, S. E., Voicescu, S. A., Marro, L., Than, J., Guay, M., Denning, A., McGuire, D., Bower, T., Lavigne, E., Murray, B., Weiss, S., and van den Berg, F. (2016a). "Exposure to wind turbine noise: Perceptual responses and reported health effects," *J. Acoust. Soc. Am.* **139**, 1443–1454.
- Michaud, D. S., Keith, S. E., Feder, K., Voicescu, S. A., Marro, L., Than, J., Guay, M., Bower, T., Denning, A., Lavigne, E., Whelan, C., Janssen, S. A., Leroux, T., and van den Berg, F. (2016b). "Personal and situational variables associated with wind turbine noise annoyance," *J. Acoust. Soc. Am.* **139**, 1455–1466.
- Miedema, H. M. E., and Vos, H. (1998). "Exposure-response relationships for transportation noise," *J. Acoust. Soc. Am.* **104**, 3432–3445.
- Møller, H., and Pedersen, C. S. (2011). "Low-frequency noise from large wind turbines," *J. Acoust. Soc. Am.* **129**(6), 3727–3744.
- Nagelkerke, N. (1991). "A note on a general definition of the coefficient of determination," *Biometrika* **78**, 691–692.
- National Park Service (2014). "Data store: Project code 2217356, geospatial sound modeling." U.S. National Park Service, Department of the Interior, available at <https://irma.nps.gov/DataStore/Reference/Profile/2217356> (Last viewed October 11, 2018).
- Nelson, D. (2007). "Perceived loudness of wind turbine noise in the presence of ambient sound," in *Proceedings of the Second International Meeting on Wind Turbine Noise, INCE Europe*, Lyon, France.
- NREL (2018). "Wind integration national dataset toolkit," National Renewable Energy Laboratory (NREL), U.S. Department of Energy, available at <https://www.nrel.gov/grid/wind-toolkit.html> (Last viewed October 11, 2018).
- NYSERDA (2017). "Land Agreements—NYSERDA," New York State Energy Research and Development Authority, available at <https://www.nysenda.ny.gov/-/media/Files/Publications/Research/Biomass-Solar-Wind/NY-Wind-Energy-Guide-3.pdf> (Last viewed July 1, 2019).
- Old, I., and Kaliski, K. (2017). "Wind turbine noise dose response—comparison of recent studies," in *Proceedings of Wind Turbine Noise 2017*, Institute of Noise Control Engineering, Rotterdam, Netherlands.
- Pawlaczyk-Luszczynska, M., Dudarewicz, A., Zaborowski, K., Zamosjska-Daniszweska, M., and Waszkowska, M. (2015). "Annoyance related to wind turbine sound," *Arch. Acoust.* **39**, 89–102.
- Pawlaczyk-Luszczynska, M., Zaborowski, K., Dudarewicz, A., Zamosjska-Daniszweska, M., and Waszkowska, M. (2014). "Response to noise generated by wind farms in people living in nearby areas," in *Proceedings of Noise-Con 2014*, Institute of Noise Control Engineering, Fort Lauderdale, Florida.
- Pedersen, E., and Pernilla, L. (2008). "The impact of visual factors on noise annoyance among people living in the vicinity of wind turbines," *J. Environ. Psychol.* **28**, 379–389.
- Pedersen, E., and Persson Waye, K. (2004). "Perception and annoyance due to wind turbine noise—a dose-response relationship," *J. Acoust. Soc. Am.* **116**, 3460–3470.
- Pedersen, E., and Persson Waye, K. (2007). "Wind turbine noise, annoyance and self-reported health and well-being in different living environments," *Occ. Environ. Med.* **64**, 480–486.
- Pedersen, E., van den Berg, F., Bakker, R., and Bouma, J. (2009). "Response to noise from modern wind farms in The Netherlands," *J. Acoust. Soc. Am.* **126**, 634–643.
- Picard, R. (2010). "GEONEAR: Stata module to find nearest neighbors using geodetic distances, Statistical Software Components S457146," Boston College Department of Economics.
