

Modeling Measurement Error in Dose-Response Models of Community Annoyance to Low-Noise Supersonic Flight

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Presentation Overview

- 1. Sonic boom and the NASA Quesst mission
- 2. Generalized linear mixed measurement error models
 - Functional: Simulation extrapolation (SIMEX)
 - Structural: Bayesian hierarchical models
- 3. Discussion and conclusions



What happens to the dose-response relationship if we use a surrogate for dose (in dB) instead of the actual level?

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Population Average Dose Response Curves: Galveston, TX

Sonic Boom Moves with the Aircraft

Created by pressure waves as object moves faster than the speed of sound¹

- Thunder-like boom(s) due to two rapid pressure changes
- Like wake of a boat-carried for duration of supersonic travel
- Width of 'carpet' approximately 1 mile per 1,000 feet altitude

June 4, 2023–Virginia, Maryland, D.C.

- ▶ F-16 aircraft scrambled to contact unresponsive Cessna aircraft
- NORAD, FAA statements
- Generated news stories and social media reactions

¹NASA Sonic Boom Fact Sheet [Accessed 4/23/2024]

Testing in the 1960s Contributed Data Supporting Current Ban



National Opinion Research Center (Borsky, 1965)

Overland civil supersonic flight prohibited since 1973 (14 CFR §91.817)

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Aircraft Design Can Reduce the Sonic Boom to a 'Thump'

Just how quiet will NASA's X-59 be?

NASA's single-seat X-59 experimental aircraft will produce a barely audible sonic thump to people on the ground when cruising at supersonic speeds. In technical terms, the X-59's sonic thump will be around 75 Perceived Level decibels (PLdB) or less. PLdB is one of numerous scales, in decibels, that is used to understand human response to sounds and is used particularly for short duration sounds. Proving a sonic boom can be reduced to a sonic thump could enable a new fleet of quiet, commercial supersonic aircraft that can fly over land.



- Sonic Boom: Six Decades of Research (Maglieri et al., 2014)
- Loudness of X-59 shaped sonic boom (Doebler & Rathsam, 2019)
- Prospective commercial designs in engineering literature (Sun & Smith, 2022)

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X-59 and the NASA Quesst Mission



Build and Test X-59

Acoustic Validation

Community Studies

- Collect community response data for noise certification standards (Rathsam et al., 2023)
- Community test campaigns with X-59 expected to begin in 2026
- NASA conducted a survey test in Nashville, TN, in Autumn 2023 (Rathsam 2024)

If X-59 has not yet made its first flight, how could NASA conduct pilot studies?

Waveforms and Sonic Boom Perception and Response (WSPR)



NASA developed inverted dive maneuver (Haering et al., 2006)

Test details in Page et al. (2014)

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110 total boom events at Edwards AFB, CA

- 84 low-boom maneuvers ('sonic thumps')
- 5 NASA-planned 'traditional' sonic booms
- 21 Unplanned booms due to USAF activity

Dose interpolation in 1 sq. mile area

• Estimated dose uncertainty, $\widehat{\sigma}_{u} = 3.7$ dB

	Mean Level (PL dB)	Std. Dev (PL dB)
Planned	82.8	7.8
Adventitious	97.4	9.2
Overall	85.1	9.6

Table: Summary statistics for doses as measured

Small convenient sample at Edwards AFB, CA

- Prompt single-event survey
- Daily summary survey
- Experimentation with survey modes

How much did the sonic boom bother, disturb, or annoy you?

