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Examining the effectiveness of blanket curtailment strategies in reducing bat fatalities at terrestrial wind farms in North America

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Abstract:	Blanket curtailment of turbine operations during low wind conditions has become an accepted operational minimization tactic to reduce bat mortality at terrestrial wind facilities. Site-specific studies have demonstrated that operational curtailment effectively reduces impacts, but the exact nature of the relationship between increased cut-in speed and fatality reduction in bats remains unclear. To evaluate the efficacy of differing blanket curtailment regimes in reducing bat fatality, we examined data from turbine curtailment experiments in the United States and Canada in a meta-analysis framework. We tested multiple statistical models to explore possible linear and non-linear relationships between turbine cut-in speed and bat fatality reduction. Because the overall sample size for this meta-analysis was small (n = 35 control-treatment studies from 16 field sites), we conducted a power analysis to assess the number of control-impact curtailment studies that would be needed to understand the relationship between fatality rate and change in cut-in speed under different fatality reduction scenarios. We also identified the characteristics of individual field studies that may influence their power to detect fatality reduction due to curtailment. Using a response ratio approach, we found a 56% reduction in fatality rates when using any blanket curtailment strategy that changes the cut-in speed from 0.5 to 3.5 m/s above the control (p < 0.001). However, we did not find strong evidence for linear (p = 0.07) or non-linear (p > 0.11) associations between increasing cut-in speeds and fatality reduction. The power analyses showed that the power to detect effects in the meta-analysis was low if fatality reductions were less than 50%. Synthesizing across all analyses, we need more well-designed curtailment studies to determine the effect of increasing curtailment speed and the effect size is likely of a magnitude that we had limited power to detect.
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The data used in this study were obtained from a combination of publicly available and anonymous curtailment studies. The project name of public studies and the source we used to obtain each study is listed in Table 1 of the article. Data were compiled from their original reports by the authors of the curtailment study review within CanWEA report (2018) and by the American Wind Wildlife Institute (AWWI) in the American Wind Wildlife Information Center (AWWIC) program. The AWWIC summarizes bird and bat data collected at 227 operating U.S. wind energy projects (more details are found at: <https://awwi.org/resources/awwic-bat-technical-report/>). The data sourced from AWWIC were supplied to the authors in response to the submission and acceptance of a detailed proposal to the Wind Wildlife Research Fund request for proposals. In order to request data used in this article, researchers will need to submit a detailed proposal to AWWI at info@awwi.org or respond to a Wind Wildlife Research Fund request for proposals. AWWIC is a collaborative of independent data owners, managed by AWWI, therefore data usage proposals will be evaluated and approved by all data owners.

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1 **A review of the effectiveness of blanket curtailment strategies in reducing bat fatalities at terrestrial**
2 **wind farms in North America**

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7

8 **Abstract**

9 Blanket curtailment of turbine operations during low wind conditions has become an accepted
10 operational minimization tactic to reduce bat mortality at terrestrial wind facilities. Site-specific studies
11 have demonstrated that operational curtailment **effectively** reduces impacts, but the exact nature of the
12 relationship between **increased cut-in speed** and fatality reduction in bats remains unclear. To evaluate the
13 efficacy of differing blanket curtailment regimes in reducing bat fatality, we examined data from turbine
14 curtailment experiments in the United States and Canada in a meta-analysis framework. We tested
15 multiple statistical models to explore possible linear and non-linear relationships between turbine cut-in
16 speed and bat fatality reduction while controlling for control cut-in speed. Because the overall sample size
17 for this meta-analysis was small (n = 36 control-treatment studies from 16 field sites from the American
18 Wind Wildlife Information Center and a recent review), we conducted a power analysis to assess the
19 number of control-impact curtailment studies that would be needed to understand the relationship
20 between fatality rate and change in cut-in speed under **different fatality reduction scenarios**. We also
21 identified the characteristics of individual field studies that may influence their power to detect fatality
22 reduction due to curtailment. Using a response ratio approach, we found any curtailment strategy reduced
23 fatality rates by 56% for studies included in this analysis ($p < 0.001$). However, we did not find strong
24 evidence for linear ($p = 0.07$) or non-linear ($p > 0.11$) associations between increasing cut-in speeds and
25 fatality reduction. **The power analyses showed that the power to detect effects in the meta-analysis was**
26 **low if fatality reductions were less than 50%**. Synthesizing across all analyses, we need more well-
27 designed curtailment studies to determine the effect of increasing curtailment speed and the effect size is
28 likely of a magnitude that we had limited power to detect.

29

30 **Introduction**

31 Wind energy development is increasing rapidly worldwide and hundreds of thousands of bat
32 fatalities are estimated to occur per year due to collisions with terrestrial wind energy facilities in North
33 America [1–3]. Turbine attraction is the leading explanation for high observed fatality rates, particularly
34 in migratory tree bats [4,5]. Between 70% and 80% of bats killed at wind energy facilities in the U.S. are
35 migratory tree bats, including hoary bat (*Lasiurus cinereus*), eastern red bat (*L. borealis*), and silver-
36 haired bat (*Lasionycteris noctivangans*; [3,6–8]. While fatality rates are variable among sites, the
37 magnitude of mortality for some North American bat species is high enough to be considered a serious
38 conservation concern [9,10].

39 Curtailment of turbine operations during low wind conditions, particularly in late summer and fall
40 when fatality rates are highest, has become an accepted operational minimization tactic to reduce bat
41 fatality at terrestrial wind facilities [11]. By increasing the cut-in speed, or the wind speed at which a
42 turbine generator begins to produce electricity, curtailment reduces turbine blade spinning rates. Below
43 the cut-in speed, turbine blades still spin with the wind but do so much more slowly, especially if blades
44 are “feathered” or pitched to catch as little wind as possible. Because bats tend to be more active at lower
45 wind speeds, increasing turbine cut-in speed can significantly reduce bat fatality [1,12]. However, a great
46 deal of variability has been reported in the level of fatality reduction achieved by curtailment, likely due
47 to the effect of myriad factors (e.g., curtailment regime, time of year, weather, turbine dimensions, and
48 landscape characteristics; [8]) on fatality risk. While site-specific studies have demonstrated that
49 operational curtailment is effective at reducing impacts, the exact nature of the relationship between
50 increases in cut-in speed and fatality reduction in bats remains unclear.

51 For this study, “blanket” curtailment, in which wind speed and time of day/year are used to
52 determine when to curtail, has both operational and financial implications for wind facility operators [13].
53 At present, the exact nature of the trade-off between turbine energy production and bat fatality
54 minimization is poorly understood. Larger increases in cut-in speeds will further reduce power

55 generation. Still, the implications for fatality reduction are less clear, in part because this type of
56 assessment requires intensive monitoring and is subject to errors introduced by imperfect detection and
57 small sample sizes. Despite limited evidence that raising blanket cut-in speeds above 4.5 m/s will further
58 reduce bat fatalities [14], regulators now have required operational minimization for some new wind
59 projects in the United States and Canada at wind speeds up to 6.9 m/s [15]. A synthesis of the available
60 data from designed curtailment studies will allow us to quantify better the relative benefits of increasing
61 turbine cut-in speed for reducing bat collision fatality.

62 A meta-analysis framework is used to synthesize data across studies to determine the effect of
63 curtailment on bat fatality reduction. Meta-analysis provides a method to account for multiple types of
64 uncertainty and use predictor variables to explain patterns between studies [16]. Random effects meta-
65 analyses are needed to account for the uncertainty in effects from each study and the uncertainty in the
66 true effect size to which all studies contribute. Using such an approach, we aim to evaluate the current
67 knowledge of the effectiveness of blanket curtailment regimes in reducing bat fatalities at terrestrial wind
68 projects in North America. We identified three objectives: 1) evaluate existing control-treatment
69 curtailment study data for bats in a meta-analysis framework to examine the relative benefit of increased
70 curtailment cut-in speeds and examine the importance of geography and turbine dimensions on fatality
71 reduction; 2) assess the power of the meta-analysis approach to quantify fatality reduction using a data
72 simulation approach; and 3) understand how different site or survey characteristics (e.g., fatality rates,
73 study length, and carcass persistence) influence the power of individual curtailment field studies to detect
74 a difference in bat fatality rates between control and treatment groups. These analyses are combined to
75 identify the most likely effect of blanket curtailment on bat fatality reduction, how much additional
76 information is needed to be certain of these effects, and how to design curtailment experiments to
77 maximize the value of their results.

78 **Methods**

79 The study's overall goal was to understand the relationship between blanket curtailment cut-in
80 speed and bat fatality reduction at wind facilities in the United States and Canada. To achieve this goal,
81 we used a response ratio approach that focused on the differences in fatality rates between control and
82 curtailment treatments in available studies. We used a meta-analysis approach (hereafter referred to as the
83 “*meta-analysis*”) to control for variability among studies. As we did not have a predetermined assumption
84 about the nature of the relationship between fatality rate and the change in cut-in speed between control
85 and treatment, we tested multiple statistical models that allowed for both linear and non-linear
86 relationships between cut-in speed and the response to determine which best described the observed
87 pattern. Both the absolute cut-in speed and change in cut-in speed were allowed to influence the predicted
88 fatality rate. Once the best models were selected, we used them to understand how covariates like study
89 location and turbine dimensions could influence the relationship between fatality rate and change in cut-in
90 speed.

91 Because the sample size for this analysis was small (n=36 control-treatment pairs), we also
92 assessed the likelihood that the above *meta-analysis* would provide statistically significant results and
93 determined the number of control-treatment pairs needed in this meta-analytical framework to be
94 confident in our understanding of the relationship between fatality rate and change in cut-in speed. Thus,
95 we conducted two types of power analyses. The first power analysis (the “*meta-analysis power analysis*”)
96 was designed to quantify the power of the meta-analysis under different hypothetical scenarios about the
97 relationship between fatality rate and change in cut-in speed. The first of these scenarios was an *a*
98 *posteriori* scenario based on the results of the best meta-analysis model using existing data, and four
99 additional *a priori* scenarios with different relationships between fatality reduction and cut-in speed were
100 also examined. The second power analysis (the “*fatality estimation power analysis*”) was designed to
101 inform future curtailment studies and fatality monitoring efforts at operating wind energy facilities. This
102 analysis assessed the relative quality of different fatality studies at the project scale and identified site and
103 survey characteristics (e.g., fatality rate, study length, and carcass persistence) that influenced the power

104 of individual curtailment field studies to detect a difference in bat fatality rates between control and
105 treatment groups. All analyses were conducted in R [17], and all analysis scripts were documented in
106 *Supplementary Information*.

