

Modeling approaches to estimate community annoyance due to sonic booms using data from repeated surveys

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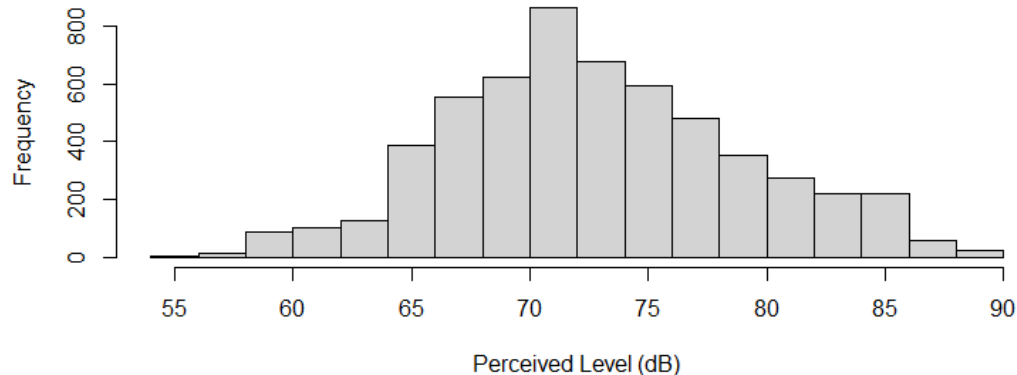
Introduction

- › NASA is developing the X-59 aircraft, for researching the effects of low-magnitude sonic booms (thumps)
- › Westat is part of the project team, responsible for conducting community surveys to estimate community annoyance levels based on noise level from X-59 supersonic flights
- › Use data from previous flight test (QSF18) to develop and apply candidate approaches
- › QSF18 study used different plane and different maneuver, but methods still applicable to X-59

QSF18 Study

- › Flights took place over a two-week period in November 2018 in Galveston, Texas
- › 52 sonic thumps delivered over the test period
- › Noise monitors used to measure sound levels across the survey area

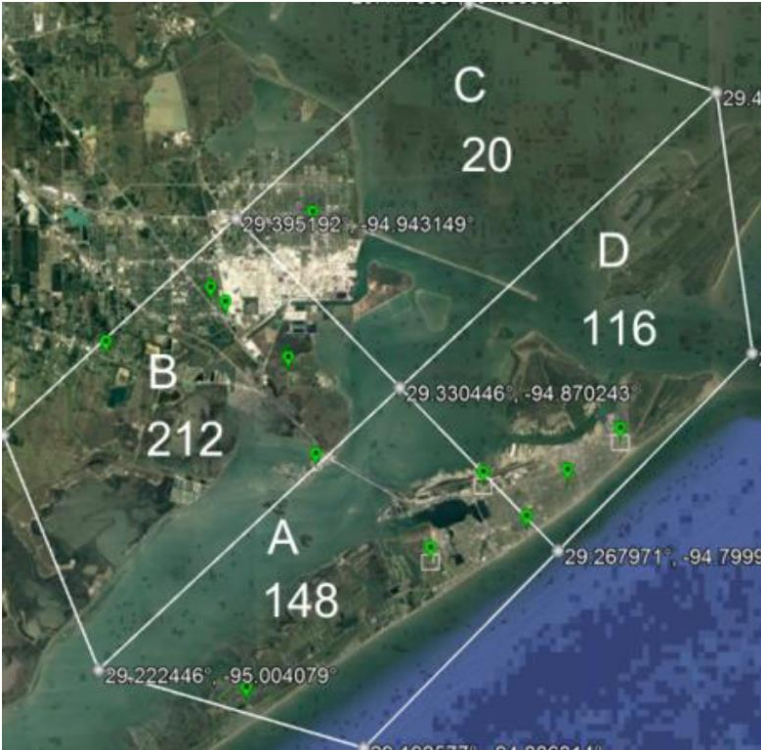
- › 5634 total observations from 373 participants
- › Each observation has an estimated noise level (PL) based on the participant's location at the time of the flight



