Information Theoretic Approach: AIC!!

Finding patterns in nocturnal seabird flight-call behaviour

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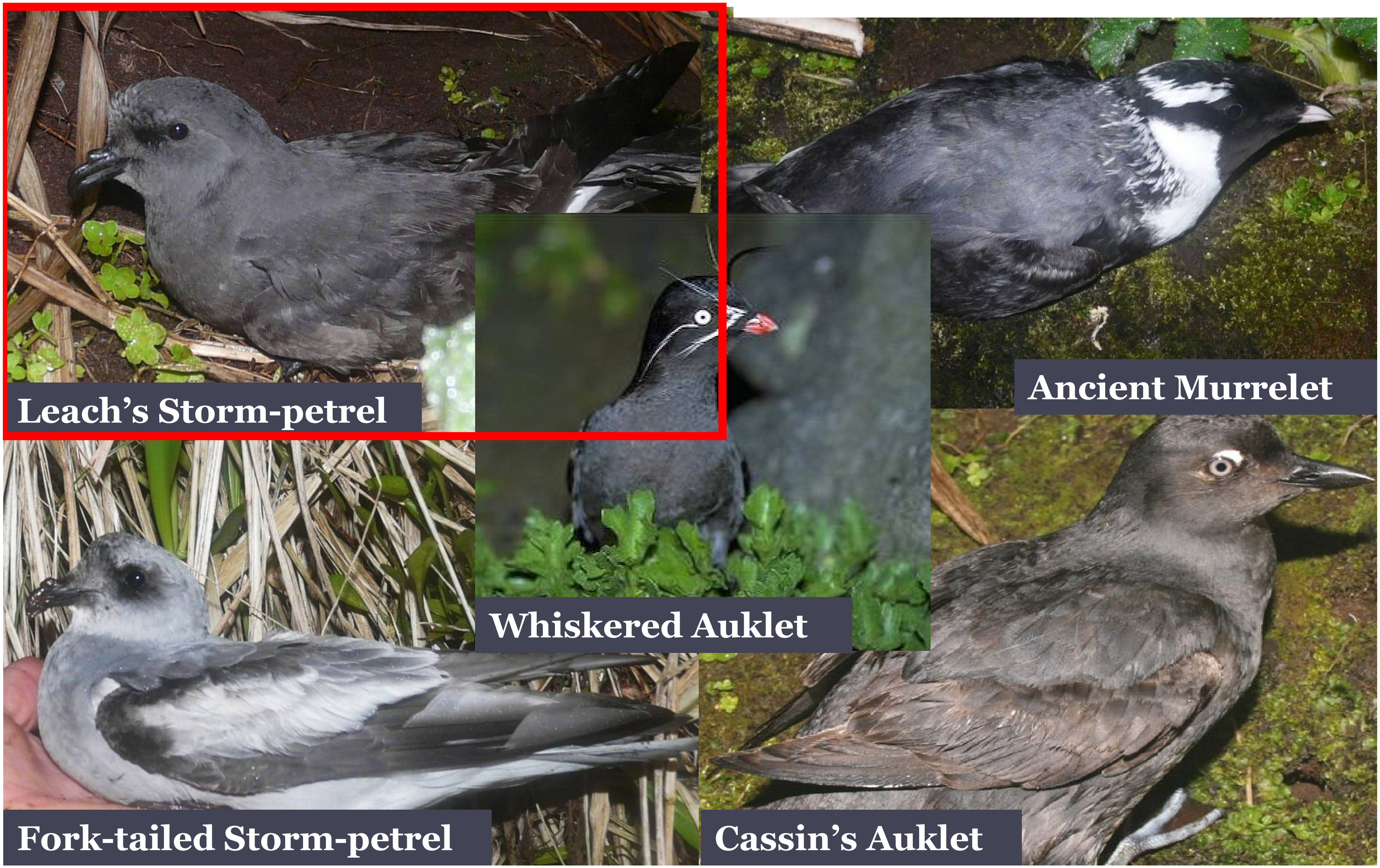
9 November 2009

Nocturnality in seabirds

- Active around colonies only at night
- Must attract and recognize mates using auditory or olfactory cues
- Loud, well defined night-time vocalizations (context specific and linked to behaviour)
- Nocturnal behaviour is a strategy to avoid avian predators (require ambient light to hunt)

Nocturnal seabirds



Leach's Storm-petrel life history

- Late age at first breeding (3-5 years)
- "Prospectors": non-breeding individuals assessing future nesting habitats
- Social Attraction
- Well defined contexts for different calls:
  - Flight calls – chuckle call given in flight in many situations
  - Burrow calls – purr call to attract mates to a burrow, heard exclusively at active colonies

Amatignak Island Aleutian Islands, Alaska

- Used as a fox farm from early 20th century until eradication in 1991
- Leach's Storm-petrel populations were presumably extirpated by introduced foxes
- Currently, no known breeding population of Leach's Storm-petrel
- Four passive acoustic recorders were placed on the cardinal points of the island
- Placed in storm-petrel habitat

Acoustic recording device – Song-meter

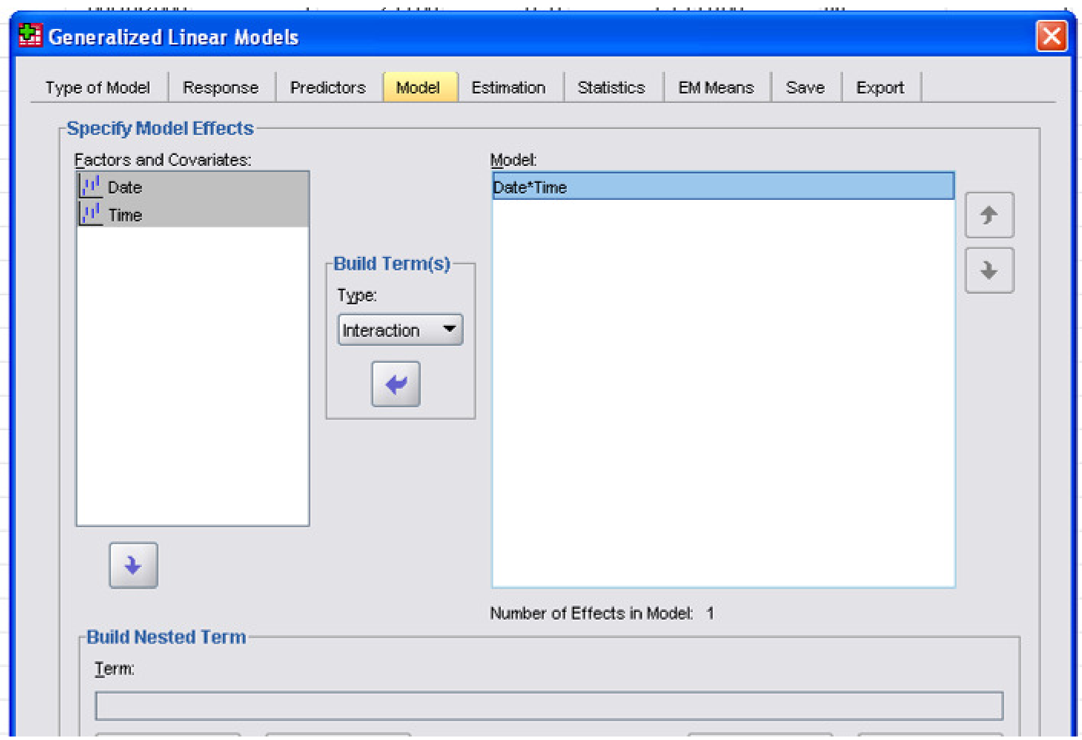
- Set to record from June 18 to August 4
- Recording Schedule: 15 minutes on/off from 00:30 to 6:30 HST
- Calls recorded by the Song-meters were identified by recognition software

Data organization

- Response variable: # calls/15 minutes per night
- Explanatory variables:
  - Site
  - Moon phase
  - Cloud Cover
  - Wind Speed
  - Wind Direction
  - Precipitation
  - Wave Height
- Explanatory variables were grouped into minimal categories or model will not have enough df!