- 11-point scale
- 'Highly Annoyed' dichotomization



WSPR Survey Responses

Quiet Supersonic Flights 2018 (QSF18)

- The Galveston advantage
- Address-based sample capped at 500
- Estimate dose over 60 sq. mile area
- Estimated dose uncertainty, $\widehat{\sigma}_{u} = 4.9$ dB
- ▶ Test details in Page et al. (2020a,b)







QSF18 Estimated Doses

QSF18 Survey Responses

Risk Reduction Study Data Summaries and Notation

Subject-Specific Model

$$p(x_{ij}, c_i) = logit^{-1} (\beta_0 + \beta_1 x_{ij} + c_i)$$

$$\phi (c_i | \sigma_c) \sim N (0, \sigma_c)$$

$$\beta_0, \beta_1, \sigma_c \text{ parameters to be estimated}$$

 $i \in \{1, \ldots, I\}$ indexes study subject $j \in \{1, \ldots, J_i\}$ indexes the j^{th} sonic boom

 y_{ij} binary indicator of high annoyance

 x_{ij} actual dose, Perceived Level (dB) w_{ij} dose as measured, Perceived Level (dB) $\hat{\sigma}_u$ estimated standard deviation

Study	WSPR	QSF18
No. Subjects, I	49	371
No. Supersonic Maneuvers	110	52
Total Responses	1,981	4,998
Total Highly Annoyed, $\sum_{i} \sum_{j} y_{ij}$	133	47
Range of Doses, <i>w_{ij}</i> , in PL dB	63 to 106	56 to 90
Deviation, $\hat{\sigma}_u$, in PL dB	3.7	4.9

Table: Summary of NASA study data

Subject-Specific Models, Population Average Models, and \hat{d}_{50}

Subject-specific (conditional) model depends on predicted subject intercepts \widehat{c}_i

Policy instrument is population average (marginal) model; see, e.g., (Pavlou et al., 2015; Hedeker et al., 2018; Wakefield, 2013, Sec. 9.13.1)

$$p(x) = \int_{-\infty}^{\infty} logit^{-1} \left(\widehat{\beta}_0 + \widehat{\beta}_1 x + k \right) \phi(k|\widehat{\sigma}_c) dk$$
(1)

Dose (in dB) that elicits high annoyance from subject i with probability p

$$\widehat{d}_{p} = \left[\log\left(p/(1-p)
ight) - (\widehat{eta}_{0} + \widehat{c}_{i})
ight]/\widehat{eta}_{1}$$

Fact: For $\hat{c}_i = 0$, $\hat{d}_{50} = \frac{-\hat{\beta}_0}{\hat{\beta}_1}$ is also 50th percentile on marginal curve

What happens when we use w_{ij} in lieu of x_{ij} in a dose-response model? N.B. Cruze (NASA LaRC) Dose-Response Models of Community Annoyance 14/41

Terminology and Literature

Measurement error renders regression estimators *inconsistent*, i.e., $\text{plim}_{n\to\infty} \widehat{\beta}_n \neq \beta$

- Direction and magnitude of bias depends on many things
- Restrict attention to following case
 - ► Nondifferential, i.e., $Y \perp \!\!\!\perp W | X$
 - Classical, constant-variance measurement error, i.e., W = X + U for $U \sim N(0, \sigma_u^2)$
- Attenuation bias in logistic regression (Stefanski & Carroll, 1985)

Vast literature on measurement error theory and application

- Books: Fuller (1987), Gustafson (2004), Carroll et al. (2006), Yi et al. (2021)
- ▶ Review articles: Keogh et al. (2020), Shaw et al. (2020), Sevilimedu & Yu (2022)
- Acoustics: Doebler et al. (2022), Erciulescu & Opsomer (2023), Horonjeff (2023)

Distinction between functional and structural methods

Biases in Subject-Specific Model Affect Population Average Response

Cruze et al. (2022) examined QSF18 data

- Naive estimators only
- Biases from numerical analysis employed
- Other GLMM examples (Kim et al., 2013)

Use 25-node AGHQ naive estimator

- Repeated use in SIMEX estimator
- Comparison with naive Bayesian models

uadrature, 1 Node (Laplace Equivalent) adrature 15 Nodes Pseudolikelihood Bayesian Hierarchical Model Probability of High Annoyance 무. 0.05 8 Perceived Level (dB)