- › Annoyance is measured on a five-point scale:
 - Not at all annoyed
 - Slightly annoyed
 - Moderately annoyed
 - Very annoyed
 - Extremely annoyed
- › Top two categories are considered 'highly annoyed'
- › Challenge: only 1.1% of responses were highly annoyed

- › Demographic data
 - Gender
 - Age
 - Household size
 - Kids under 6
 - Geographic quadrant
 - Education
- › No weights included in the data set
- › Since X-59 study will include weights calibrated to Census Bureau totals, simulate weights for QSF18 data $\sim \text{unif}(50, 250)$

Quadrants



Multilevel Logistic Regression

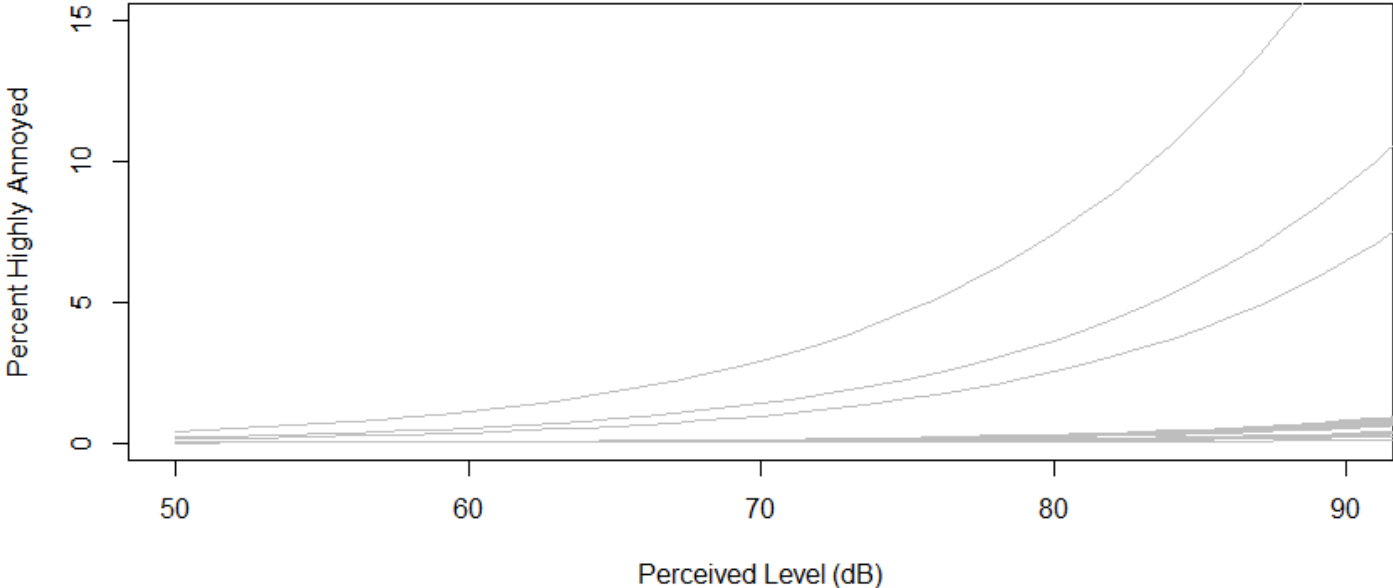
- › Multilevel logistic regression model with participant-level random effects is a common method of creating a dose-response curve for this type of data
- › Model log-odds of high annoyance (HA) based on noise level PL_{ij} and covariates X_j , with random effects for each participant j :

$$p_{ij} = \text{logit}^{-1}(\beta_0 + \beta_1 * PL_{ij} + \beta_2 X_j + u_j) = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 * PL_{ij} + \beta_2 X_j + u_j)]}$$