Null hypothesis testing – traditional statistical inference

- Question 1: Does the number of flight calls during each time period differ between nights?
- Model: In SPSS Generalized Linear Model (poisson with log link)



Count of Flight calls = e^{μ} + poisson error

$\mu = \beta_o + \beta_{date*time} * date*time$

Null hypothesis testing – traditional statistical inference

```
* Generalized Linear Models.
GENLIN Count BY Time Date (ORDER=ASCENDING)
  /MODEL Time*Date INTERCEPT=YES
 DISTRIBUTION=POISSON LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100 MAXSTEPHALVING=5 PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-
012 ANALYS
   ISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT DESCRIPTIVES MODELINFO FIT SUMMARY
  /SAVE MEANPRED(MeanPredicted) RESID(Residual).
```

Goodness of Fit[b]

	Value	df	Value/df
Deviance	11714.514	995	11.773
Scaled Deviance	11714.514	995	
Pearson Chi-Square	11355.754	995	11.413
Scaled Pearson Chi-Square	11355.754	995	
Log Likelihood[a]	-7297.999		
Akaike's Information Criterion (AIC)	15707.998		
Finite Sample Corrected AIC (AICC)	16331.121		
Bayesian Information Criterion (BIC)	18680.738		
Consistent AIC (CAIC)	19236.738		

Dependent Variable: Count
Model: (Intercept), Time * Date

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Fit/df = 11,

hence overdispersion

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
24466.981	555	.000

Dependent Variable: Count
Model: (Intercept), Time * Date

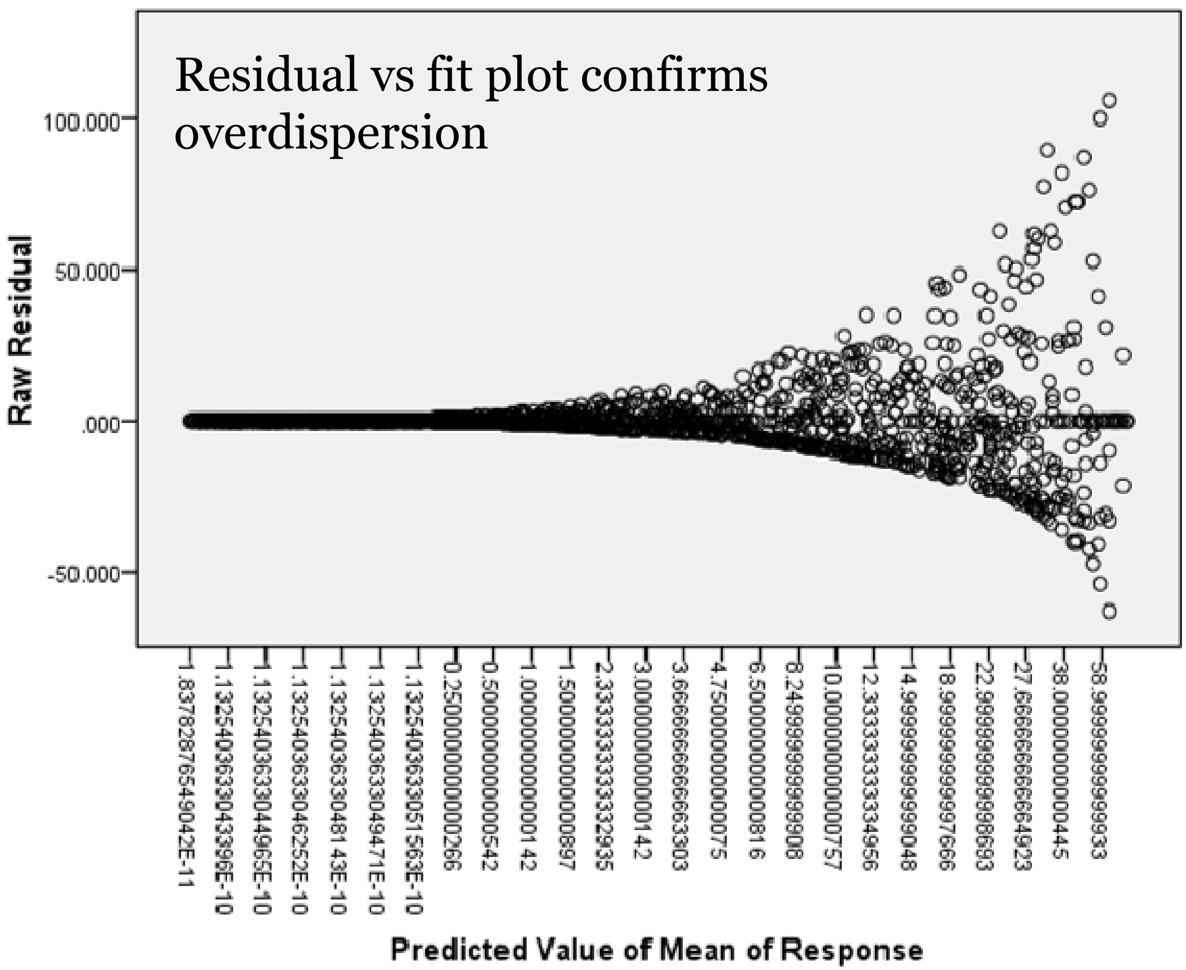
a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	6000.060	1	.000
Time * Date	10430.637	385	.000

Dependent Variable: Count
Model: (Intercept), Time * Date

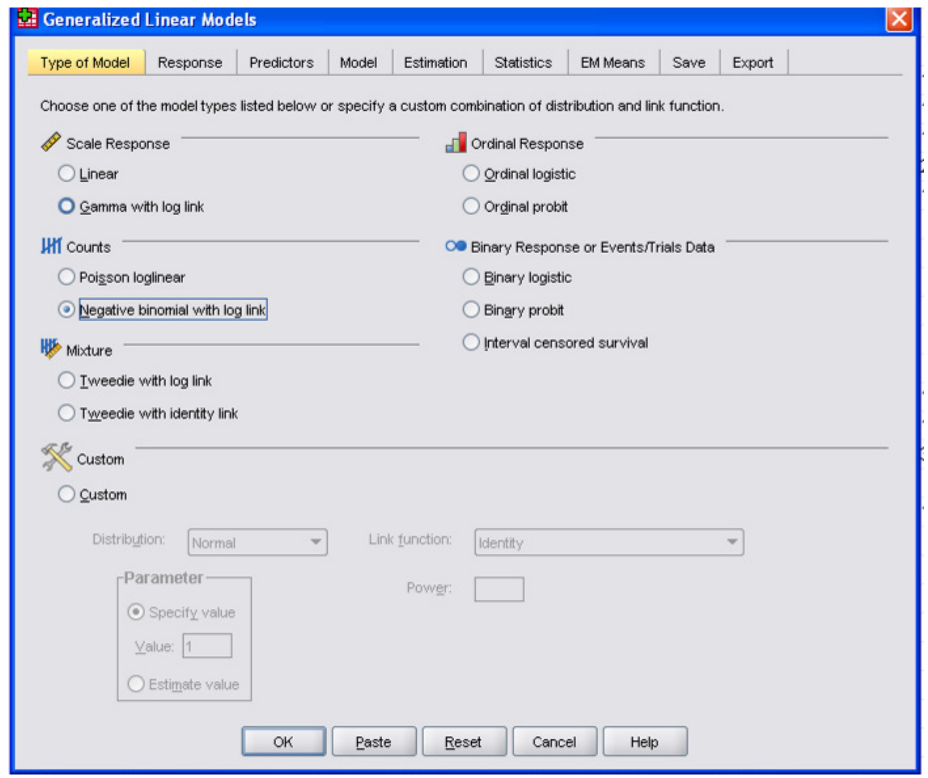
Null hypothesis testing – traditional statistical inference