107 *Data Inclusion*

108 Data for this analysis were collected in part from the American Wind Wildlife Information Center
109 (AWWIC, Accessed in August 2019), which compiles private and public data from post-construction
110 fatality monitoring studies at individual wind energy projects in the United States (n=43) [7]. Data from
111 several additional studies in the U.S. and Canada were harvested from publicly available reports (n =22
112 with overlap to the AWWIC studies) [14]. Paired control-treatment curtailment studies (hereafter
113 ‘studies’) with blanket curtailment treatments were of primary interest for this analysis. Studies were
114 included in the analysis if there was both a **treatment and control group of turbines** with fatality estimates
115 at different cut-in speeds at the same project site (Fig. 1). Data were excluded from analysis if there was
116 no change in cut-in speed between treatments (e.g., testing other fatality reduction methods) or no
117 measurement of treatment effect (e.g., no control treatment). The remaining studies in the database (n=36;
118 Table 1) were conducted at 17 wind energy project sites in the U.S. and Canada from 2005-2016. There
119 were instances where multiple experimental cut-in speeds were tested simultaneously at the same project,
120 resulting in multiple studies from the same project and year that shared a control. Studies without
121 precision estimates for their fatality ratios were included in the analysis by applying the global average
122 standard error.

123 Figure 1. PRISMA meta-analysis data flow diagram for the study. After receiving a list of all projects in AWWIC
124 and the CanWea syntheses that reported turbine curtailment we removed duplicates between the two sources.
125 Individual studies within those projects were determined to be suitable for analysis if they used a blanket curtailment
126 treatment and there were multiple cut-in speeds that could be compared.

127

128 Fatality estimates in the AWWIC database, which were reported from the original studies, had
129 already been adjusted for detection probability (observer ability to detect carcasses that are present) and
130 carcass persistence (rate of removal of carcasses by scavengers) using searcher efficiency trials and

131 carcass persistence trials, respectively [18]. There are multiple approaches for correcting fatality estimates
 132 that differ in their assumptions regarding how to account for detection error resulting from carcass
 133 removal and searcher efficiency [18,19].

134 **Table 1.** Bat fatality curtailment study data from the AWWIC and CanWEA databases, including project name,
 135 year, geographic region, and rotor diameter in meters (RD); control cut-in speed (Cont.), experimental cut-in speed
 136 (Exp.), and change in cut-in speed (Δ), all in m/s; and treatment effect information, including the mean fatality ratio
 137 \pm SE (Fatal. Ratio) and percent decrease in fatality between treatments (%). Studies from the same project and year
 138 were tested simultaneously and share a control. Some studies lacked information on fatality uncertainty; for these,
 139 the global average standard error was applied to the fatality ratio.

Project Name	Year	Region	RD	Cut-in Speed			Effect		Source
				Cont.	Exp.	Δ	Fatal. Ratio	%	
Anonymous East	2014	East	77	3.5	4.5	1.0	0.50 \pm 0.16	50	AWWIC ²
Anonymous East	2015	East	77	3.5	5.5	2.0	1.00 \pm 0.42	0	AWWIC
Anonymous East	2015	East	77	3.0	4.0	1.0	0.91 \pm 0.36	9	AWWIC
Anonymous East	2016	East	77	3.0	5.0	2.0	0.69 \pm 0.33	31	AWWIC
Anonymous East	2016	East	77	3.0	6.0	3.0	0.53 \pm 0.34	47	AWWIC
Casselman Wind	2008	East	77	3.5	5.0	1.5	0.13 \pm 0.14	87	AWWIC
Casselman Wind	2008	East	77	3.5	6.5	3.0	0.26 \pm 0.18	74	AWWIC
Casselman Wind	2009	East	77	3.5	5.0	1.5	0.32 \pm 0.17	68	AWWIC
Casselman Wind	2009	East	77	3.5	6.5	3.0	0.24 \pm 0.15	76	AWWIC
Criterion	2012	East	93	4.0	5.0	1.0	0.38 \pm 0.14	62	AWWIC
Laurel Mountain	2011	East	82	3.5	4.5	1.0	0.42 \pm 0.15	58	AWWIC
Pinnacle Wind Force	2012	East	95	3.0	5.0	2.0	0.53 \pm 0.15	47	AWWIC
Pinnacle Wind Force	2013	East	95	3.0	5.0	2.0	0.42 \pm 0.21	58	AWWIC
Pinnacle Wind Force	2013	East	95	3.0	6.5	3.5	0.25 \pm 0.14	75	AWWIC
Anonymous Midwest	2010	Midwest/West	82	3.5	4.8	1.3	0.53 \pm 0.25	47	CanWEA ³
Anonymous Midwest	2010	Midwest/West	82	3.5	4.0	0.5	0.28 \pm 0.13	72	CanWEA
Anonymous Pac. SW	2012	Midwest/West	101	3.5	4.8	1.3	0.80 \pm 0.37	20	CanWEA
Anonymous Pac. SW	2012	Midwest/West	101	3.5	4.0	0.5	0.65 \pm 0.30	35	CanWEA
Anonymous Pac. SW	2012	Midwest/West	101	3.5	4.8	1.3	0.62 \pm 0.29	38	CanWEA
Fowler Ridge 1	2010	Midwest/West	89	3.5	5.0	1.5	0.50 \pm 0.11	50	AWWIC
Fowler Ridge 1	2010	Midwest/West	89	3.5	6.5	3.0	0.21 \pm 0.07	79	AWWIC
Fowler Ridge 1	2011	Midwest/West	89	3.5	4.5	1.0	0.64 \pm 0.29	36	AWWIC
Fowler Ridge 1	2011	Midwest/West	89	3.5	5.5	2.0	0.38 \pm 0.18	62	AWWIC
Fowler Ridge 1	2012	Midwest/West	89	3.5	5.0	1.5	0.16 \pm 0.06	84	AWWIC
Lakefield	2016	Midwest/West	77	3.5	5.0	1.5	0.56 \pm 0.34	44	AWWIC
Summerview	2005	Midwest/West	80	4.0	7.0	3.0	0.61 \pm 0.28	39	CanWEA
Summerview	2007	Midwest/West	80	4.0	5.5	1.5	0.94 \pm 0.26	6	CanWEA
Wild Cat 1	2013-15	Midwest/West	100	5.0	7.0	2.0	0.20 \pm 0.07	80	AWWIC
Wild Cat 1	2016	Midwest/West	100	5.0	6.9	1.9	0.41 \pm 0.33	59	AWWIC
Bull Hill	2013	Northeast	100	3.0	5.0	2.0	0.70 \pm 0.23	30	AWWIC
Enbridge Wind	2012	Northeast	82	3.5	5.5	2.0	0.38 \pm 0.18	62	CanWEA
Raleigh Wind	2014	Northeast	77	3.5	4.5	1.0	0.23 \pm 0.05	77	CanWEA
Sheffield	2012	Northeast	94	4.0	6.0	2.0	0.37 \pm 0.13	63	AWWIC
Talbot Wind ¹	2013	Northeast	101	3.5	5.5	2.0	0.04 \pm 0.18	96	CanWEA ¹
Wolfe Island	2011	Northeast	93	3.2	4.5	1.3	0.52 \pm 0.24	48	CanWEA
Wolfe Island	2011	Northeast	93	3.2	5.5	2.3	0.40 \pm 0.18	60	CanWEA

140 ¹ This study was a statistical outlier that did not meet the assumptions of the meta-analysis and thus was excluded

141 ² Data obtained from the American Wind Wildlife Information Center (AWWIC) database, which includes both public and

142 private data.
143 3 Data obtained from a review by the Canadian Wind Energy Associate [CanWEA 14] and public reports cited therein.

144

145 Studies in this analysis primarily used the Huso and Shoenfield estimators [20,21]. However, some
146 studies used the Erickson estimator [22], MNRF estimator [23], or custom calculations to adjust fatality
147 estimates for carcass persistence and searcher efficiency. Adjusted bat fatality estimates per turbine were
148 presented in the database with upper and lower 90-95% confidence intervals (CIs). As the experimental
149 period and hours per night when experiments were implemented varied among studies, fatality estimates
150 were converted to bat fatality per turbine-hour by dividing fatalities per turbine by the total number of
151 hours of curtailment (number of nights*hours per night). Study periods varied somewhat between
152 individual curtailment studies, with some studies examining specific time periods throughout the night or
153 focusing on different windows of time during fall migration; our approach controls for study-specific
154 variability by pairing control-treatment groups for analysis, but does assume that the relationship between
155 turbine-hours and fatalities is robust to potential variation in the effect of curtailment through time. Few
156 studies reported species-specific fatality rates, so fatality estimates were for all bat species combined.

157 *Meta-analysis*

158 The effect size of each study was calculated as a log-transformed ratio between the estimated
159 fatality of the treatment and the control, both in the unit of bat fatalities per turbine hour (i.e., the log-
160 transformed response ratio, hereafter ‘RR’). In instances where only a percent decrease was reported, this
161 was used to calculate the RR ($\log(1-(\% \text{ decrease}/100)) = \text{RR}$). This effect size approach controls for
162 differences in study design ranging from site-specific effects to the choice of fatality estimator.

163 Manufacturer cut-in speed can vary among turbine makes and models. In most studies, the control
164 group’s cut-in speed was 3.5 m/s (a common cut-in speed set by turbine manufacturers), though values
165 ranged from 3.0 to 5.0 m/s. Experimental cut-in speeds varied from 4.0 to 7.0 m/s. Due to this variation
166 and the small sample size of available studies, the change in cut-in speed between treatment and control

167 (Δ cut-in speed) was used as the estimate of treatment magnitude. Thus, the analysis focused on the effect
168 of relative rather than absolute change in curtailment cut-in speed.

