Accommodating Space and Time in SEM for Ecology & Evolutionary Biology

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How might structure in surveys affect SEM results?

• Parameter estimates & variation biased
  – Depends on structure of sampling

• Parameter estimates & variation inconsistent
  – Dependent on groups with largest range of variation and/or sample size

• Covariance matrix may also be biased

• Fit measures likely incorrect

An Grouped Outline

1. Analysis of Nested Survey Data
2. Multilevel Generalized Piecewise SEM
3. Additional Spatial Techniques
4. Panel Models for Lagged Time Effects
5. Growth Curve Models & Time Series

Clusters and Strata in Surveys

• Strata: levels that divide a population into different classes
  – E.g. age classes of an organism, grades in high school, income level

• Clusters
  – Blocks sampled at random
  – Not all blocks may be sampled
  – Can be levels of nesting
Example Survey

Sample of Algal Composition

- Islands randomly sampled – CLUSTER
- West/East side of island - STRATA

Example Survey

Sample of High School Test Scores

- District = CLUSTER
- No strata
- UNLESS: grade = STRATA

How do we Correct our Estimation?

1. Create a weight matrix based on the survey structure and then either

2. Correct error and $\chi^2$ of model fit using a corrected estimator or robust correction (e.g., S-B)

Or

3. Use weight matrix with WLS estimation

The lavaan.survey package

- Blends lavaan fits & survey structure
- Survey structure described using survey package
- Produces models with corrected errors and fit statistics
Survey Package

- Designed to provide robust estimation & SE under clustered, stratified surveys
  - [http://r-survey.r-forge.r-project.org/survey/index.html](http://r-survey.r-forge.r-project.org/survey/index.html)

svydesign to Describe Survey

```r
svydesign(
  ids =~ district,
  strata=grade,
  probs =~1, data=d)
```

- probs =~1 means schools from each cluster have an equal probability of being sampled in the survey

svydesign to Describe Survey

```r
svydesign(
  ids =~ district,
  strata=grade,
  probs =~1, data=d)
```

- strata are a common cluster type within all groups

A Multi-Stream Experiment

Also wells grouped in blocks within a stream

Cardinale et al 2009
Nonlinear Relationship Between Nutrient Addition and Richness

Note that Treatment’s Don’t Covary with Regional Richness

But...no Nutrient Effect?

The Survey Design

Cardinale et al 2009

Cardinale et al 2009

Cardinale et al 2009
But...no Nutrient Effect?

Colinearity still problematic in separating linear v. nonlinear effect – but, there is an N->SA effect!

Exercise: Shipley’s Nested Data

- Simulated data from a fit model
- 20 sites
- 5 trees measured per site

```r
> Shipley <- read.table("./Shipley.dat")
> head(Shipley)

| site | tree | lat     | year | Date   | DD     | Growth | Survival | Live
|------|------|---------|------|--------|--------|--------|----------|------
| 1    | 1    | 40.38063| 1970 | 115.4956| 160.5703| 61.36852| 0.9996238| 1
| 2    | 1    | 40.38063| 1970 | 118.4959| 158.9896| 43.77182| 0.8433521| 1
| 3    | 1    | 40.38063| 1970 | 115.8836| 159.9262| 44.74663| 0.9441110| 1
| 4    | 1    | 40.38063| 1970 | 110.9889| 161.1282| 48.20004| 0.9568825| 1
| 5    | 1    | 40.38063| 1970 | 120.9946| 157.3778| 50.02237| 0.9759584| 1
| 6    | 1    | 40.38063| 1972 | 114.2315| 160.6120| 56.29615| 0.9983398| 1
```

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| 2    | 1    | 40.38063| 1970 | 118.4959| 158.9896| 43.77182| 0.8433521| 1
| 3    | 1    | 40.38063| 1970 | 115.8836| 159.9262| 44.74663| 0.9441110| 1
| 4    | 1    | 40.38063| 1970 | 110.9889| 161.1282| 48.20004| 0.9568825| 1
| 5    | 1    | 40.38063| 1970 | 120.9946| 157.3778| 50.02237| 0.9759584| 1
| 6    | 1    | 40.38063| 1972 | 114.2315| 160.6120| 56.29615| 0.9983398| 1
```
Exercise: Shipley’s Nested Data