Null hypothesis testing – traditional statistical inference

- Question 1: Does the number of flight calls during each time period differ between nights?
- Model: In SPSS Generalized Linear Model (negative binomial with log link)
- Count of Flight calls = e^{μ} + negative binomial error

$\mu = \beta o + \beta_{(date*time)} * (date*time)$



Null hypothesis testing – traditional statistical inference

```
* Generalized Linear Models.
GENLIN Count BY Time Date (ORDER=ASCENDING)
  /MODEL Time*Date INTERCEPT=YES
 DISTRIBUTION=NEGBIN(1) LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100 MAXSTEPHALVING=5 PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-012 ANALYS
    ISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT DESCRIPTIVES MODELINFO FIT SUMMARY
  /SAVE PEARSONRESID(PearsonResidual).
```

Goodness of Fit[b]

	Value	df	Value/df
Deviance	1483.371	995	1.491
Scaled Deviance	1483.371	995	
Pearson Chi-Square	949.557	995	.954
Scaled Pearson Chi-Square	949.557	995	
Log Likelihood[a]	-3006.213		
Akaike's Information Criterion (AIC)	7124.426		
Finite Sample Corrected AIC (AICC)	7747.549		
Bayesian Information Criterion (BIC)	10097.166		
Consistent AIC (CAIC)	10653.166		

Dependent Variable: Count
Model: (Intercept), Time * Date

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Fit/df = 1,

hence no overdispersion

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
3815.888	555	.000

Dependent Variable: Count
Model: (Intercept), Time * Date

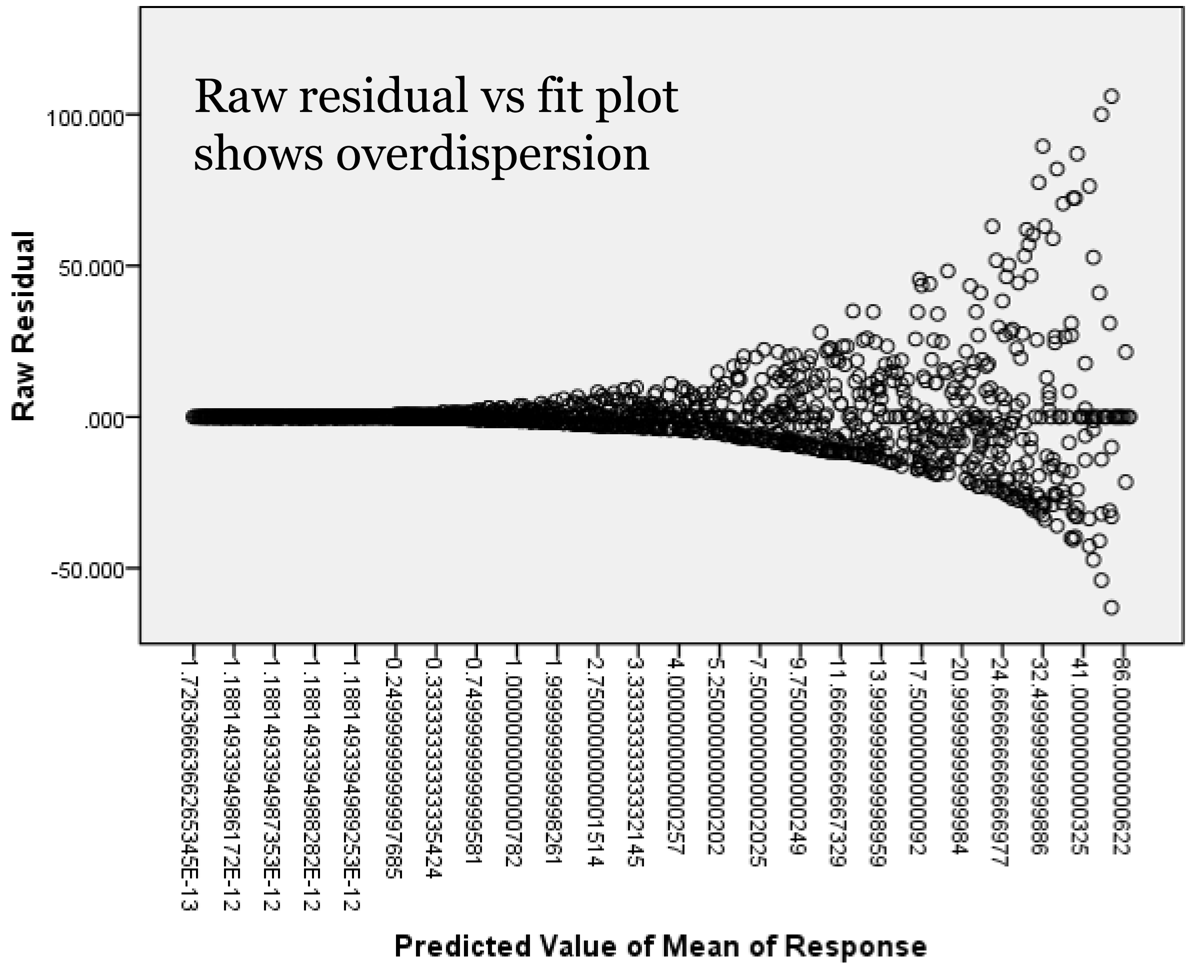
a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	1730.913	1	.000
Time * Date	1316.321	385	.000