169 We used a random effects meta-analysis that accounts for heterogeneity in the true effect
170 (between-study variance) and sampling error (within-study variance; [24]). The inclusion of between-
171 study variance (i.e., the random effect τ) allows for the incorporation of additional uncertainty in the
172 analysis by assuming the true effect is a random variable that is realized at different magnitudes in
173 different studies. Confidence intervals (90% or 95% depending on the estimator used) for control and
174 treatment fatality estimates were converted into standard error (SE) estimates assuming an approximately
175 normal distribution. While confidence intervals were slightly asymmetrical, a normal approximation was
176 the best available strategy for conversion given the variation in fatality estimators used across studies. For
177 independent studies (i.e., those with no shared control), standard error estimates of the RR were
178 calculated using the delta method [25,26]. In instances where multiple studies shared a common control
179 (i.e., were conducted simultaneously at the same project site; $n=23$), the correlation among the studies
180 was calculated by decoupling the associated dependence into a single estimate of uncertainty for each
181 study [26,27]. In instances where no estimate of uncertainty was provided in the original study, the mean
182 SE of all studies after decoupling was applied to the estimate.

183 To conduct the meta-analysis and explore the possible relationships between Δ cut-in speed and
184 bat fatality rates, we ran two types of models with the RR as the dependent variable and Δ cut-in as the
185 primary explanatory variable, with control cut-in speed included as an additional covariate. Using the
186 ‘metagen’ and ‘metareg’ functions from the *meta* R package [28] we tested: 1) *non-linear categorical*
187 model specifications where studies were binned into three discrete categories to simplify model fitting
188 (1= Δ cut-in values ≥ 0.5 and < 1.4 m/s, 2= Δ values ≥ 1.4 and < 2.6 m/s, and 3= Δ values ≥ 2.6 m/s); and
189 2) *linear continuous* model specifications that treated Δ cut-in as a continuous variable. As the categorical
190 model ignored the ordinal relationships among treatment groups, the continuous model was implemented
191 to help determine the degree of bias in this approach. We also explored the influence of bin choice on the

192 fit of the categorical model (Appendix A) and other types of models that test for non-linear relationships
193 in fatality ratio and Δ cut-in (e.g., continuous quadratic relationships) before determining the best
194 approach for this question.

195 For all model types, variation in individual study precision (within-study variance) was accounted
196 for using a weighted regression approach, so that studies with higher precision influenced the model
197 parameter estimates more than studies with lower precision. Study weight was determined as a function of
198 the inverse square of the study standard error plus the overall between-study variance (τ^2). τ^2 was
199 estimated using a restricted maximum likelihood approach [29]. One study (Talbot Wind) was determined
200 to be an outlier and was removed due to disproportionately high leverage compared other studies.
201 Additional covariates included rotor diameter (RD) and geographic region. Geographic region (Northeast,
202 East, Midwest/West) was based upon EPA ecoregions (<https://www.epa.gov/eco-research/ecoregions>) but
203 consolidated to ensure enough studies per category for inclusion in the model (Table 1). Hub height was
204 considered for inclusion as a covariate but had little variation across studies (n=30 studies with hub height
205 of 80 m). There was not enough data to consider interactions among these covariates. We also lacked data
206 to consider controlling site dependencies among studies using a random effect. We examined between-
207 study heterogeneity and model goodness of fit using Cochran's Q (QE), τ^2 , and I^2 model statistics [30].
208 Model selection was performed based on AIC_c values and model weights were calculated based on these
209 values for each model type separately.

210 *Meta-analysis Power Analysis*

211 To determine the number of studies required in a random effects meta-analysis to detect relative
212 changes in RR with changing cut-in speed reliably, we implemented a power analysis at the meta-analysis
213 scale using a simulation approach [31]. We conducted meta-analysis power analyses for the *non-linear*
214 *categorical* and *linear continuous* descriptions of the relationship between Δ cut-in speed and RR. For the
215 categorical relationship power analysis, simulations were designed using the Δ cut-in speed categories
216 defined above to replicate the meta-analysis under multiple scenarios. **The number of studies per Δ cut-in**

217 category, fatality reduction for the first Δ cut-in speed category (β_0), and the subsequent reduction in the
218 second and third categories (β_1, β_2), were varied across simulations. The following linear regression
219 equation was used for the categorical model:

$$220 \quad RR = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon + \tau$$

221 where X_1 and X_2 are dummy covariates that represent Δ cut-in Categories 2 and 3, respectively. The
222 uncertainty from the Gaussian error term (ε) and inter-study differences (τ) were added by using a normal
223 distribution with a mean of 0 and a standard deviation equal to that observed in the fatality ratio of
224 control-treatment data (Table 1; SD = 0.24). We used a uniform distribution to randomly assign a SE to
225 each simulated study, which ranged between the minimum and maximum of the observed study standard
226 errors (Table 1; range: 0.05-0.34). Once the model was simulated, we used the methods described above
227 to estimate parameters. Each scenario was simulated 10,000 times with 5, 10, 20, and 30 studies per Δ
228 cut-in category to achieve precise estimates of power. The statistical power of each parameter (β_0, β_1 , and
229 β_2) and sign error (the probability that the estimate was the same sign as the given parameter; [32]) were
230 calculated to determine the effectiveness of the model in estimating the scenario parameters. Power was
231 determined by examining whether the results were significantly different from the value of no effect (1
232 for β_0 , and 0 for β_1 and β_2 ; $\alpha = 0.05$), and the sign error was computed by comparing the signs of the true
233 parameter value and the estimated value.

234 For the *linear continuous* models, Δ cut-in speed was randomly assigned to each study. To do
235 this, we used the same category framework (where 5, 10, 20, or 30 studies were assigned to each Δ cut-in
236 category), and studies in this category were randomly assigned a Δ cut-in speed from that category that
237 was observed in the studies included in the meta-analysis. These values were then scaled (centered on
238 zero) and used to build a linear model:

$$239 \quad RR = \beta_0 + \beta_1 X_1 + \varepsilon + \tau$$

240 where X_1 is the scaled continuous Δ cut-in speed value for each study.

241 Five scenarios were simulated for the power analysis for the two model types (Table 2). Each
 242 scenario was replicated at four different sample sizes (5, 10, 20, and 30 studies per Δ cut-in category).
 243 Four of these scenarios were selected *a priori* to explore our power to detect different types of
 244 relationships between fatality ratio and Δ cut-in. We included three scenarios thought to represent
 245 plausible hypotheses based on observed results to date: 1) a 25% linear decrease in fatality per 1 m/s
 246 increase in cut-in speed; 2) a 50% initial decrease in fatality with Category 1 Δ cut-in speed and
 247 subsequently stable fatality rates; and 3) an initial 50% decrease in fatality with Category 1 Δ cut-in speed
 248 and then 10% subsequent declines in fatality for Categories 2-3. The fourth scenario, a more extreme 50%
 249 exponential decrease per 1 m/s increase in cut-in speed, was intended to provide context for interpreting
 250 the results of other scenarios. We also included an *a posteriori* ‘current knowledge’ scenario that used
 251 parameter estimates obtained from the top model in our *meta-analysis* (above).

252
 253 Table 2. Parameters used in simulation scenarios for the meta-analysis scale power analysis of bat fatality with
 254 changes in cut-in speed. A total of 20 scenarios for each model type were run with different β_0 , β_1 , and β_2 values and
 255 differing numbers of studies per category (*n* Studies). Parameters are log-transformed.

Model	Scenario	β_0	β_1	β_2	<i>n</i> Studies
Non-Linear Categorical	Current Knowledge	-0.67	-0.19	-0.46	5, 10, 20, 30
	25% Linear Decrease	-0.29	-0.41	-1.1	5, 10, 20, 30
	50% Decrease then Stable	-0.69	0.00	0.00	5, 10, 20, 30
	50% Decrease then 10% Decline	-0.69	-0.22	-0.51	5, 10, 20, 30
	50% Exponential Decrease	-0.69	-0.69	-0.99	5, 10, 20, 30
Linear Continuous	Current Knowledge	-0.84	-0.17		5, 10, 20, 30
	25% Linear Decrease	-0.59	-0.59		5, 10, 20, 30
	50% Decrease then Stable	-0.52	-0.27		5, 10, 20, 30
	50% Decrease then 10% Decline	-0.70	-0.5		5, 10, 20, 30
	50% Exponential Decrease	-1.04	-0.89		5, 10, 20, 30

256
 257 Thus, this power analysis represented a combination of *a priori* and *a posteriori* approaches designed to
 258 understand the efficacy of the current study, estimate the number of studies needed to reduce uncertainty
 259 in the meta-analysis, and inform the likelihood that the observed data could be generated by the *a priori*
 260 scenarios.

261 *Fatality Estimation Power Analysis*

262 To understand the traits of effective curtailment experiments and provide guidelines for future
263 studies, we used a data simulation approach to determine the effectiveness of project-scale curtailment
264 studies at detecting differences in bat fatality rates using a hierarchical simulation approach [33]. Three
265 different data sets were simulated to replicate the process by which true fatalities rates are estimated in
266 curtailment field studies. First, the true number of bat mortalities was simulated using a Poisson process.
267 New fatalities were generated each night for each turbine using a fatality rate per turbine-night as a
268 Poisson mean. Second, carcass persistence rate was estimated using a carcass persistence trial format.
269 Here, we used the exponential distribution to simulate the survival rates of 50 carcasses at the site based
270 on the predefined median number of days of carcass persistence. Carcass searches were assumed to occur
271 every three days for the duration of the study, and the survival probability of the carcasses was used to
272 estimate daily carcass persistence probabilities for the survey. Third, searcher efficiency data were
273 simulated based on 100 detection trials using a binomial distribution. These data sets were combined to
274 determine the number of carcasses detected by the surveyors at each survey interval. Detection
275 probability for each carcass was a function of carcass persistence, which changed in a time-dependent
276 manner following the fatality event, and searcher efficiency, which was constant across time. The number
277 of observed mortalities was determined using a binomial draw from the combined probability of
278 persistence and detection for each fatality.