```
shipSurv <- svydesign(ids =~site + tree, 
                      probs=-1, 
                      data=Shipley)
```

```
shipFit <- sem(shipMod1, data=Shipley, 
estimator="MLM")
```

```
shipCorrect <- lavaan.survey(shipFit, shipSurv)
```

```
> round(diag(vcov(shipFit)),3)
Survival~Growth        Growth~Date            Date~DD             DD~lat
0.000              0.000              0.000              0.002
Survival~~Survival     Growth~~Growth         Date~~Date             DD~~DD
0.000              1.945              2.044              9.699
Survival~1           Growth~1             Date~1               DD~1
0.001              5.763              4.891              9.552
```

```
> round(diag(vcov(shipCorrect)),3)
Survival~Growth        Growth~Date            Date~DD             DD~lat
0.000              0.004              0.005              0.007
Survival~~Survival     Growth~~Growth         Date~~Date             DD~~DD
0.000              25.883              66.531              7.191
Survival~1           Growth~1             Date~1               DD~1
0.003              61.384              105.752             29.643
```

An Grouped Outline

1. Analysis of Nested Survey Data
2. Multilevel Generalized Piecewise SEM
3. Additional Spatial Techniques
4. Panel Models for Lagged Time Effects
5. Growth Curve Models & Time Series
D-Separation in Piecewise models beyond linear regression

1. We have models that deal with
   1. Hierarchical/nested data (mixed models)
   2. Nonlinear relationships
   3. Non-normal error distributions (glm's)

2. The test of the effect of a variable in one of those models serves the same purpose as a partial correlation test in a linear model

3. These p-values can be used for tests of D-Separation


The Simulated Data

Nested Structure in the Data

Piecewise Hierarchical Model Fitting

#e.g., for DD -> lat
Shipley<-read.table("./Shipley.dat")
library(nlme)

#model with random intercept
#tree nested in site
Date_dd<-lme(Date~DD,data=Shipley,
    random=-1|site/tree,na.action=na.omit)
The Basis Set Needs to Accommodate the Nested Structure

Evaluate Independence Claims with Hierarchical Models

Evaluate Independence Claims with Hierarchical Models

To calculate the partial regression slope, use hierarchical models

```r
# Independence claim: (Date,lat)|{DD}
fit1<-lme(Date~DD+lat,data=Shipley,
random=-1|site/tree,na.action=na.omit)
summary(fit1)$tTable
```

```r
> summary(fit1)$tTable
     Value Std.Error DF t-value p-value
(Intercept) 198.915223483 7.337099813 1330 27.11087876 3.185667e-129
DD          -0.497660383 0.004936809 1330 -100.80608521 0.000000e+00
lat          -0.009051378 0.113476607   18  -0.07976426 9.373049e-01
```
We Have Nonlinear Relationships with Non-Normal Distributions

Use generalized linear models — e.g., logit curve with a binomial error

Evaluate Independence Claims with GLMMs

#need lme4 for the glms
library(lme4)

#Independence claim with glmm (Live,lat)|{Growth}
fit4<-lmer(Live~Growth+lat+(1|site)+(1|tree),
data=Shipley, na.action=na.omit,
family=binomial(link="logit"))

> summary(fit4)@coefs

Estimate Std. Error    z value  Pr(>|z|)
(Intercept)  -14.43837636  2.65394004 -5.440355 5.317446e-08
Growth        0.35530576  0.04554481  7.801235 6.130440e-15
lat           0.03051257  0.02819180  1.082321 2.791099e-01

> summary(fit4)@coefs

Putting it All Together in Shipley's Test

#note, since we're logging things
#we can use log(a)+log(b) = log(a*b)

> fisherC  <<- -2* log(9.373049e-01 * 3.836896e-01 *

7.667083e-01 * 2.791099e-01 *

3.159286e-01 * 1.519170e-01)

> fisherC
[1] 11.20225

>1-pchisq(fisherC, 2*6)
[1] 0.5116698
**AIC and D-Sep**

\[
AIC = C + 2K
\]

Why? Shipley has proven that:

\[-2 \ln(L(model | data)) = -2 \sum \ln(p) = \text{Fisher's C}\]

Shipley, B. In Press. The AIC model selection method applied to path analytic models compared using a d-separation tests. Ecology.

---

**Using piecewiseSEM for GLMMs**