Dependent Variable: Count
Model: (Intercept), Time * Date

Null hypothesis testing – traditional statistical inference



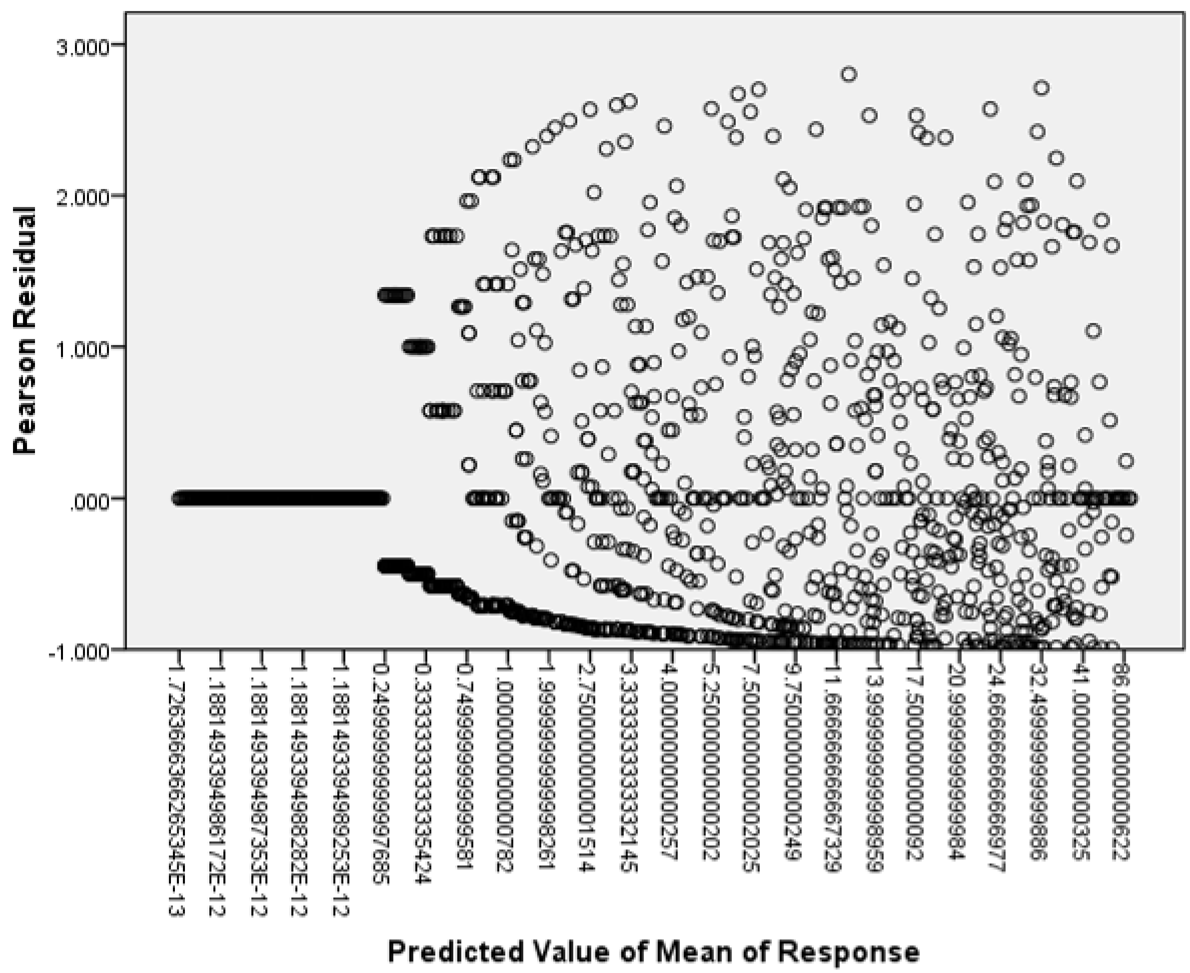
Null hypothesis testing – traditional statistical inference

For Generalized linear models, we use scaled residuals.

Such as Pearson residuals (scaled to std)

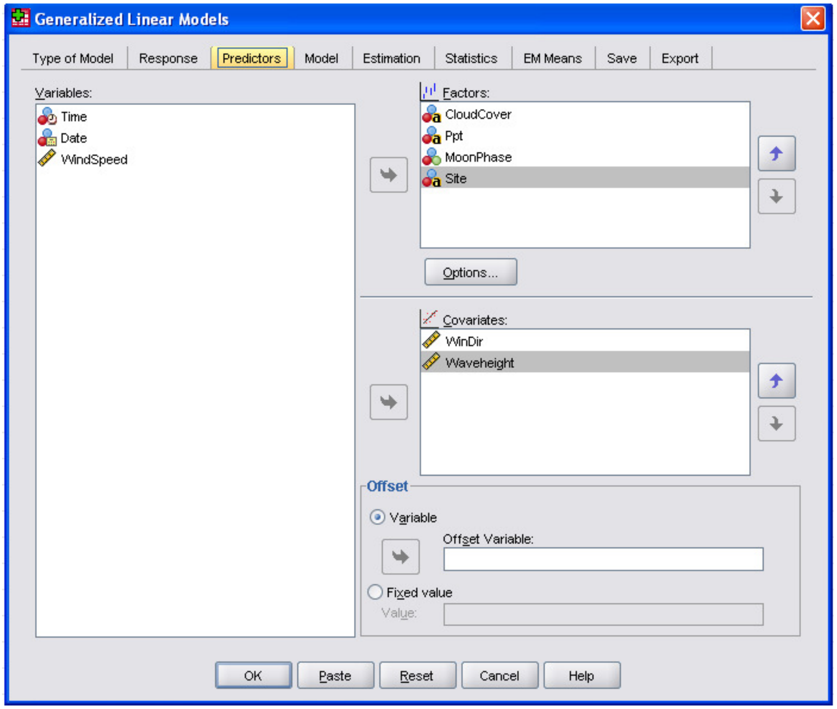
Scaled residuals do not show strong heterogeneity.

This is consistent with Pearson chisquare/df = 1 (see above)



Null hypothesis testing – traditional statistical inference

- Question 2: Does the number of flight calls per 15 minutes depend on the following explanatory variables: wind speed, wave height, moon phase, cloud cover, and precipitation?
- Model: In SPSS Generalized Linear Model (poisson with log link)



- Flight calls per 15 mins = e^{μ} + poisson error

$$\mu = \beta o + \beta_{WiS} * WiS + \beta_{WaH} * WaH + \beta_{MP} * MP + \beta_{CC} * CC + \beta_{Ppt} * Ppt$$

Null hypothesis testing – traditional statistical inference

```
* Generalized Linear Models.
GENLIN Count BY Site MoonPhase Ppt CloudCover (ORDER=ASCENDING) WITH WindSpeed Waveheight
  /MODEL Site MoonPhase Ppt CloudCover WindSpeed Waveheight INTERCEPT=YES
 DISTRIBUTION=POISSON LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100 MAXSTEPHALVING=5 PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-
012 ANALYS
   ISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
```

Goodness of Fit[b]

	Value	df	Value/df
Deviance	25679.701	1534	16.740
Scaled Deviance	25679.701	1534	
Pearson Chi-Square	38918.196	1534	25.370
Scaled Pearson Chi-Square	38918.196	1534	
Log Likelihood[a]	-14280.593		
Akaike's Information Criterion (AIC)	28593.185		
Finite Sample Corrected AIC (AICC)	28593.540		
Bayesian Information Criterion (BIC)	28678.721		
Consistent AIC (CAIC)	28694.721		

Dependent Variable: Count
Model: (Intercept), Site, MoonPhase, Ppt, CloudCover, WindSpeed, Waveheight

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Fit/df = 25,

hence overdispersion

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
10485.291	15	.000

Dependent Variable: Count
Model: (Intercept), Site, MoonPhase, Ppt, CloudCover, WindSpeed, Waveheight

a. Compares the fitted model against the intercept-only model.

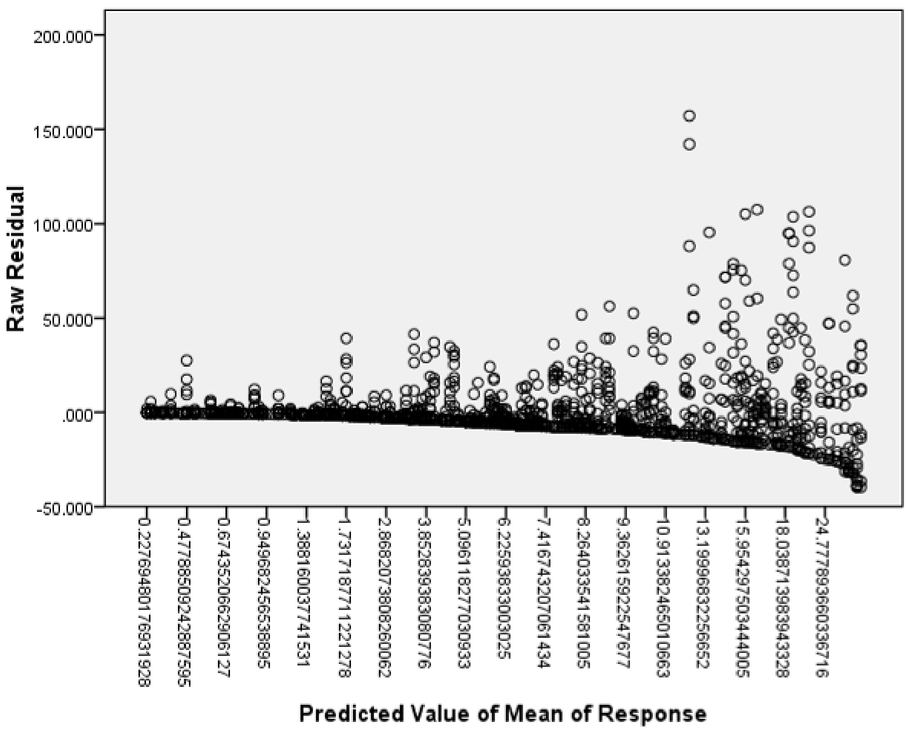
Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	5147.977	1	.000
Site	3614.896	3	.000
MoonPhase	1021.415	3	.000
Ppt	469.622	3	.000
CloudCover	369.470	4	.000
WindSpeed	959.379	1	.000
Waveheight	112.265	1	.000