279 Forty-eight scenarios were used in this power analysis to explore the effects of effect size, study
280 period, and carcass persistence on study design, and were based upon information from an early version
281 of the subset AWWIC database with curtailment studies (June 2019). Simulation parameters were
282 selected based on averages and ranges from the interim database, and are useful approximations of values
283 in typical curtailment studies. The curtailment treatment effect was defined as either a 25% or 50%
284 reduction in fatality rates (n=24 scenarios for each effect). These values were selected based on the 50%
285 reduction approximated the average fatality reduction. The number of turbines (10 or 15), number of

286 experiment nights (45 or 90), fatality rate (0.1 or 0.3 mortalities/turbine-night), and carcass persistence
287 rate (3, 6, or 9 mean days of persistence) were varied to determine the effect of these variables on
288 statistical power. The number of turbines and experiment nights are combined as turbine-nights to
289 describe study effort. Chosen carcass persistence values tended to be on the lower end of the range of
290 observed values to test the power of these studies in more challenging environmental conditions.
291 Detection probability was fixed at 50% for all studies, the approximate median of the described studies.

292 Data were simulated for each scenario using base functions in R v. 3.6 [17] and package *simsurv*
293 [34]. Package *GenEst* [35] was then used to estimate the true number of fatalities for each treatment group
294 with the simulated data sets. This process was repeated 50,000 times to obtain consistent estimates of
295 statistical power. This generalized fatality estimator ('GenEst') differs from those used by studies in the
296 AWWIC database but is considered the current best practice for estimating fatality from wind turbines
297 when the sample size is sufficiently large to estimate known biases [35]. The Bayesian posterior
298 distribution of the number of fatalities for each treatment group was estimated using the function 'estM'
299 in package *GenEst*. Simulated carcass observations, carcass persistence trial data, and searcher efficiency
300 data were used as inputs along with assumed static values for the proportion of area searched (50% for all
301 turbines) and the search schedule (once every three days for all turbines). The mean number of mortalities
302 in the 25% and 50% reduction treatment groups (along with 95% credible intervals) were estimated using
303 a parametric bootstrapping approach (n = 1000). The 95% credible interval of the difference of the
304 *GenEst*-derived fatality estimates between these two groups was calculated to determine overlap with
305 zero and used to estimate statistical power for each scenario, and was determined by subtracting the
306 bootstrapped simulations for each treatment group. If a simulation study group did not detect any
307 carcasses, we did not include it in the power analysis calculation.

308

309 **Results**

310 Fatality ratios in the database representing fatality reduction due to curtailment ranged from 0.13
311 (87% decrease in fatalities) to 1.00 (0% decrease in fatalities) with an arithmetic mean of 0.46 (53%
312 decrease; n=35 studies). Lower fatality ratio values represented a greater reduction in bat fatality per
313 turbine-hour, while a value of one indicates no difference between curtailment treatment and control (0%
314 decrease). When examining fatality ratios by Δ cut-in category, the mean fatality ratio for **Category 1** was
315 **0.60 (n = 12)**, **Category 2** was **0.41 (n = 18)**, and **Category 3** was 0.37 (n = 6), suggesting a possible non-
316 linear relationship with Δ cut-in speed (Fig. 1).

317 Figure 2. The relationship between bat fatality and curtailment difference (Δ cut-in; calculated as a change in m/s
318 between the treatment and control groups) for 16 wind farms in North America. **Some wind farms have multiple**
319 **data points as there were multiple years of experiments or multiple treatments tested within a year (n=36 studies).**
320 Error bars represent the standard error of the fatality ratio. Talbot Wind was excluded from the meta-analysis as an
321 outlier.

322

323 *Meta-analysis*

324 Thirty-five individual studies (from 16 projects) were included in the meta-analysis modeling.
325 The estimated fatality ratio across all studies (i.e., the estimate before controlling for Δ cut-in speed) was
326 0.44 (95% CI: 0.36-0.49, $z = -9.18$, $p < 0.001$; Fig. 2). For both categorical and continuous model types,
327 the models with Δ cut-in and control cut-in as covariates represented the best model fit, as indicated by
328 AIC_c (Appendix A). Comparing across model types, the linear model represented the best fit ($AIC_c =$
329 55.67), likely due to model simplicity; the categorical model showed slightly worse fit ($AIC_c=58.48$). A
330 forest plot was used to show that there was not evidence of publication bias.

331 The best fit linear model had a large and significant amount of residual heterogeneity between
332 studies ($QE_{32} = 50.50$, $p = 0.02$), with an among-study variance estimate (τ^2) of 0.10 (CI: 0.00, 0.19), while
333 the percentage of overall variation across studies due to heterogeneity (I^2) was 39.2% (CI: 1.1-53.9%).
334 Based on the linear model, the RR tended to decrease with increasing Δ cut-in (slope parameter $\beta = -0.17$,
335 CI: -0.36-0.02; Fig 3); this relationship nearly met the requirement for statistical significance ($z = -1.78$, p
336 = 0.07). Control cut-in speed was not a significant covariate ($\beta = -0.14$, CI: -0.32-0.05, $z = -1.47$, $p =$

337 0.14). There was no significant effect of rotor diameter (95% CI: -0.16- 0.24, $z = 0.35$, $p = 0.72$) or
338 geographic region (Midwest vs. East, CI: -0.35- 0.49, $z = 0.32$, $p = 0.75$; Northeast vs. East, CI: -0.65,
339 0.33, $z = -0.63$, $p = 0.53$) on bat fatality ratios. The addition of these covariates did result in a slight
340 decrease in model heterogeneity, however (rotor diameter: $QE_{31} = 50.0$, $p = 0.02$, $\tau^2 = 0.11$, τ^2 CI = 0.00-
341 0.20, $I^2 = 40.1\%$, I^2 CI=1.9-55.2%; geographic region: $QE_{30} = 46.3$, $p = 0.03$, $\tau^2 = 0.11$, τ^2 CI = 0.00-0.21,
342 $I^2 = 38.7\%$, I^2 CI=0.0-55.3%).

343 Figure 3. The effect of curtailment regime on bat fatalities at terrestrial wind farms in North America from a meta-
344 analysis incorporating within- and among-study variance. The plot shows the fatality ratio (black square) and 95%
345 CI (error bars) of individual studies along with the mean effect size for each Δ cut-in category (grey diamonds). The
346 95% confidence interval of the overall effect is shown at the bottom (black diamond). Individual studies were
347 weighted (out of 100%) based on study uncertainty (CI, in brackets) and distance from category mean effect, with
348 square size indicating relative weighting. A fatality ratio of 1 indicates no difference in fatality rate between the
349 control and experimental curtailment treatments.

350
351 The best fit model with a categorical response to Δ cut-in speed also had a large and significant
352 amount of residual heterogeneity between studies ($QE_{31} = 50.76$, $p = 0.01$), with an among-study variance
353 estimate (τ^2) of 0.11 (CI: 0.01-0.21), while the percentage of overall variation across studies due to
354 heterogeneity (I^2) was 41.2% (CI: 2.9-56.0%). When examining fatality reduction by Δ cut-in speed, the
355 model predicted a fatality ratio estimate for Category 1 of 0.52 and represented a significant reduction in
356 fatality rates ($\beta = -0.67$, CI: -0.97 to -0.37, $z = -4.38$, $p < 0.0001$).

357 Figure 4. Meta-analysis estimated linear (black line) and categorical (pink) effect of Δ cut-in speed on bat fatality
358 ratio at North American wind energy projects. Black dots represent fatality ratios for individual studies; note that
359 uncertainty in individual study estimates, which influenced the meta-analysis parameter estimates, are not shown
360 here (see Table 2 for these values). Categorical model points are based on mean Δ cut-in speed for the category.
361 Error bars are 95% confidence intervals of estimates.

362
363 The model estimates for fatality ratios for Categories 2 and 3 were 0.42 and 0.34 respectively, but the
364 marginal change of increasing Δ cut-in from Category 1 to Category 2 ($\beta_1 = -0.19$, CI: -0.59-0.20, $z = -$
365 0.96, $p = 0.33$) and from Category 1 to Category 3 ($\beta_2 = -0.46$, CI: -1.02-0.11, $z = -1.58$, $p = 0.11$) were
366 small, with high amounts of uncertainty in the estimates (Fig. 3). Control cut-in speed was not a
367 significant covariate ($\beta = -0.13$, CI: -0.32-0.06, $z = -1.31$, $p = 0.19$). Analysis of study-scale covariates

368 revealed no significant effect of rotor diameter (95% CI: -0.19- 0.23, $z = 0.16$, $p = 0.87$) or geographic
369 region (Midwest vs. East, CI: -0.35- 0.55, $z = 0.45$, $p = 0.65$; Northeast vs. East, CI: -0.71, 0.32, $z = -0.73$,
370 $p = 0.46$) on bat fatality ratios. The addition of these covariates did not result in decreases in model
371 residual heterogeneity.

372

373 *Meta-analysis Power Analysis*

374 Power analysis of the categorical model revealed that for most scenarios, five studies were
375 required to have adequate statistical power (>0.8) to determine an effect of curtailment on the fatality
376 ratios for Category 1 (β_0 ; 0.5-1.3 m/s Δ cut-in; Fig. 4). The exception was the 25% linear decrease
377 scenario, which required over 30 studies to achieve adequate power due to smaller changes at lower Δ
378 cut-in speeds. The statistical power of β_1 and β_2 (Δ cut-in Categories 2-3) were more variable across
379 scenarios (Fig. 4). For β_1 (1.5-2.3 m/s Δ cut-in speed), the 50% exponential decrease scenario had
380 sufficient power at 20 or more studies, and the 25% linear decrease scenario had sufficient power at 30
381 studies per group, but no other scenario met the criteria for sufficient power. For β_2 (3-3.5 m/s Δ cut-in
382 speed), two scenarios achieved sufficient power with less than 10 studies per group (50 % exponential
383 decrease, 25% linear decrease), while another two achieved sufficient power with 20-30 studies per group
384 (50% decrease followed by 10% decreases, and current knowledge scenario). Sign error decreased with
385 increasing sample size for all parameters except those that were set at zero (β_1 and β_2 in the 50% decrease
386 then stable scenario) and decreased below 10% at 10 studies per category for most other parameter
387 estimates.