```r
library(piecewiseSEM)

shipley2009.modlist = list(
  lme(DD~lat, random = ~1|site/tree, na.action = na.omit, data = Shipley),
  lme(Date~DD, random = ~1|site/tree, na.action = na.omit, data = Shipley),
  lme(Growth~Date, random = ~1|site/tree, na.action = na.omit, data = Shipley),
  glmer(Live~Growth+(1|site)+(1|tree),
        family=binomial(link = "logit"), data = Shipley) )
```

---

**Using piecewiseSEM for GLMMs**

```r
> sem.fit(shipley2009.modlist, data=Shipley)

$missing.paths

<table>
<thead>
<tr>
<th>missing.path</th>
<th>estimate</th>
<th>std.error</th>
<th>DF</th>
<th>crit.value</th>
<th>p.value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Date &lt;- lat</td>
<td>-0.009</td>
<td>0.113</td>
<td>18</td>
<td>-0.080</td>
<td>0.937</td>
</tr>
<tr>
<td>2 Growth &lt;- lat</td>
<td>-0.099</td>
<td>0.111</td>
<td>18</td>
<td>-0.893</td>
<td>0.384</td>
</tr>
<tr>
<td>3 Live &lt;- lat</td>
<td>0.030</td>
<td>0.030</td>
<td>NA</td>
<td>1.028</td>
<td>0.304</td>
</tr>
<tr>
<td>4 Growth &lt;- DD</td>
<td>-0.011</td>
<td>0.036</td>
<td>1329</td>
<td>-0.297</td>
<td>0.767</td>
</tr>
<tr>
<td>5 Live &lt;- DD</td>
<td>0.027</td>
<td>0.027</td>
<td>NA</td>
<td>1.004</td>
<td>0.315</td>
</tr>
<tr>
<td>6 Live &lt;- Date</td>
<td>-0.047</td>
<td>0.030</td>
<td>NA</td>
<td>-1.562</td>
<td>0.118</td>
</tr>
</tbody>
</table>
```
Using piecewiseSEM for GLMMs

\[
\text{lat} \rightarrow \text{DD} \rightarrow \text{Date} \rightarrow \text{Growth} \rightarrow \text{Live}
\]

\[
> \text{sem.fit(} \text{shipley2009.modlist, data=} \text{Shipley)}
\]

\[
Fisher.C \\
Fisher.C \quad k \quad P \\
11.54 \quad 12.000 \quad 0.484
\]

AIC from piecewiseSEM

\[
\text{lat} \rightarrow \text{DD} \rightarrow \text{Date} \rightarrow \text{Growth} \rightarrow \text{Live}
\]

\[
> \text{sem.fit(} \text{shipley2009.modlist, data=} \text{Shipley)}
\]

\[
\text{AIC} \\
\text{AIC} \quad \text{AICc} \quad \text{K} \quad \text{n} \\
1 \quad 49.54 \quad 50.079 \quad 19 \quad 1431
\]

What do we gain from random effects in piecewiseSEM?

\[
\text{lat} \rightarrow \text{DD} \rightarrow \text{Date} \rightarrow \text{Growth} \rightarrow \text{Live}
\]

#Want to compare to a lavaan fit?

\[
> \text{sem.lavaan(} \text{shipley2009.modlist, data=} \text{Shipley)}
\]

Hierarchical structure & non-normality necessary for fit

Variation Explained

\[
\text{lat} \rightarrow \text{DD} \rightarrow \text{Date} \rightarrow \text{Growth} \rightarrow \text{Live}
\]

- Mixed Models have two kinds of R²
  - Marginal: R² due to fixed effects only
  - Conditional: R² due to fixed & random effects

\[
> \text{sem.model.fits(} \text{shipley2009.modlist)}
\]

\[
\begin{array}{llllll}
\text{Class} & \text{Family} & \text{Link} & \text{Marginal} & \text{Conditional} & \text{AIC} \\
1 & \text{lme gaussian identity} & 0.4864825 & 0.6990231 & 9166.9738 \\
2 & \text{lme gaussian identity} & 0.4095855 & 0.9838829 & 4694.9821 \\
3 & \text{lme gaussian identity} & 0.1079098 & 0.8366353 & 7611.3338 \\
4 & \text{glmerMod binomial logit} & 0.5589201 & 0.6291994 & 261.0824
\end{array}
\]
Exercise: Multilevel Model with Richness Model

- Use piecewiseSEM to fit and evaluate this model
- Use the squared term (may need to center)
- Stream and Sub nested within Stream are your random effects

Solution: Multilevel Model with Richness Model