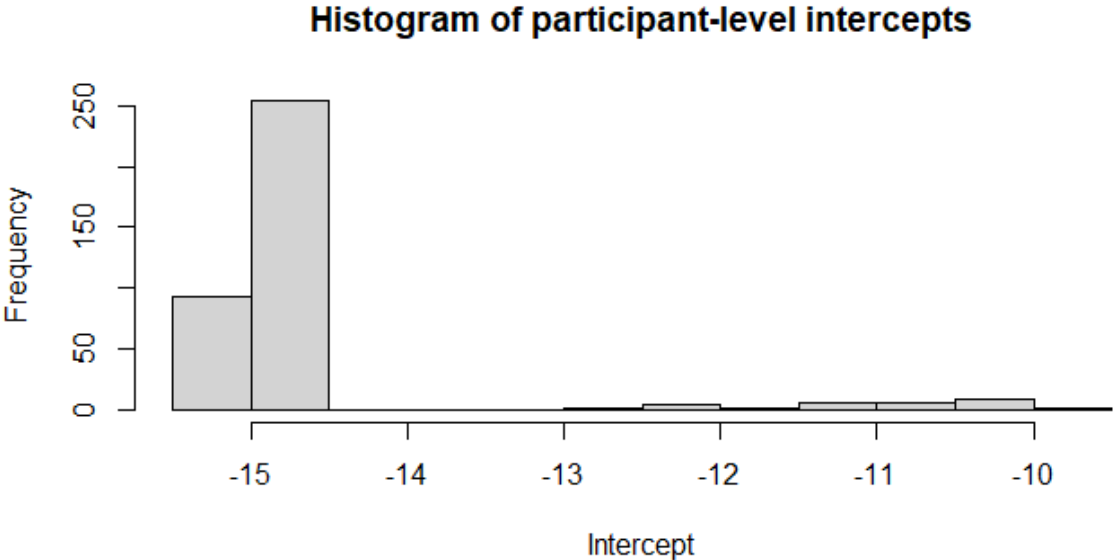
$HA_{ij} \sim \text{Binom}(1, p_{ij})$
 $u_j \sim N(0, \sigma^2)$

- › For demonstration, use gender and geographical quadrant as covariates
- › Note: Unweighted, so resulting curve will not be representative of the population

Sample of 100 Participant-Level Dose-Response Curves



Participant-Level Intercepts



Proposed Two-Stage Model

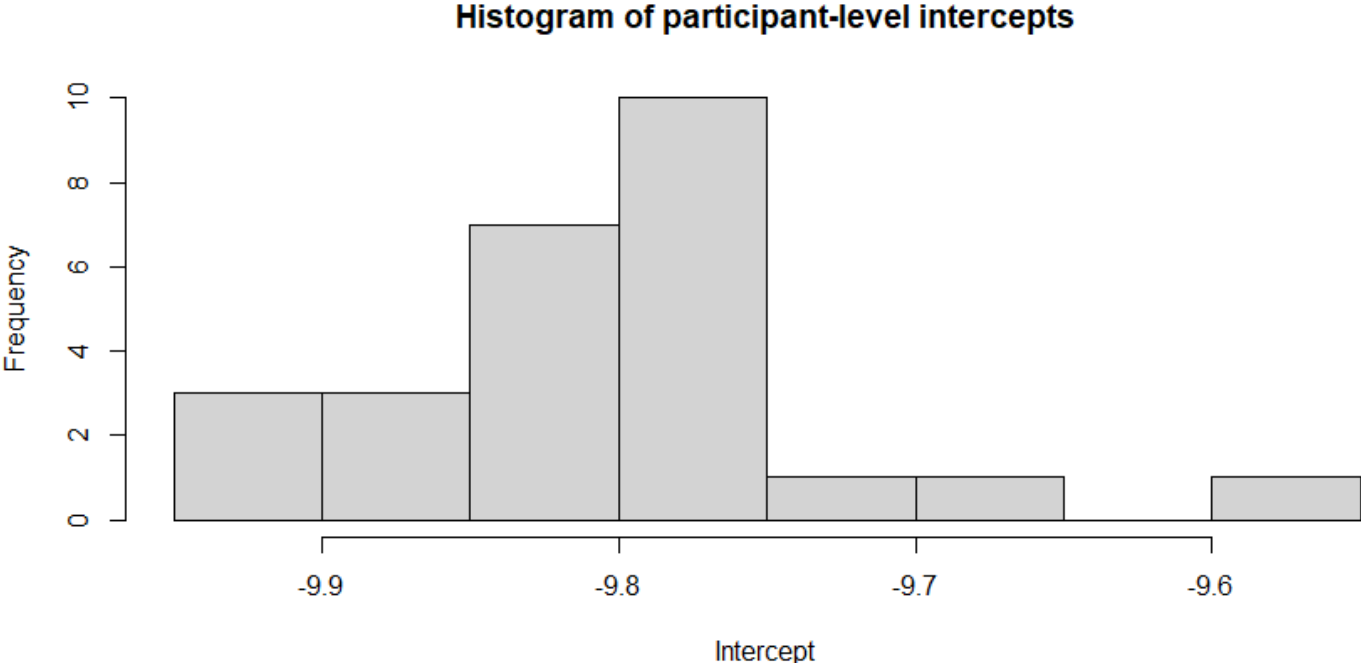
- › Break up modeling into two stages
- › Stage 1: Model probability of ever being highly annoyed given demographics of participant j
 - Logistic regression:

$$p^{(1)}(X_j) = \text{logit}^{-1}(\beta_0 + \beta_1 X_j) = \frac{1}{1 + \exp[-(\beta_0 + \beta_1 X_j)]}$$

- › Stage 2: Model probability of high annoyance given demographics of participant j and noise level PL_{ij} given participant j was ever highly annoyed
 - Multilevel logistic regression:

$$p^{(2)}(PL_{ij}, X_j) = \text{logit}^{-1}(\alpha_0 + \alpha_1 X_j + \alpha_2 PL_{ij} + u_j) = \frac{1}{1 + \exp[-(\alpha_0 + \alpha_1 X_j + \alpha_2 PL_{ij} + u_j)]}$$

2nd Stage Participant-Level Intercepts



Marginal Dose-Response Curve

- › To accurately account for the participant-level random effects in predicting the dose-response curve for the population, we integrate over the distribution of random effects (Pavlou et al. 2015)
- › For a given PL noise level, the predicted fraction of people highly annoyed among those ever highly annoyed with covariates X is

$$\hat{p}^{(2)}(PL, X) = \int_{-\infty}^{\infty} \text{logit}^{-1}(\hat{\beta}_0 + \hat{\beta}_1 * PL + \hat{\beta}_2 X + u) f(u) du$$

where $f(u)$ is a normal distribution with mean 0 and variance equal to the estimated random effect variance

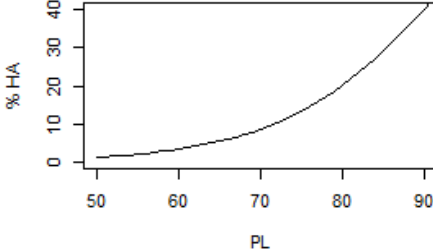
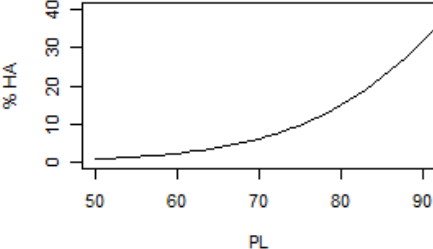
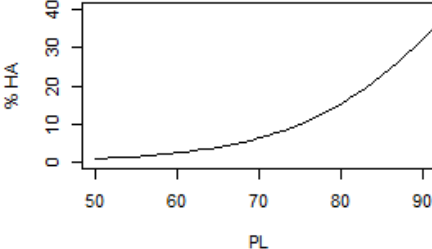
2nd-Stage Marginal Poststrata Curves