- Pohl, J., Gabriel, J., and Hübner, G. (2018). "Understanding stress effects of wind turbine noise—The integrated approach," *Energy Policy* **112**, 119–128.
- Rand, J., and Hoen, B. (2017). "Thirty years of North American wind energy acceptance research: What have we learned?," *J. Energy Res. Soc. Sci.* **29**, 135–148.
- R Core Team (2018). "R: A language and environment for statistical computing," R Foundation for Statistical Computing, Vienna, Austria, available at <https://www.R-project.org/> (Last viewed October 11, 2018).
- RenewableUK. (2013). "Wind turbine amplitude modulation: Research to improve understanding as to its cause and effect." Available at https://www.renewableuk.com/resource/collection/4E7CC744-FEF2-473B-AF2B-135FF2AA3A43/ruk_wind_turbine_amplitude_modulation_dec_2013_v2_1.pdf (Last viewed May 14, 2019).
- Robin, X., Turck, N., Hainard, A., Tiberti, N., Lisacek, F., Sanchez, J.-C., and Müller, M. (2011). "pROC: An open-source package for R and S+ to analyze and compare ROC curves," *BMC Bioinform.* **12**, 77.
- Rogelj, J., Shindell, D., Jiang, K., Fifita, S., Forster, P., Ginzburg, V., Handa, C., Kheshgi, H., Kobayashi, S., Kriegler, E., Mundaca, L., Séférian, R., and Vilarino, M. V. (2018). "Mitigation pathways compatible with 1.5°C in the context of sustainable development," in *Global Warming of 1.5°C*, available at https://www.ipcc.ch/site/assets/uploads/sites/2/2019/05/SR15_Chapter2_Low_Res.pdf.
- RSG, Epsilon Associates, Inc., and Northeast Wind. (2016). "Massachusetts study on wind turbine acoustics," Massachusetts Clean Energy Center and Department of Environmental Protection, available at <http://files.masscec.com/research/wind/MassCECWindTurbinesAcousticsStudy.pdf> (Last viewed October 11, 2018).
- Rylander, R., Sorensen, S., and Kajland, A. (1976). "Traffic noise exposure and annoyance reactions," *J. Sound Vib.* **47**, 237–242.
- Schomer, P., Mestre, V., Fidell, S., Berry, B., Gjestland, T., Vallet, M., and Reid, T. (2012). "Role of community tolerance level (CTL) in predicting the prevalence of the annoyance of road and rail noise," *J. Acoust. Soc. Am.* **131**, 2772–2786.
- Schultz, T. J. (1978). "Synthesis of social surveys on noise annoyance," *J. Acoust. Soc. Am.* **64**, 377–405.
- Tiebout, C. (1956). "A pure theory of local expenditures," *J. Political Econ.* **64**(5) 416–424.
- van den Berg, F. (2008). "Criteria for wind farm noise: Lmax and Lden," *Euronoise 2008*, Paris, France (June 29–July 4), pp. 4043–4048.
- van den Berg, F., Pedersen, E., Bouma, J., and Bakker, R. (2008). "Windfarm perception: Visual and acoustic impact of wind turbine of wind turbine farms on residents," Report FP6-2005-Science-and-Society-20. University of Groningen, Groningen, The Netherlands and University of Gothenburg, Gothenburg, Sweden.
- van Kamp, I., and van den Berg, F. (2017). "Health effects related to wind turbine sound, including low-frequency sound and infrasound," *Acoust. Australia* **46**, 31–57.
- Vincenty, T. (1975). "Direct and inverse solutions of geodesics on the ellipsoid with application of nested equations," *Survey Rev.* **22**(176), 88–93.
- WHO Europe. (2018). "Environmental noise guidelines for the European region," World Health Organization Regional Office for Europe, available at <http://www.euro.who.int/en/health-topics/environment-and-health/noise/environmental-noise-guidelines-for-the-european-region> (Last viewed October 11, 2018).
- Zwicker, E., and Fastl, H. (2007). *Psychoacoustics, Facts and Models*, 3rd ed. (Springer-Verlag, Berlin).