388 Figure 5. The relationship of statistical power and sign error with sample size in the categorical meta-analysis-scale
389 power analysis of curtailment studies to reduce bat fatality rates. We examined the relationship between the number
390 of studies per category of Δ cut-in speed (Category 1 = $\beta_0 = 0.5$ -1.3 m/s Δ cut-in speed, Category 2 = $\beta_1 = 1.5$ -2.3 Δ
391 cut-in speed, Category 3 = $\beta_2 = 3$ -3.5 m/s Δ cut-in speed) and 1) the statistical power to detect change between
392 categories (at top), and 2) the rate at which models would be expected to incorrectly predict the sign of parameter
393 estimates (at bottom). Colors represent different curtailment regime scenarios. The horizontal dashed lines represent
394 the 0.8 power threshold and 50% sign error threshold, respectively.

395

396 In comparison, the continuous model often had higher power, particularly for constant or
397 increasing relationships between RR and Δ cut-in (Fig. 5). Power to detect linear trends (β_1), particularly
398 for the scenarios with decreases at Δ cut-in speeds greater than 1.3 m/s, was greater than 0.8 even with
399 only 5 studies per group. Only the 50% then stable and current knowledge scenarios showed poor power,
400 likely needing 20-30 studies per group to measure the decrease accurately. The average value (or
401 intercept, β_0) was more difficult to precisely estimate, though this parameter is less important to the
402 present study as it does not estimate the change in effect with Δ cut-in. As the current knowledge scenario
403 had the smallest slope out of all the scenarios, it required the largest sample size to have sufficient
404 statistical power—around 30 studies per category. Sign error was low across all scenarios; it was lower
405 than 10% whenever the number of studies per group was greater than 10.

406 Figure 6. The relationship of statistical power and sign error with sample size in the linear continuous meta-analysis-
407 scale power analysis of curtailment studies to reduce bat fatality rates. We examined the relationship between the
408 number of studies per Δ cut-in speed category (Category 1 = $\beta_0 = 0.5$ -1.3 m/s Δ cut-in speed, Category 2 = $\beta_1 = 1.5$ -
409 2.3 Δ cut-in speed, Category 3 = $\beta_2 = 3$ -3.5 m/s Δ cut-in speed) and 1) the statistical power to detect change in
410 fatality ratio (at top), and 2) the rate at which models would be expected to incorrectly predict the sign of parameter
411 estimates (at bottom). Colors represent different curtailment regime scenarios. The horizontal dashed lines represent
412 the 0.8 power threshold and 50% sign error threshold, respectively.

413

414 *Fatality Estimation Study Power Analysis*

415 At the scale of individual curtailment experiments at wind facilities, many factors influenced
416 these studies' statistical power and sign error. More turbine-nights increased the power of studies in all
417 scenarios (Fig. 6). However, the importance of turbine-nights varied with several variables outside of
418 researcher control, such as effect size and carcass persistence. With a 25% fatality reduction between
419 experimental and control treatments, no tested scenario achieved statistical power of 0.8 when the control
420 fatality rate was low (0.1 mortalities/turbine-night). For scenarios with a 25% reduction in fatality,
421 statistical power was high only when fatality rate, carcass persistence, and turbine-nights were also high
422 (Fig. 6A). The statistical power of studies in the 50% fatality reduction scenarios was more resilient to
423 changes in sampling period and carcasses persistence than the lower-reduction scenarios. Statistical
424 power was above the 0.8 threshold across almost all scenarios with high fatality rates (0.3 fatalities per

425 turbine-night), and a large number of turbine-nights yielded strong statistical power even when the fatality
426 rate was lower (Fig. 6B). Sign error followed a similar pattern, errors occurred more often when fatality
427 rates and fatality reduction from curtailment were low (Fig. 6C). When fatality reduction was 50%, sign
428 error was almost always less than 10% (Fig. 6D). In summary, these simulation results suggest that many
429 curtailment study designs could be effective at detecting differences between treatments in situations with
430 high fatality rates and high carcass persistence. None of the tested study designs were effective in
431 detecting change when fatality reduction and carcass persistence were low. Based on the studies in our
432 database (which had a median number of 14 turbines and 75 experimental nights, 1050 turbine-nights,
433 and 16 of 36 studies with percent fatality reductions <50%), many studies could have low power and high
434 sign error if fatality rate and carcass persistence is low.

435 Figure 7. The relationship of statistical power (A, B) and sign error (C, D) with sample size for curtailment
436 treatment groups using a simulation approach (n=50,000) using the Generalized Mortality Estimator (*GenEst*).
437 Variation in power across turbine-nights of study (T-N), fatality rates, and carcass persistence (in mean days of
438 persistence) is shown when curtailment is simulated to reduce fatality by 25% (A, C) and 50% (B, D). Simulations
439 assume a three-day search interval for fatality searches and 50% searcher efficiency.

440

441 **Discussion**

442 Like past studies, we found evidence that turbine blanket curtailment reduces fatality rates of bats
443 at wind farms at sites that have implemented the technique (as reviewed by Arnett et al. [36]). However,
444 the marginal effect of increasing turbine cut-in speed on fatality rates is more difficult to assess. Using a
445 *meta-analysis* approach, we estimated that the effect of a 0.5-1.3 m/s increase in cut-in speed resulted in a
446 fatality ratio of 0.52, or a 48% reduction in bat fatalities. Estimated reductions in bat fatalities at higher Δ
447 cut-in speeds were not found to be significantly different than this value and had high modeled
448 uncertainty. The sample size was small, particularly at higher Δ cut-in speeds. Within the context of the
449 *meta-analysis power analysis*, we only had the statistical power to consistently detect reductions of ~50%
450 per 1 m/s Δ cut-in speed. Combined with our meta-analysis results, it appears unlikely that larger
451 increases in Δ cut-in speeds beyond Category 1 result in >50% additional fatality reduction (e.g., the 50%
452 exponential decrease scenario). Given that we lacked statistical power to detect changes in fatality ratio

453 less than 50%, it is possible the true effect could still be large enough to be ecologically relevant to bat
454 conservation and management. Other concurrent efforts to address a blanket curtailment found that
455 increased curtailment speeds did significantly affect bat mortality [37]. While the methods and data set
456 differ from the present study, Whitby et al. [37] corroborates our estimate of effect size and also show
457 how volatile these results can be when sample sizes are low.

458 Uncertainty in fatality reduction was variable across studies. While this imprecision was
459 accounted for in the meta-analysis framework and propagated into parameter estimates, uncertainty
460 should be minimized through careful study design to maximize the value of each study. Through our
461 *fatality estimation power analysis*, we found that with high fatality rates (≥ 0.3 fatalities per turbine-night)
462 and carcass persistence (≥ 6 -9 days), experimental studies were consistently successful in detecting 25-
463 50% fatality reductions. However, studies with low fatality rates (0.1 fatalities per turbine-night) and
464 carcass persistence (3 days) were not adequate to detect 25% differences in fatality rates between
465 treatment and controls groups even with high numbers (>2500) of turbine-nights. These results suggest
466 that effective monitoring studies can be conducted when assumptions are met (e.g., detection probability
467 is at least 50%), some number of studies could have low statistical power when using the *GenEst*
468 modeling framework. As the additive effect of further increases in cut-in speed is uncertain, continuing to
469 conduct high quality curtailment experiments with a high number of experimental turbine-nights,
470 particularly if fatality rates are expected to be low, would provide data to better estimate the effect of
471 blanket curtailment and inform conservation and management activities for bats [38].

472 *Assessing the likelihood of curtailment effects on bat fatalities*

473 While the overall effect of blanket curtailment on bat fatality was clear, the relative effect of
474 incrementally larger increases in curtailment cut-in speed was not. This result was likely due to both small
475 effect size and sample size. The results of the current knowledge scenario in the *meta-analysis power*
476 *analysis* suggested a low likelihood of detecting an effect of higher cut-in speeds with either the non-
477 linear categorical or linear continuous models, likely requiring around 25 additional studies at higher cut-

478 in speeds to precisely measure the effect. While *a posteriori* power analyses, such as this scenario, are
479 redundant with the statistical test on which they are based, these tests can still be useful for evaluating
480 study success and determining how much additional sampling effort is required [32].

481 However, as the current knowledge scenario parameter estimates are not precisely measured, the
482 *a priori* scenarios provide additional guidance on what effects are observable consistently within the
483 current analytical framework. At the current sample size, we have the power to detect differences in the
484 categorical framework at Δ 2 m/s for the scenarios with the highest magnitude decrease (25% linear and
485 50% exponential) and detect linear trends for these same scenarios as well as the 50% initial decline/10%
486 long-term decline scenario. Given the lack of effects detected in the *meta-analysis* using the categorical
487 model (at higher Δ cut-in speeds), and the marginal effects detected in the linear model, it is unlikely that
488 the 25% linear or 50% exponential decrease scenarios represent the true effect. Thus, a smaller decrease is
489 more likely, though more data are needed to measure the effect precisely.

490 It is unlikely that fatality reduction and absolute cut-in speed are linearly related, as there is a high
491 potential for varying effects across sites [5,39], but control cut-in speed was not an important predictor in
492 our models, suggesting that the RR approach was effective in standardizing effect sizes across studies.
493 Neither rotor diameter nor geographic region explained much variation in RR, which may relate to the
494 scale of the variable; in ecoregion, just three broad geographic areas were used due to sample size
495 limitations. Previous research has also indicated that bat fatalities increased exponentially with tower
496 height [8,40], suggesting that more research is needed on the importance of turbine dimensions. Bat
497 mortality risk has also previously been related to habitat characteristics such as forested areas, slope,
498 temperature, and humidity [41,42], and mountain ridges have been recognized as important during
499 migration [43]. If more studies are completed across a wider range of study conditions, then detecting
500 sources of fatality reduction variation would be more effective. Testing curtailment efficacy at locations
501 with lower overall fatality rates could also be instructive and curtailment studies are suggested for sites
502 that typically have high enough fatality rates to elicit conservation concern.