Quadrant A

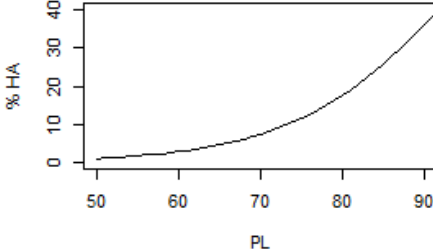
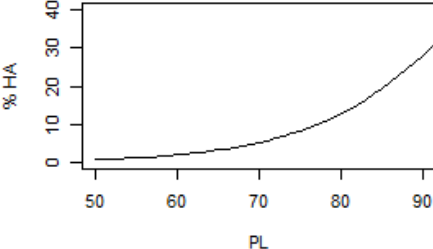
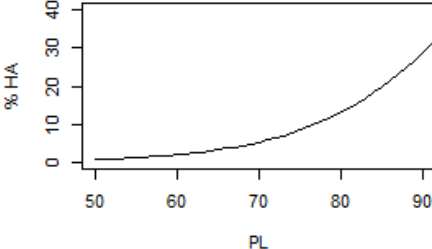
Quadrants B&C

Quadrant D

Male



Female

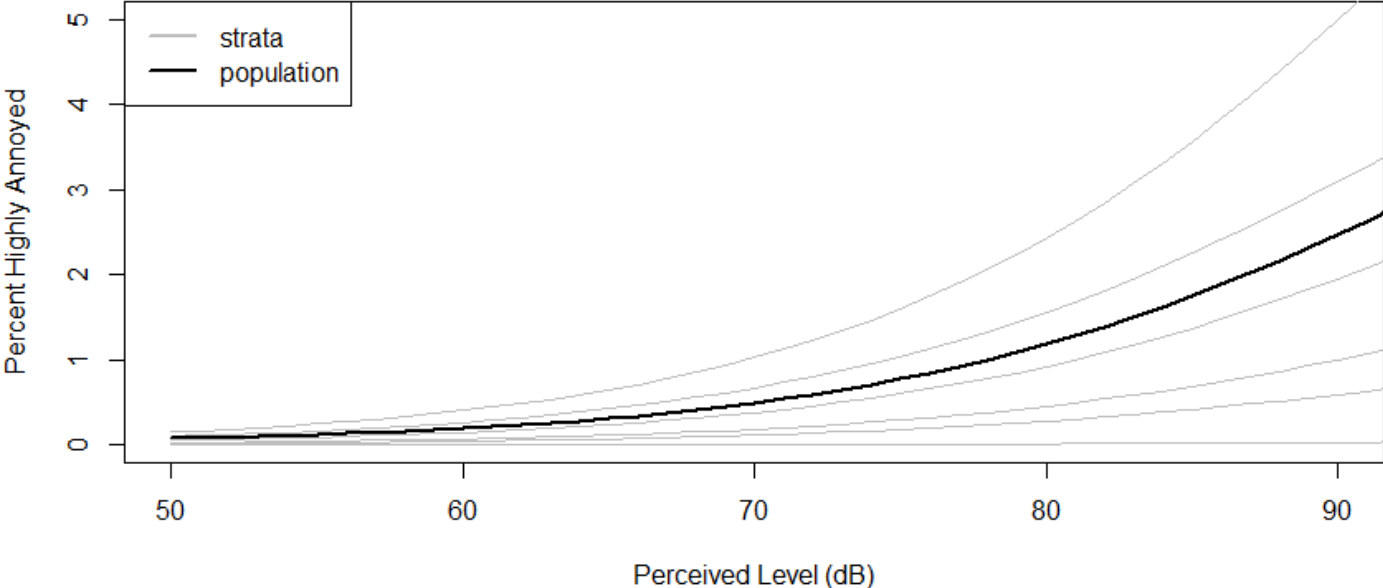


Multilevel Regression and Poststratification

- › To generalize the dose-response curve to the population, we use Multilevel Regression and Poststratification (MRP) (Gelman & Little, 1997)
- › Using the fitted multilevel regression model, create marginal dose-response curves for each poststratum
- › Create a weighted average of these curves based on the proportion of the population within each poststratum
- › Let $X^{(g)}$ be the g^{th} combination of categorical variables in the study, where $g = 1, \dots, G$ and $N = \sum_{g=1}^G N_g$. Then the estimated probability of high annoyance for the population is