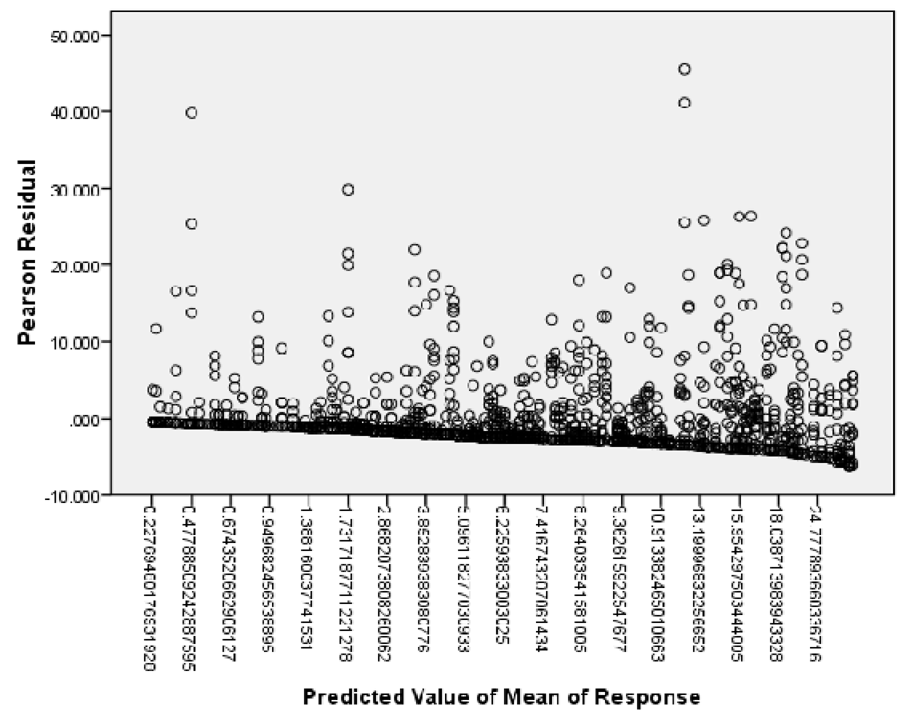
Dependent Variable: Count
Model: (Intercept), Site, MoonPhase, Ppt, CloudCover, WindSpeed, Waveheight

Null hypothesis testing – traditional statistical inference

Raw residuals show strong heterogeneity

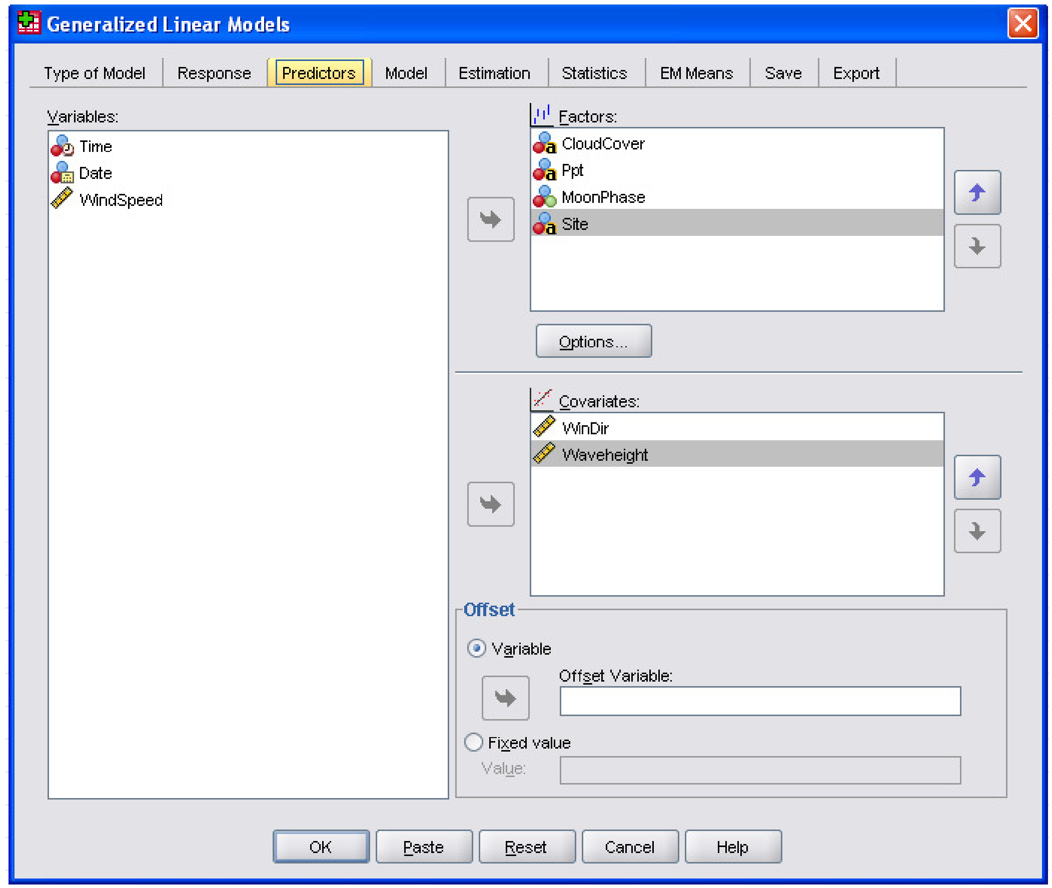


Pearson residuals do not show such strong heterogeneity



Null hypothesis testing – traditional statistical inference

- Question 2: Does the number of flight calls per 15 minutes depend on the following explanatory variables: wind speed, wave height, moon phase, cloud cover, and precipitation?
- Model: In SPSS Generalized Linear Model (negative binomial with log link)



- Flight calls per 15 mins = e^{μ} + negative binomial error

$$\mu = \beta o + \beta_{WiS} * WiS + \beta_{WaH} * WaH + \beta_{MP} * MP + \beta_{CC} * CC + \beta_{Ppt} * Ppt$$

Null hypothesis testing – traditional statistical inference

```
* Generalized Linear Models.
GENLIN Count BY CloudCover Ppt MoonPhase Site (ORDER=ASCENDING) WITH Waveheight WindSpeed
  /MODEL CloudCover Ppt MoonPhase Site Waveheight WindSpeed INTERCEPT=YES
 DISTRIBUTION=NEGBIN(1) LINK=LOG
  /CRITERIA METHOD=FISHER(1) SCALE=1 COVB=MODEL MAXITERATIONS=100 MAXSTEPHALVING=5 PCONVERGE=1E-006(ABSOLUTE) SINGULAR=1E-
012 ANALYS
   ISTYPE=3(WALD) CILEVEL=95 CITYPE=WALD LIKELIHOOD=FULL
  /MISSING CLASSMISSING=EXCLUDE
  /PRINT DESCRIPTIVES MODELINFO FIT SUMMARY
  /SAVE MEANPRED(MeanPredicted) RESID(Residual) PEARSONRESID(PearsonResidual).
```

Goodness of Fit[b]

	Value	df	Value/df
Deviance	3811.847	1534	2.485
Scaled Deviance	3811.847	1534	
Pearson Chi-Square	5428.509	1534	3.539
Scaled Pearson Chi-Square	5428.509	1534	
Log Likelihood[a]	-4225.235		
Akaike's Information Criterion (AIC)	8482.471		
Finite Sample Corrected AIC (AICC)	8482.826		
Bayesian Information Criterion (BIC)	8568.007		
Consistent AIC (CAIC)	8584.007		

Dependent Variable: Count
Model: (Intercept), CloudCover, Ppt, MoonPhase, Site, Waveheight, WindSpeed

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Overdispersion corrected:
Deviance/df reduce to ratio of 3.5

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
1373.394	15	.000

Dependent Variable: Count
Model: (Intercept), CloudCover, Ppt, MoonPhase, Site, Waveheight, WindSpeed

a. Compares the fitted model against the intercept-only model.