503 Differentiation of fatality rates by species or species group could also help reduce our uncertainty.
504 Species-level traits such as migratory strategy, dispersal distance, and habitat association likely play an
505 important role in fatality risk [44]. For instance, long-distance migrants such as hoary bats, silver-haired
506 bats, and eastern red bats comprise a majority of fatalities at terrestrial wind energy facilities in North
507 America [3,8]. The project-specific risk is then correlated to species distributions, migratory routes, and
508 flight heights, among other characteristics [45]. Incorporating species-level information could improve
509 our understanding of bat fatality reduction, but this would require that species-level fatality estimates, or
510 at least species-group fatality estimates (i.e., migratory tree bats vs. *Myotis* spp.), be reported from
511 curtailment studies to allow for comparisons. Such estimates were not consistently reported by the studies
512 included in our analysis, often due to insufficient sample size.

513 The precision of *meta-analysis* parameters is likely to be overestimated in this study. While the
514 random effects meta-analysis framework adds uncertainty to model estimates based on among-study
515 variance [24], we did not account for site dependence as modeling approaches yielded unstable results.
516 Additionally, turbine operation, mortality estimator selection, and blanket curtailment implementation
517 varies substantially between sites (including time of year, time of night, species composition affected,
518 choice of cut-in speed, and turbine feathering), and these differences could affect the results in ways that
519 are difficult to incorporate into meta-analyses due to incomplete documentation of these protocols. While
520 we controlled for some of these potential biases by including variables like control cut-in speed and multi-
521 treatment controls, the remaining uncertainties will likely be reduced best with increased sample size or
522 protocol documentation.

523 *Recommendations for future studies*

524 If blanket curtailment greater than 1.5 m/s above manufacturer specifications continues to be
525 implemented at wind facilities, additional experiments should be conducted to understand the relative
526 benefit of these increased cut-in speeds for reducing bat fatalities. The number of studies that tested Δ cut-
527 in speeds greater than 1.5 m/s were relatively few, and more studies that target these larger changes are

528 needed. Estimates from the *meta-analysis power analysis* suggest that as many as 25 additional studies at
529 Δ 2 m/s cut-in speed would be needed to effectively exclude the possibility of a 20% reduction in fatality
530 (and even more are needed to detect an additional 10% reduction). Conducting studies that compare
531 multiple treatment groups against a control during the same time period at the same location would
532 provide greater inferential power to answer such questions; though the costs of each individual study
533 would increase compared to single treatment studies, more could be gained in terms of understanding the
534 benefits of higher Δ cut-in speeds. At the individual study level, statistical power is dependent on many
535 factors outside of the control of study designers (e.g., fatality rates and carcass persistence). Prior
536 knowledge of these parameters is valuable for designing effective studies, particularly if carcass
537 persistence rates are expected to be lower than average (e.g., due to high scavenging activity at the site).

538 To facilitate inclusion of studies in future meta-analyses, curtailment experiments should report
539 fatality estimates for both control and treatment groups, carcass persistence rates, searcher efficiency,
540 search frequency, search area coverage, number of turbine-nights of study, curtailment regime (including
541 whether feathering occurred), and turbine makes/models, with associated uncertainty values when
542 relevant. When sample size allows, fatality estimates should be reported by species or species group (e.g.,
543 *Myotis*) rather than for all bat species combined to facilitate taxon-specific assessments of curtailment
544 efficacy.

545 Newer operational minimization strategies have been developed to achieve similar fatality
546 reductions as blanket curtailment but with lower energy loss at higher cut-in speeds [46,47]. “Smart”
547 curtailment strategies, for example, which use additional environmental data besides wind speed to
548 inform the assessment of mortality risk and vary curtailment implementation, show promise to reduce the
549 economic impact of curtailment on wind energy projects [48–50]. Several deterrent systems that
550 discourage bats from approaching turbines are also in development and show some promise for reducing
551 fatalities while minimizing power loss [11,50–52], and could be particularly beneficial if used in
552 combination with curtailment at lower wind speeds. While such approaches are still being evaluated, they

553 may eventually represent a more cost-effective alternative to blanket curtailment, particularly blanket
554 curtailment at higher wind speeds.

555 *Conclusions*

556 The results of our *meta-analysis* suggest that blanket curtailment is effective at reducing bat
557 fatalities at terrestrial wind energy facilities, with the meta-analysis describing a mean fatality ratio of
558 0.44, or a 68% reduction in bat fatalities. Given our small sample size, particularly at higher Δ cut-in
559 speeds, our statistical power was limited to test the benefit of increasing cut-in speeds more than 1-1.3
560 m/s above the control cut-in speed. The power analysis suggests that differences in fatality ratio of 50% or
561 greater were often detectable even with small sample sizes (> 80% chance of significance), so it is likely
562 that the true value of incremental increases in Δ cut-in speed is below this 50% threshold. Whitby et al.
563 [37] suggest this is the case and that result combined with our marginally important effect in this study
564 provides more evidence that higher cut-in speeds can yield fewer mortalities. Though the small sample
565 sizes, low power in the present study, and variation in our respective results should engender caution
566 when interpreting these findings. Given the scope of bat fatalities at terrestrial wind farms in North
567 America [3,53], we must learn more about the management effectiveness of curtailment, particularly at
568 larger Δ cut-in speeds. Further development of “smart” curtailment strategies may also reduce fatalities
569 while moderating impacts to project finances [49].

570 The number of available studies in the current analysis limited our analytical options and findings
571 in several ways. If blanket curtailment continues to be a common strategy at wind speeds at ~5 m/s or
572 above (i.e., Δ cut-in speed of >1.5 with a standard factory cut-in speed of 3.5 m/s), we would recommend
573 conducting additional experimental curtailment studies with blanket curtailment treatments at these higher
574 cut-in speeds to strengthen our understanding of the relationship between increasing cut-in speeds and bat
575 fatality rates. Such studies must be carefully designed, ideally using an adaptive management framework
576 [54], to consider such variables as the expected fatality rate and carcass persistence rate when selecting a
577 search interval and defining the number of turbine-nights to monitor. Studies at sites with expected low

578 fatality rates and low carcass persistence, in particular, must be carefully designed, and power analyses
579 are an important tool to ensure adequate statistical power to detect changes across treatment and control
580 groups. While such studies would improve our understanding of the relationship between fatality and cut-
581 in speed, given the results of our power analysis, a large number of these studies may be required to
582 develop reliable estimates across sites for larger Δ cut-in speeds. While this could be costly, the potential
583 effect of increasing cut-in speed on bat mortality could be ecologically important for species of
584 conservation concern.