QSF18 Population Average Dose Response Curves

Naive Estimators-Maximum Likelihood

Estimator	\widehat{eta}_0 (SE)	\widehat{eta}_1 (SE)	$\widehat{\sigma}_{c}$	\widehat{d}_{50} (dB)
AGHQ	-19.29 (1.70)	0.154 (0.015)	3.34	125.3
Laplace	-20.34 (2.20)	0.155 (0.015)	3.98	131.2
PQL	-18.41 (1.02)	0.153 (0.010)	2.68	120.3

Table: WSPR: Maximum Likelihood Estimates and Standard Errors

Estimator	\widehat{eta}_{0} (SE)	\widehat{eta}_1 (SE)	$\widehat{\sigma}_{c}$	\widehat{d}_{50} (dB)
AGHQ	-18.67 (2.40)	0.151 (0.028)	2.49	123.6
Laplace	-22.29 (2.65)	0.158 (0.031)	7.13	141.1
PQL	-18.90 (0.79)	0.153 (0.010)	2.72	123.5

Table: QSF18: Maximum Likelihood Estimates and Standard Errors

Simulation Extrapolation (SIMEX)

Functional method developed by Cook & Stefanski (1994), expanded by Stefanski & Cook (1995), Carroll et al. (1996) and others; see Sevilimedu & Yu (2022)

Intuition

- Learn impacts of measurement error experimentally (Simulation)
- 'Undo' these effects based on observed pattern (Extrapolation)

Estimating SIMEX standard errors

- Larger than naive standard errors
- Asymptotic sandwich estimators (Carroll et al., 1996)
- ▶ Jackknife estimators (Stefanski & Cook, 1995; Carroll et al., 2006, Appendix B.4.1)

Simulation Extrapolation (SIMEX): Simulation

Consider $b = 1, \ldots, B$ remeasurements of W_{ij} for $\lambda \ge 0$

 $W_{b,ij}\left(\lambda
ight)=W_{ij}+\sqrt{\lambda}U_{b,ij}$

 $\widehat{\Theta}_{b}(\lambda)$ denotes naive estimator using remeasured predictors $\{W_{b,ij}(\lambda)\}_{\forall i,i}$ with average

$$\widehat{\Theta}(\lambda) \equiv B^{-1} \sum_{b=1}^{B} \widehat{\Theta}_{b}(\lambda)$$
(2)

 $\left\{\lambda_m, \widehat{\Theta}\left(\lambda_m\right)\right\}_{m=1}^M$ constitute the simulation phase for M levels of λ and large B

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Simulation Extrapolation (SIMEX): Extrapolation

Fit model to averaged, error-contaminated estimates $\widehat{\Theta}(\lambda)$

- $\widehat{\Theta}_{SIMEX} \equiv \widehat{\Theta} (\lambda = -1)$, i.e., extrapolate to $\lambda = -1$
- 'Existence lemmas' of Stefanski & Cook (1995)
- In practice, linear, quadratic, or rational linear forms



SIMEX is an approximate method and quadratic extrapolation often works well

WSPR-SIMEX with AGHQ Estimator, $\lambda_m \in \{0.5, 1, 1.5, 2\}$, B = 250



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QSF18–SIMEX with AGHQ Estimator, $\lambda_m \in \{0.5, 1, 1.5, 2\}$, B = 250



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SIMEX Results-Subject-Specific Models

Estimator	\widehat{eta}_0 (SE)	\widehat{eta}_1 (SE)	$\widehat{\sigma}_{c}$	\widehat{d}_{50} (dB)
Naive (AGHQ)	-19.29 (1.70)	0.154 (0.015)	3.34	125.3
SIMEX-L	-20.95 (1.80)	0.172 (0.016)	3.42	121.8
SIMEX-Q	-21.75 (1.86)	0.181 (0.017)	3.45	120.2

Table: Naive and SIMEX estimates from WSPR study

Estimator	\widehat{eta}_{0} (SE)	\widehat{eta}_1 (SE)	$\widehat{\sigma}_{c}$	\widehat{d}_{50} (dB)
Naive (AGHQ)	-18.67 (2.40)	0.151 (0.028)	2.49	123.6
SIMEX-L	-21.07 (2.63)	0.183 (0.031)	2.48	115.1
SIMEX-Q	-25.29 (3.02)	0.239 (0.037)	2.48	105.8