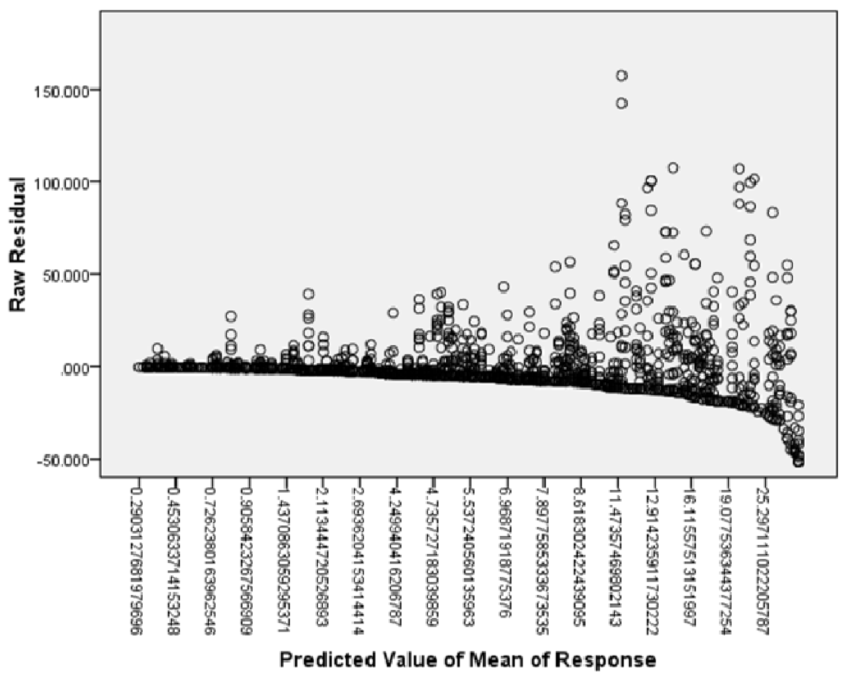
Tests of Model Effects

	Type III		
Source	Wald Chi-Square	df	Sig.
(Intercept)	487.883	1	.000
CloudCover	25.025	4	.000
Ppt	77.680	3	.000
MoonPhase	91.175	3	.000
Site	810.399	3	.000
Waveheight	21.426	1	.000
WindSpeed	92.833	1	.000

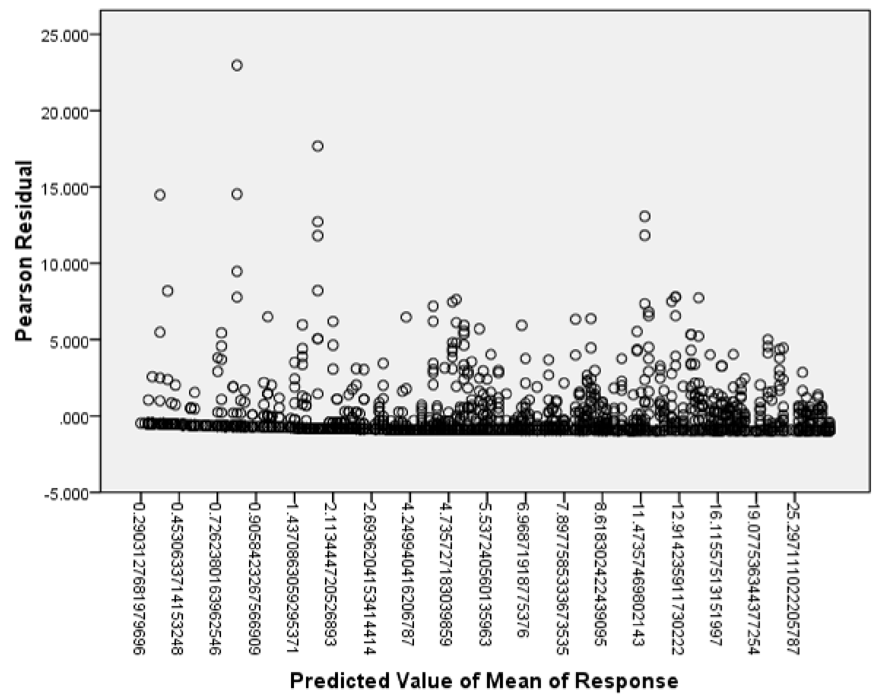
Dependent Variable: Count
Model: (Intercept), CloudCover, Ppt, MoonPhase, Site, Waveheight, WindSpeed

Null hypothesis testing – traditional statistical inference

Raw residuals show strong heterogeneity



Pearson residuals do not show such strong heterogeneity



Null hypothesis testing – traditional statistical inference

- Traditional methods (hypothesis testing) estimate model parameters and their precision
- This assumes that the model structure is known and correct (i.e. true model) and that only parameters in that model are to be estimated

Information Theoretic Approach

With data model structure is not known.

So….

- Traditional methods (hypothesis testing) estimate model parameters and their precision
- This assumes that the model structure is known and correct (i.e. true model) and that only parameters in that model are to be estimated

Information Theoretic Approach

- Burnham and Anderson (1998)
- No simple "true model", modeling is an approximation of explainable information in the empirical data
- Methods allow data-based selection of a "best" model and ranking of remaining models in a pre-defined set
- Traditional statistical inference can then be based on this selected best model
- Recommended for analysis of data from observational studies
- AIC - Selection of most parsimonious model as a basis for statistical inference

AIC - Aikaike's Information Criterion (1973)

- Represents an estimate of the relative distance between the FITTED model and the unknown TRUE mechanism that actually generated the observed data

- AIC = -2 log(L(Θ|y)) + 2K

- log(L(Θ|y) = numerical value of the loglikelihood at its maximum point (max likelihood estimates)
- Y = x,g or log (L(Θ|x,g)
- Likelihood = probability model with parametersΘ
- X = empirical data, g = approximate model
- "the likelihood of a numerical value of the unknown parameter Θ given the data x and a particular model g"
- K = number of estimable parameters in the model
- Compute AIC for each candidate model and select the model with the smallest AIC

AIC - Aikaike's Information Criterion (1973)

- Based on a set of a priori (well founded) candidate models
- "global model" includes ALL potentially relevant effects and causal mechanisms based on the biology of the situation
- Model with best AIC is "closest" to the known reality that generated the data
- If ALL models are poor, AIC will select the one estimated to be the best, but even that relatively best model might be poor in an absolute sense

- It is not the absolute size of the AIC value, it is the relative values (ΔAIC) that are important
- The larger the ΔAIC, the less plausible that the model is best given the data