585

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594

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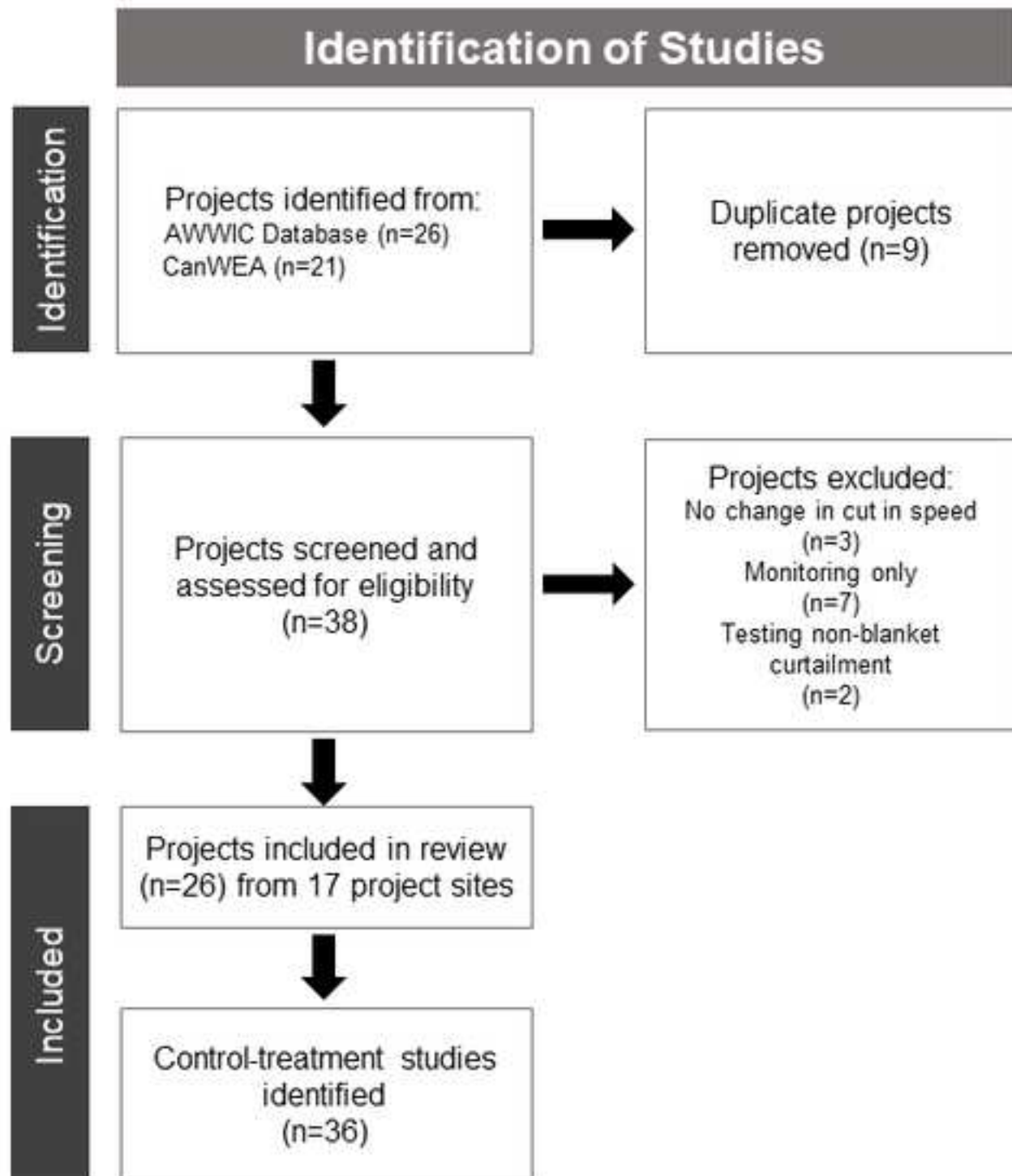
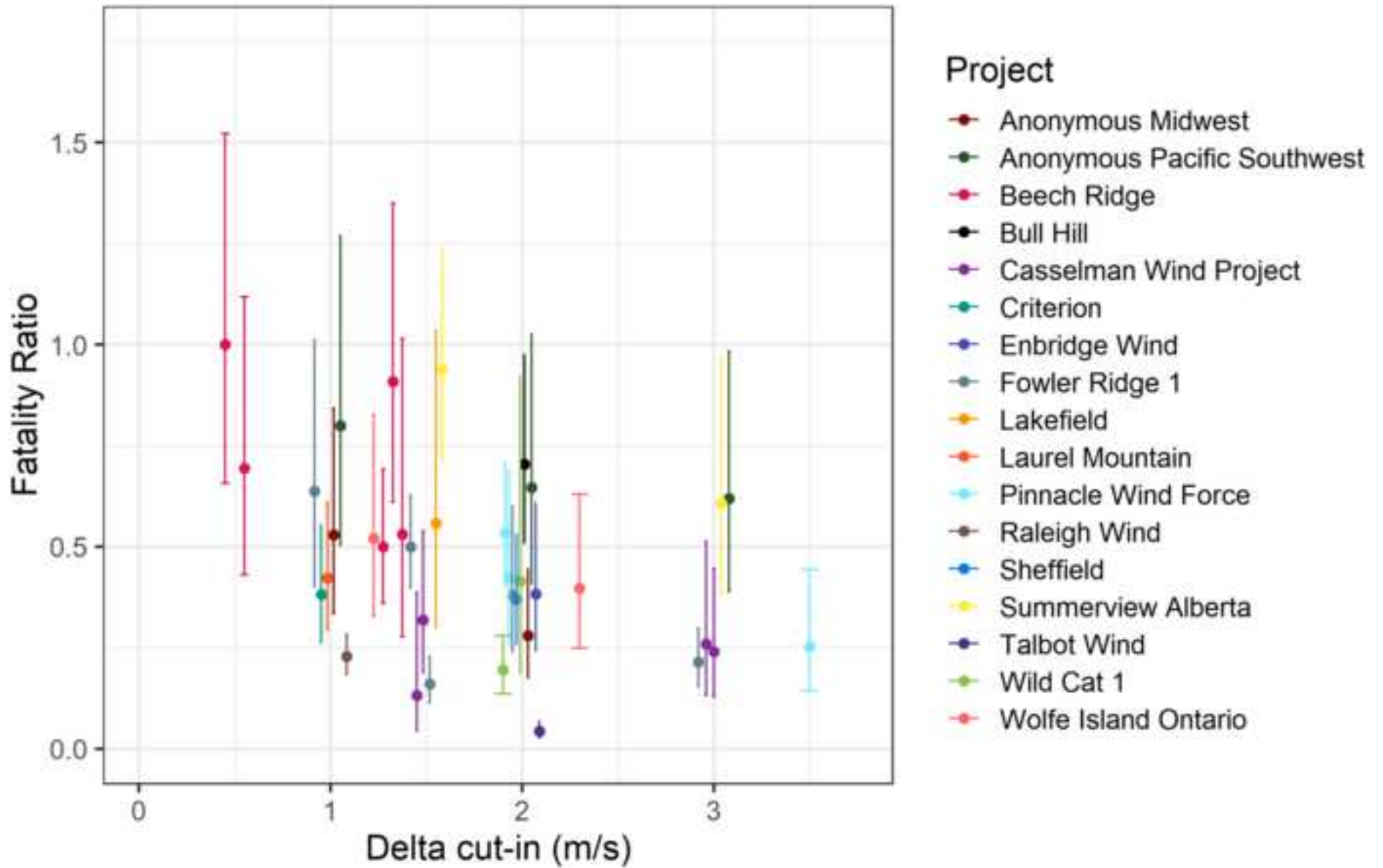