Table: Naive and SIMEX estimates from QSF18 study

SIMEX Results–Population Average Dose-Response Curves



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Naive Estimators-Bayesian Hierarchical Models

Bayesian methods treat parameters as random quantities-sampling versus optimization

$$f\left(\beta_{0},\beta_{1},\sigma_{c}|\boldsymbol{w},\boldsymbol{y}\right) \propto \\ \prod_{i=1}^{I} \prod_{j=1}^{J_{i}} p\left(w_{ij},c_{i}\right)^{y_{ij}} \left[1-p\left(w_{ij},c_{i}\right)\right]^{1-y_{ij}} \phi\left(c_{i}|\sigma_{c}\right) \\ \times f\left(\beta_{0}\right) f\left(\beta_{1}\right) f\left(\sigma_{c}\right)$$
(3)

Early NASA efforts-normal, inverse-gamma priors in naive models (Lee et al., 2019, 2020)

Discussion on selection of priors for mixed models (Browne & Draper, 2006; Gelman, 2006; Gelman et al., 2008; Polson & Scott, 2012)

Naive Estimators-Bayesian Hierarchical Models

Following Gelman et al. (2008) and Polson & Scott (2012) choose Cauchy priors:

```
eta_0 \sim t(0, 10, 1), eta_1 \sim t(0, 2.5, 1), \sigma_c \sim t^+(0, 1, 1)
```

Practical computing: R and JAGS; 4 chains, length 30,000 iterates; 10,000 posterior samples

Data	Estimator	\widehat{eta}_{0} (SD)	\widehat{eta}_{1} (SD)	$\widehat{\sigma}_{c}$ (SD)	\widehat{d}_{50} (dB)
WSPR	Bayes	-19.22 (1.69)	0.154 (0.015)	3.43 (0.72)	125.0
WSPR	AGHQ	-19.29 (1.70)	0.154 (0.015)	3.34 (—)	125.3
QSF18	Bayes	-18.62 (2.40)	0.150 (0.029)	2.50 (0.50)	124.1
QSF18	AGHQ	-18.67 (2.40)	0.151 (0.028)	2.49 (—)	123.6

Table: Posterior means and standard deviations compared to naive AGHQ estimates

Structural Bayesian Hierarchical Measurement Error Models

A 'recipe' (Gustafson, 2004): outcome, measurement, exposure models and priors

$$f(\mathbf{x}, \beta_0, \beta_1, \sigma_c | \mathbf{w}, \mathbf{y}) \propto \prod_{i=1}^{I} \prod_{j=1}^{J_i} p(x_{ij}, c_i)^{y_{ij}} [1 - p(x_{ij}, c_i)]^{1 - y_{ij}} \phi(c_i | \sigma_c)$$

$$\times f(w_{ij} | x_{ij})$$

$$\times f(x_{ij})$$

$$\times f(x_{ij})$$

$$\times f(\beta_0) f(\beta_1) f(\sigma_c)$$
(5)

- ► Retain classical measurement error model: $w_{ij}|x_{ij} \sim N(x_{ij}, \hat{\sigma}_u)$
- For Retain Cauchy priors: $eta_0 \sim t(0,10,1)$, $eta_1 \sim t(0,2.5,1)$, $\sigma_c \sim t^+(0,1,1)$
- Structural: distributional assumption about exposure model $f(x_{ij})$
- See also: Richardson & Gilks (1993), Carroll et al. (1997), Richardson & Leblond (1997)

Specifying the Exposure Model

- 1. NASA controls noise stimulus
 - Record of study design, e.g., test 'thump' versus 'boom' in WSPR (Page et al., 2014)
 - Target levels as possible mode(s) (Page et al., 2020a, Tables 4-2, 4-3)
- 2. NASA subject matter expertise (Doebler et al., 2023; Doebler & Rathsam, 2019, p. 4)
 - Geographic differences in mean and spread
 - Sonic boom 105 PL dB versus X-59 design target 75 PL dB
 - "...distant thunder sone spectrum matches the X-59's sone spectrum quite well..."