ΔAIC	Level of model support
0-2	Substantial
4-7	Considerably less
>10	None

AICc - penalty for small sample size

- AIC may perform poorly if there are too many parameters (K) in relation to size of the sample (n)
- AICc introduces a bias correction term
- AIC = -2 log(L(Θ|y) + 2K (n/n-k-1)
- Unless the sample size is large with respect to number of estimated parameters, use of AICc is recommended
- If n/K is small (<40) AICc must be used

QAIC – modification for overdispersed data

- Overdispersion: violations of assumptions such as residual independence and homogeneity
- Sampling variance exceeds the theoretical (model-based) variance

Goodness of Fit[b]

	Value	df	Value/df
Deviance	3811.847	1534	2.485
Scaled Deviance	3811.847	1534	
Pearson Chi-Square	5428.509	1534	3.539
Scaled Pearson Chi-Square	5428.509	1534	
Log Likelihood[a]	-4225.235		
Akaike's Information Criterion (AIC)	8482.471		
Finite Sample Corrected AIC (AICC)	8482.826		
Bayesian Information Criterion (BIC)	8568.007		
Consistent AIC (CAIC)	8584.007		

Dependent Variable: Count
Model: (Intercept), CloudCover, Ppt, MoonPhase, Site, Waveheight, WindSpeed

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Informal rule: Overdispersed if ratio exceeds 2

QAICc - modification for overdispersed data

- Quasi-likelihood allows the use of AICc with overdispersed data
- QAICc = -2 log(L(Θ| Ĉ) + 2K (n/n-k-1)
- Use variance inflation factor estimated from the global model
- Ĉ = χ^2/df
- The number of parameters (K) must include one for the estimation of Ĉ
- Ĉ should be > 1, but should not exceed about 4
- Larger values (6-10) are caused by a model structure that is inadequate
- Quasi-likelihood methods of variance inflation are only appropriate after a reasonable structural adequacy of the model is achieved
- Ĉ should be calculated only for the global model, do not make separate estimates for each candidate model

Data organization

- Response variable: # calls/15 minutes per night
- Explanatory variables:
  - Site
  - Moon phase
  - Cloud Cover
  - Wind Speed
  - Wind Direction
  - Precipitation
  - Wave Height
- Explanatory variables must be organized into minimal categories or model will not have enough df!

AIC – Nocturnal seabird flight call example

- Candidate models:
  - Global Model: Flight calls = S + WiS + WaH + MP + CC + Ppt
  - Flight calls = S + MP + CC
  - Flight calls = MP + CC
  - Flight calls = MP
  - Flight calls = S + MP
  - Flight calls = S + WaH + Ppt
  - Flight calls = WaH + Ppt
  - Flight calls = MP + CC + Ppt + WaH
  - Flight calls = S + MP + CC + Ppt + WaH
  - Flight calls = WiS + WaH + Ppt
  - Flight calls = S + WiS + WaH + Ppt
  - Flight calls = S
  - Flight calls = S + WaH + MP + CC
  - Flight calls = WaH + MP + CC
  - Flight calls = S + WiS + WaH + MP + CC

Possible models from global model will be large. Candidate models are based on biologically plausible interactive effects.

AIC – Nocturnal seabird flight call example

- Flight calls = S + WiS + WaH + MP + CC + Ppt
- Run GzLM with negative binomial error (to minimize overdispersion)
- Obtain numbers for calculating AIC

Goodness of Fit[b]

	Value	df	Value/df
Deviance	3811.847	1534	2.485
Scaled Deviance	3811.847	1534	
Pearson Chi-Square	5428.509	1534	3.539
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Dependent Variable: Count
Model: (Intercept), CloudCover, Ppt, MoonPhase, Site, Waveheight, WindSpeed

a. The full log likelihood function is displayed and used in computing information criteria.

b. Information criteria are in small-is-better form.

Deviance/df use to estimate Ĉ

Log likelihood

Case Processing Summary

	N	Percent
Included	1550	99.9%
Excluded	2	.1%
Total	1552	100.0%

n

Omnibus Test[a]

Likelihood Ratio Chi-Square	df	Sig.
1373.394	15	.000

Dependent Variable: Count
Model: (Intercept), CloudCover, Ppt, MoonPhase, Site, Waveheight, WindSpeed

a. Compares the fitted model against the intercept-only model.

K (estimable parameters)

AIC – Nocturnal seabird flight call example

Here are the basic calculations.

- $AIC = -2 \log(L(\Theta|y) + 2K$
- $AIC = -2 (-4225.235) + 2(15)$
- $AIC = 8480.470$
- $QAICc = -2 \log(L(\Theta| \hat{C}) + 2K (n/n-k-1)$
- $QAICc = (-2 (-4225.235))/3.539 + (2*15)(1550/(1550-15-1))$
- $QAICc = 2469.898$
- $\Delta QAICc = QAICc - \min (QAICc)$

AIC – Nocturnal seabird flight call example

To identify the most parsimonious model, I used a spreadsheet to do the calculations (next slide).

Model	Loglikelihood	K	AIC	AICc	QAICc	ΔQAICc	exp	wi
(S)+(MP)+(CC)+(Ppt)+(WiS)+(WaH)	-4225.235	15	8480.470	8480.783	2402.123	0.000	1.00	0.92
(S)+(WiS)+(MP)+(CC)+(Ppt)	-4235.814	14	8499.628	8499.902	2407.062	4.940	0.08	0.08
(S)+ (MP)+(CC)+(WaH)+(Ppt)	-4271.637	14	8571.274	8571.548	2427.307	25.185	0.00	0.00
(S)+ (WiS)+(WaH)+(Ppt)	-4316.072	8	8648.144	8648.237	2446.241	44.118	0.00	0.00
(S)+(WaH)+(MP)+(CC)	-4329.711	11	8681.422	8681.594	2457.026	54.903	0.00	0.00
(S) + (MP) + (CC)	-4365.131	10	8750.262	8750.405	2476.014	73.892	0.00	0.00
(S)+(WaH)+(Ppt)	-4371.380	7	8756.760	8756.833	2476.476	74.354	0.00	0.00
(S)+(MP)	-4377.497	6	8766.994	8767.048	2478.915	76.793	0.00	0.00
(S)	-4462.043	3	8930.086	8930.102	2523.656	121.533	0.00	0.00
(S)+(WiS)+(WaH)+(MP)+(CC)	-4666.563	9	9351.126	9351.243	2645.337	243.215	0.00	0.00
(MP)+(CC)+(WaH)+(Ppt)	-4694.983	11	9411.966	9412.138	2663.453	261.330	0.00	0.00
(WaH)+(MP)+(CC)	-4739.278	8	9494.556	9494.649	2685.408	283.285	0.00	0.00
(WiS)+(WaH)+(Ppt)	-4751.422	5	9512.844	9512.883	2689.216	287.094	0.00	0.00
(MP)+(CC)	-4791.064	7	9596.128	9596.201	2713.653	311.530	0.00	0.00
(WaH)+(Ppt)	-4816.452	4	9640.904	9640.930	2724.954	322.831	0.00	0.00
(MP)	-4820.992	3	9647.984	9648.000	2726.509	324.387	0.00	0.00

From the calculations, the globalmodel (6 explanatory variables) could not be reduced to a simpler model (next slide).