Figure 2



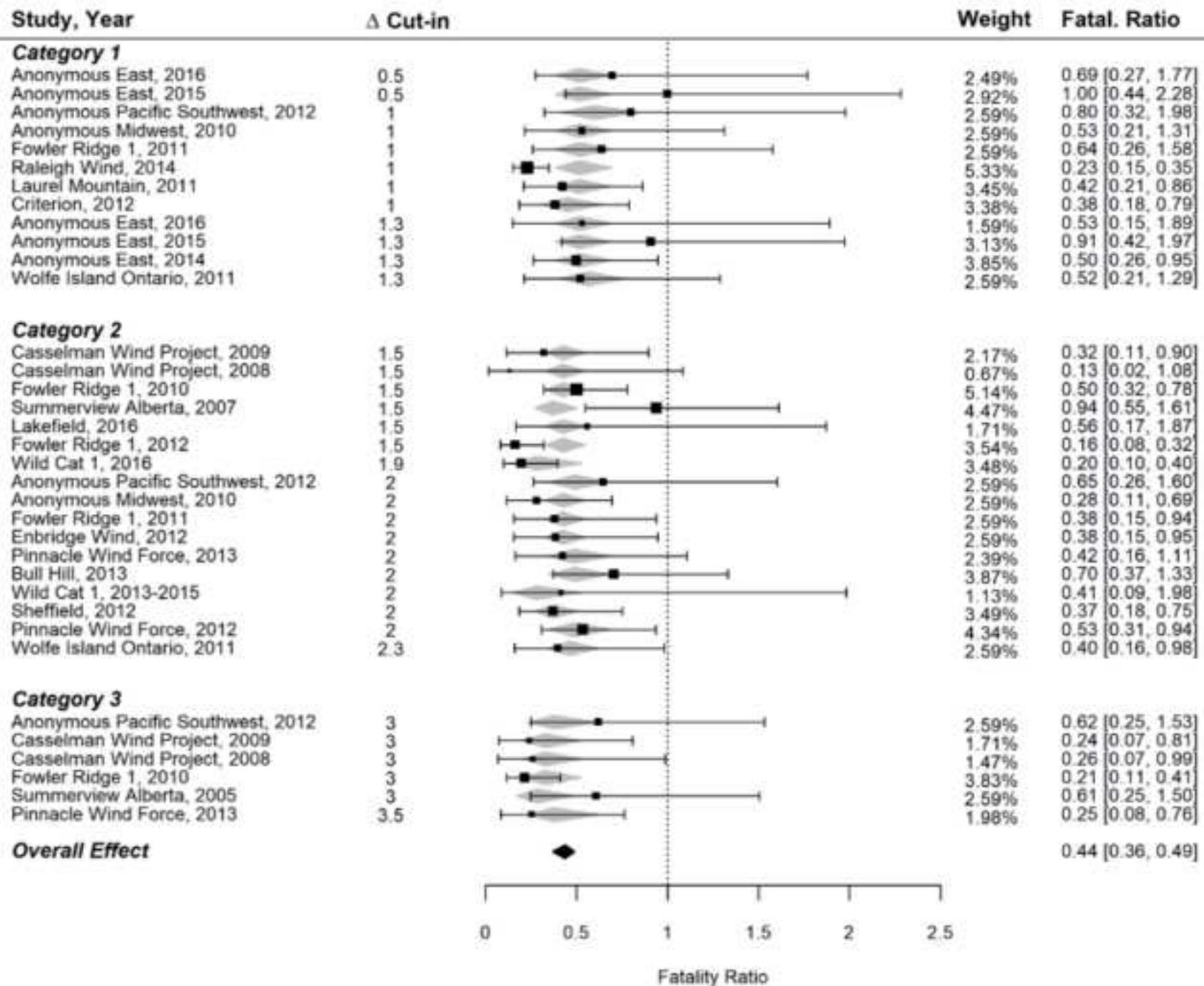


Figure 4

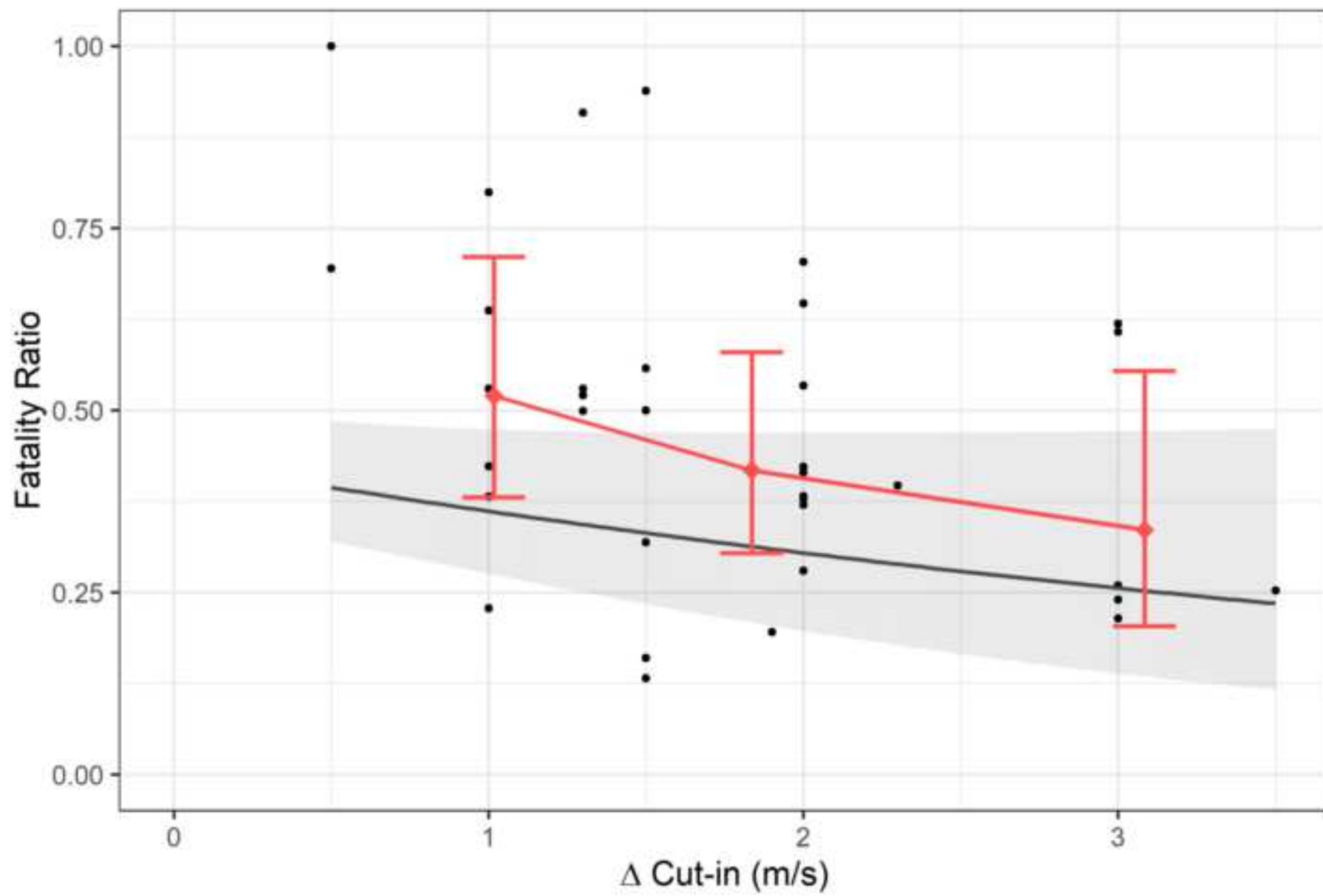
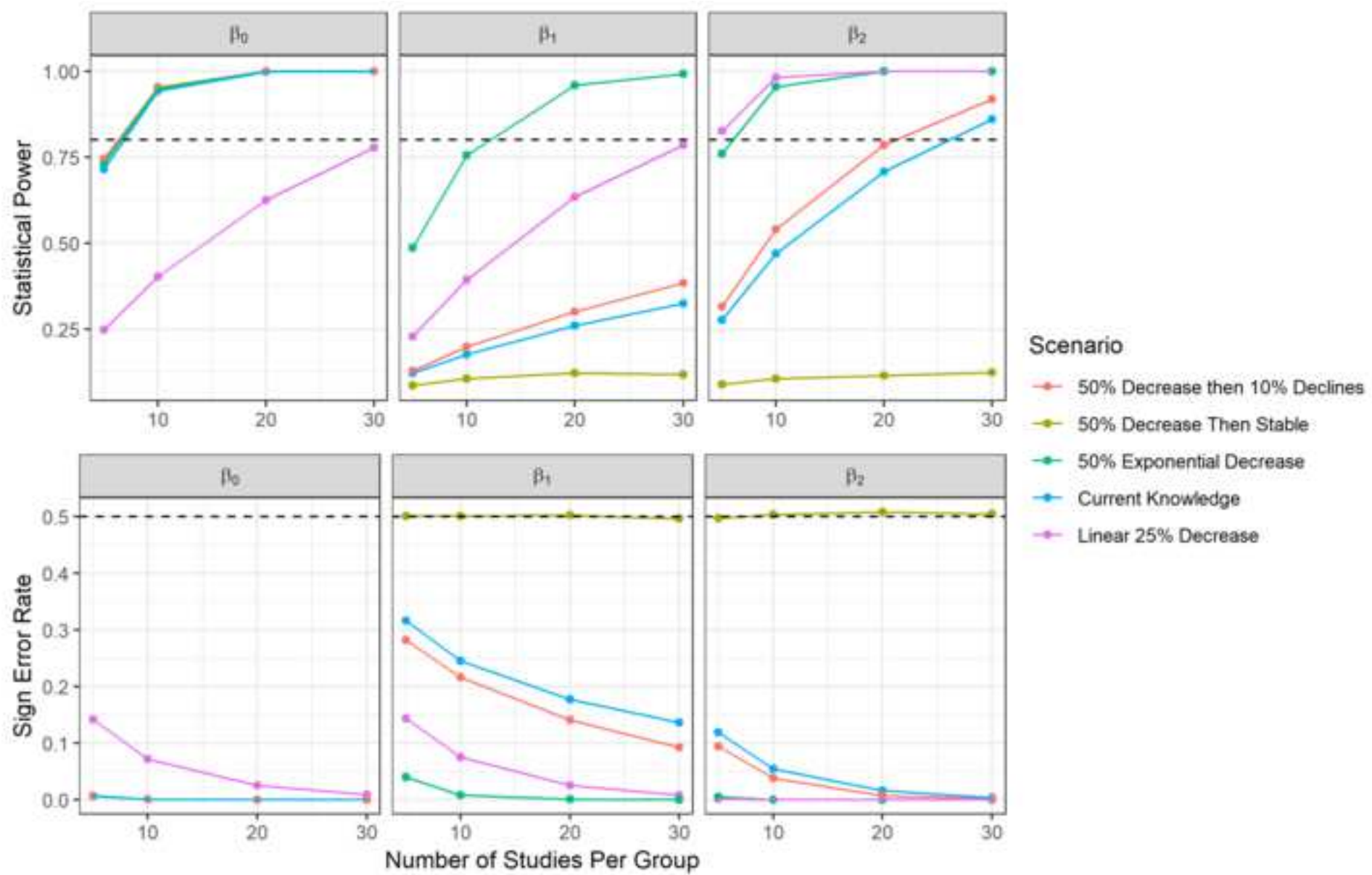
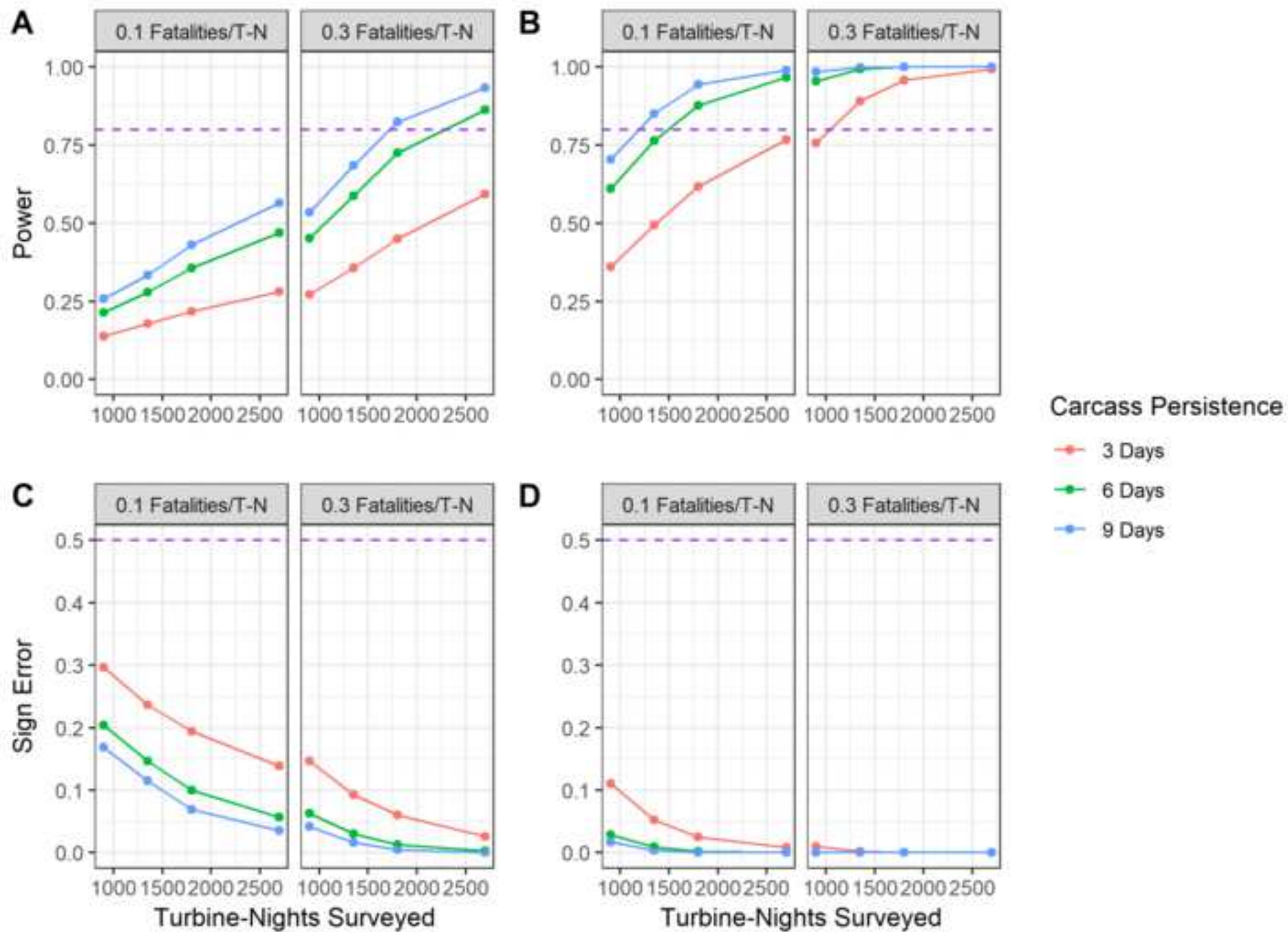


Figure 5







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