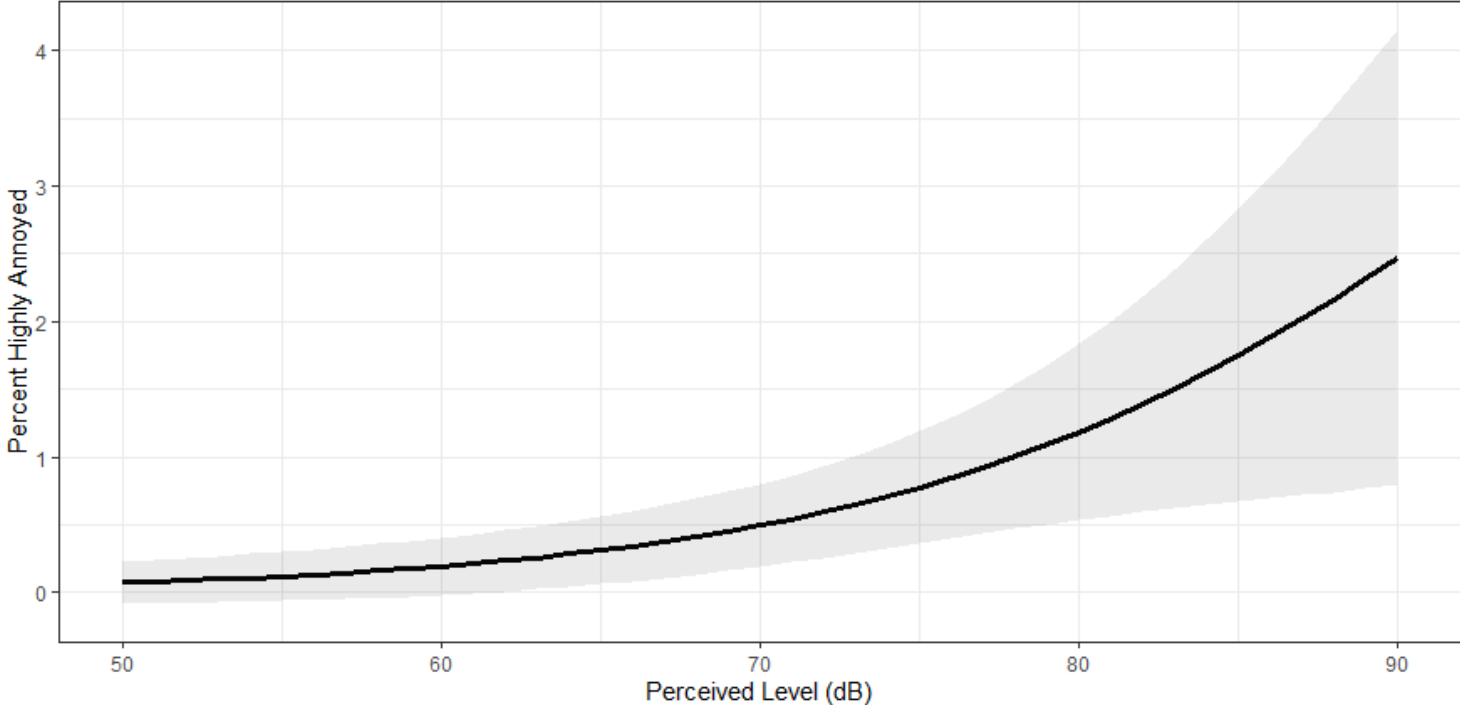
$$\hat{p}(PL) = \frac{1}{N} \sum_{g=1}^G N_g \hat{p}^{(1)}(X^{(g)}) \hat{p}^{(2)}(PL, X^{(g)})$$

Population Dose-Response Curve



- › Confidence intervals and standard errors can be estimated through bootstrapping
- › Take 100 samples with replacement from the data
- › Repeat the exact same process of fitting a multilevel logistic regression model and use MRP to estimate the study region population-level curve for the subsample
- › 100 resulting study region population-level curves
- › At each PL level, take the standard deviation of the 100 curves

Population-Level Dose Response Curve with 95% Confidence Interval



- › Two-Stage Model
- › Multilevel regression and Poststratification (MRP)
- › Bootstrap inference
- › Not included, but possible extensions:
 - Multilevel ordinal regression or monotone regression model
 - Bayesian hierarchical model to account for covariate (noise level) uncertainty