AIC – Nocturnal seabird flight call example

Model	Loglikelihood	K	AIC	AICc	QAICc	ΔQAICc	exp	wi
(S)+(MP)+(CC)+(Ppt)+(WiS)+(WaH)	-4225.235	15	8480.470	8480.783	2402.123	0.000	1.00	0.92
(S)+(WiS)+(MP)+(CC)+(Ppt)	-4235.814	14	8499.628	8499.902	2407.062	4.940	0.08	0.08
(S)+ (MP)+(CC)+(WaH)+(Ppt)	-4271.637	14	8571.274	8571.548	2427.307	25.185	0.00	0.00
(S)+ (WiS)+(WaH)+(Ppt)	-4316.072	8	8648.144	8648.237	2446.241	44.118	0.00	0.00
(S)+(WaH)+(MP)+(CC)	-4329.711	11	8681.422	8681.594	2457.026	54.903	0.00	0.00
(S) + (MP) + (CC)	-4365.131	10	8750.262	8750.405	2476.014	73.892	0.00	0.00
(S)+(WaH)+(Ppt)	-4371.380	7	8756.760	8756.833	2476.476	74.354	0.00	0.00
(S)+(MP)	-4377.497	6	8766.994	8767.048	2478.915	76.793	0.00	0.00
(S)	-4462.043	3	8930.086	8930.102	2523.656	121.533	0.00	0.00
(S)+(WiS)+(WaH)+(MP)+(CC)	-4666.563	9	9351.126	9351.243	2645.337	243.215	0.00	0.00
(MP)+(CC)+(WaH)+(Ppt)	-4694.983	11	9411.966	9412.138	2663.453	261.330	0.00	0.00
(WaH)+(MP)+(CC)	-4739.278	8	9494.556	9494.649	2685.408	283.285	0.00	0.00
(WiS)+(WaH)+(Ppt)	-4751.422	5	9512.844	9512.883	2689.216	287.094	0.00	0.00
(MP)+(CC)	-4791.064	7	9596.128	9596.201	2713.653	311.530	0.00	0.00
(WaH)+(Ppt)	-4816.452	4	9640.904	9640.930	2724.954	322.831	0.00	0.00
(MP)	-4820.992	3	9647.984	9648.000	2726.509	324.387	0.00	0.00

c-hat	3.539	n	1550

Aikaike Weights Wi = exp(-0.5 ΔQAICc)/sumofall(exp(-0.5 ΔQAICc)

AIC – Nocturnal seabird flight call example

Conclusion: Petrels respond to multiple factors

Next: Given response to multiple factors, what about interactive effects of these factors?

Here is new global model, now with interactive factors that are plausible biologically.

New Global Model

Count = e^{μ} + negative binomial error

μ = (S)+(MP)+(CC)+(Ppt)+(WiS)+(WaH)+(WiDir)+
(MP*CC)+(WiS*WiDir)+(Ppt*WaH)+ (WiDir*WiS*WaH)

AIC – Nocturnal seabird flight call example

To identify the most parsimonious model, I again used a spreadsheet to do the calculations.

Model	Loglikelihood	K	AIC	AICc	QAICc	ΔQAICc	exp	wi
(S)+(MP)+(CC)+(Ppt)+(WiS)+(WaH)	-4225.235	15	8480.470	8480.783	2402.123	0.000	1.00	0.92
(S)+(WiS)+(MP)+(CC)+(Ppt)	-4235.814	14	8499.628	8499.902	2407.062	4.940	0.08	0.08
(S)+ (MP)+(CC)+(WaH)+(Ppt)	-4271.637	14	8571.274	8571.548	2427.307	25.185	0.00	0.00
(S)+ (WiS)+(WaH)+(Ppt)	-4316.072	8	8648.144	8648.237	2446.241	44.118	0.00	0.00
(S)+(WaH)+(MP)+(CC)	-4329.711	11	8681.422	8681.594	2457.026	54.903	0.00	0.00
(S) + (MP) + (CC)	-4365.131	10	8750.262	8750.405	2476.014	73.892	0.00	0.00
(S)+(WaH)+(Ppt)	-4371.380	7	8756.760	8756.833	2476.476	74.354	0.00	0.00
(S)+(MP)	-4377.497	6	8766.994	8767.048	2478.915	76.793	0.00	0.00
(S)	-4462.043	3	8930.086	8930.102	2523.656	121.533	0.00	0.00
(S)+(WiS)+(WaH)+(MP)+(CC)	-4666.563	9	9351.126	9351.243	2645.337	243.215	0.00	0.00
(MP)+(CC)+(WaH)+(Ppt)	-4694.983	11	9411.966	9412.138	2663.453	261.330	0.00	0.00
(WaH)+(MP)+(CC)	-4739.278	8	9494.556	9494.649	2685.408	283.285	0.00	0.00
(WiS)+(WaH)+(Ppt)	-4751.422	5	9512.844	9512.883	2689.216	287.094	0.00	0.00
(MP)+(CC)	-4791.064	7	9596.128	9596.201	2713.653	311.530	0.00	0.00
(WaH)+(Ppt)	-4816.452	4	9640.904	9640.930	2724.954	322.831	0.00	0.00
(MP)	-4820.992	3	9647.984	9648.000	2726.509	324.387	0.00	0.00

From the calculations, the global model (6 single factor explanatory variables and 4 interactive effects) could not be reduced to a simpler model (next slide).

AIC – Nocturnal seabird flight call example

Model	LogLikelihood	K	AIC	AICc	QAICc	ΔQ AIC c	exp	wi
(S)+(MP)+(CC)+(Ppt)+(WiS)+(WaH)+(WiDir)+(MP*CC)+(WiS*WiDir)+(Ppt*WaH)+(WiDir*WiS*WaH)	-3791.81	45	7673.62	7676.37	3258.71	0.00	1.000	0.867
(S)+(MP)+(CC)+(WiS)+(WaH)+(WiDir)+(MP*CC)+(WiS*WiDir)+(Ppt*WaH)+(WiDir*WiS*WaH)	-3800.187	42	7684.37	7686.77	3262.46	3.76	0.153	0.133
(S)+(MP)+(CC)+(WiS)+(WaH)+(WiDir)+(MP*CC)+(WiS*WiDir)+(WiDir*WiS*WaH)	-3951.382	39	7980.76	7982.83	3387.22	128.52	0.000	0.000
(S)+(MP)+(CC)+(Ppt)+(WiS)+(WaH)	-4225.235	15	8480.47	8480.78	3593.50	334.79	0.000	0.000
(S)+(WiS)+(MP)+(CC)+(Ppt)	-4235.814	14	8499.63	8499.90	3601.42	342.72	0.000	0.000
(S)+ (MP)+(CC)+(WaH)+(Ppt)	-4271.637	14	8571.27	8571.55	3631.77	373.06	0.000	0.000
(MP)+(CC)+(Ppt)+(WiS)+(WaH)+(WiDir)+(MP*CC)+(WiS*WiDir)+(Ppt*WaH)+(WiDir*WiS*WaH)	-4239.237	42	8562.47	8564.87	3634.38	375.67	0.000	0.000

New Global Model
(S)+(MP)+(CC)+(Ppt)+(WiS)+(WaH)+(WiDir)+(MP*CC)+(WiS*WiDir)+(Ppt*WaH)+(WiDir*WiS*WaH)

AIC

WAS IT REALLY WORTH IT?!

AIC – Pros

- Makes you think A PRIORI about the biology of your data (rather than putting in a whole bunch of variables blindly to test for significance)
- Works well in situations where many variables could be affecting your data (MP+CC+WS+WD…) but many of these variables may not be appropriate in a model explaining the data observed
    - Example: Atmospheric pressure and number of shooting stars are also "significantly affecting number of storm-petrel flight calls" when run in a GzLM (this larger number of parameters results in a better fit)
    - However, ΔAIC of a model including these variables is very large because it has been penalized for the increasing number of parameters
- AIC will identify a model that excludes these superfluous variables

AIC – Cons

- The model with the largest Aikaike weight is only the best model of the candidates selected A PRIORI....
- This may not be a good model in any absolute sense (the model could be terrible, but compared to the others you have chosen it looks pretty good)
- This all depends on your selection of a good global model (my global model on slide 34 looked like the most parsimonious, but when the global model was revised on slide 35 this model has no support)
- Not good for data with lots of higher level complex interactions among variables