Literature on prior elicitation may be useful for structural methods (Johnson et al., 2010)

WSPR-Bayesian Subject-Specific Models

Exposure Model, <i>f</i> (<i>x_{ij}</i>)	\widehat{eta}_{0} (SD)	\widehat{eta}_1 (SD)	$\widehat{\sigma}_{c}$ (SD)	\widehat{d}_{50} (dB)
Naive (Bayes)	-19.22 (1.69)	0.154 (0.015)	3.43 (0.72)	125.0
$Uniform(-100, 200)^2$	-20.33 (2.02)	0.162 (0.018)	3.64 (0.79)	125.5
$\frac{84}{110}t_1 + \frac{26}{110}t_2$	-20.75 (2.01)	0.167 (0.018)	3.67 (0.79)	124.3
$\frac{84}{110}N_1 + \frac{26}{110}N_2$	-21.87 (2.14)	0.180(0.019)	3.65 (0.79)	121.5
$t(\mu = 85, \sigma = 10, \nu = 4)$	-21.93 (2.15)	0.180 (0.019)	3.69 (0.79)	121.8

Table: Posterior means and standard deviations from WSPR study; $t1 = t(\mu = 83, \sigma = 7, \nu = 4)$ and $t2 = t(\mu = 105, \sigma = 6, \nu = 4)$; $N_1 = N(\mu_1 = 83, \sigma_1 = 8)$ and $N_2 = N(\mu_2 = 97, \sigma_2 = 9)$

²Assumed by Doebler et al. (2022)

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QSF18-Bayesian Subject-Specific Models

Exposure Model, <i>f</i> (<i>x_{ij}</i>)	$\widehat{eta}_{f 0}$ (SD)	\widehat{eta}_{1} (SD)	$\widehat{\sigma}_{c}$ (SD)	\widehat{d}_{50} (dB)
Naive (Bayes)	-18.62 (2.40)	0.150 (0.029)	2.50 (0.50)	124.1
$Uniform(-100, 200)^3$	-20.34 (3.00)	0.165 (0.034)	2.69 (0.54)	123.3
<i>Triangular</i> (35, 70, 105)	-21.53 (3.35)	0.181 (0.038)	2.73 (0.58)	119.0
$N(\mu=$ 70, $\sigma=$ 12) ⁴	-22.29 (3.54)	0.193 (0.041)	2.65 (0.55)	115.5
$t(\mu=$ 70, $\sigma=$ 7, $ u=$ 4)	-24.07 (4.07)	0.217 (0.047)	2.76 (0.59)	110.9
Triangular(50, 70, 90)	-25.64 (4.54)	0.237 (0.053)	2.73 (0.59)	108.2

Table: Posterior means and standard deviations from QSF18 study

⁴Similar to Erciulescu & Opsomer (2023)

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³Assumed by Doebler et al. (2022)

Bayesian Population Average Curves



Conclusion: Measurement Error Methods Counteract Bias

WSPR versus QSF18

- Modest changes in WSPR data (3-4% reduction in \hat{d}_{50})
- ▶ Remarkable changes in QSF18 data (up to 15% reduction in \hat{d}_{50})

Functional versus structural methods

- The world has not heard shaped sonic boom before-no gold standard data
- SIMEX used experimentation and pattern to 'undo' biases
- Structural Bayesian hierarchical models embody knowledge in the exposure model
- Noted sensitivity to specification of exposure model

On potential measurement error during Quesst campaigns with X-59

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Community Test Planning and Execution Survey Team

Engineers: Jonathan Rathsam (technical lead), Matthew Boucher, Will Doebler, Aaron Vaughn Statisticians: Pete Parker, Kate Ballard, Nathan Cruze

QUESST

https://www.nasa.gov/mission/quesst/

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