```r
cardModList <- list(
  lme(SA ~ logN + logN2 + SR, data=cards, 
      random=~ 1|Stream/Sub, na.action=na.omit),
  lme(logChl ~ SA + logN, data=cards, 
      random=~ 1|Stream/Sub, na.action=na.omit)
)
```

```r
sem.coefs(cardModList, data=cards, 
           standardize="scale")
```

<table>
<thead>
<tr>
<th>response predictor</th>
<th>predictor</th>
<th>estimate</th>
<th>std.error</th>
<th>p.value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>SA</td>
<td>SR</td>
<td>0.759926</td>
<td>0.120280</td>
</tr>
<tr>
<td>2</td>
<td>SA</td>
<td>logN2</td>
<td>-0.556100</td>
<td>0.186114</td>
</tr>
<tr>
<td>3</td>
<td>SA</td>
<td>logN</td>
<td>-0.545791</td>
<td>0.186024</td>
</tr>
<tr>
<td>4</td>
<td>logChl</td>
<td>logN</td>
<td>0.313467</td>
<td>0.060019</td>
</tr>
<tr>
<td>5</td>
<td>logChl</td>
<td>SA</td>
<td>0.190575</td>
<td>0.095690</td>
</tr>
</tbody>
</table>
```
Solution: Multilevel Model with Richness Model

```r
> sem.coefs(cardModList, data=cards, standardize="scale")
response     predictor     estimate  std.error     p.value
1       SA         SR   0.7599258  0.12027921   0.0000 ***
2       SA    logN2 -0.5560977  0.18611439   0.0035  **
3       SA       logN -0.5457914  0.18602407   0.0042  **
4   logChl      logN   0.3134672  0.06001905   0.0000 ***
5   logChl        SA   0.1905575  0.09569019   0.0492   *
```

Hierarchical Structure Matters

Hierarchical Structure Matters

Final Thoughts on Piecewise Fits

- You can use anything: generalized linear models, mixed models, generalized least squares fits with temporal or spatial autocorrelation built-in
- Bayesian methods also provide flexible frameworks for piecewise models, but cannot calculate omnibus fit tests

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Spatial Effects
There are two key issues regarding space:

(1) Are there things to learn about the other factors that could explain variations in the data that vary spatially?

(2) Do we have nonindependence in our residuals?

Recent reference on the subject:

Spatial References
Reference where mechanistic questions have been asked:

(Distance from mouth of river and edge of shore served as proxies for past storm-driven saltwater intrusions.)


(Showed fine-scale matching of plant to abiotic conditions in severe environments. No evidence of mass effects.)

Adjusting for Spatial Autocorrelation
1. Is there spatial autocorrelation?
   – Calculate Moran’s I on residuals

2. If yes, it may bias the SE of parameters
   – Calculate new effective sample size
   – Recalculate parameter SE from VCOV matrix

3. Correct by recalculating SE and Z-tests
   – By hand...for now
Example: NDVI in a Boreal System

Data Contains Spatial Information

```r
> boreal <- read.table("./Boreality.txt", header=T)
> head(boreal)

point       x       y Oxalis   boreal    nBor nTot  Grn  NDVI     T61
1     1 2109.70 2093.52      0 15.38462    2   13 0.0597027 0.480180 296.367
2     2 2190.18 2105.71      1 19.04762    4   21 0.0514881 0.483990 296.367
3     3 2064.48 2052.77      1 20.00000    6   30 0.0509510 0.489213 296.367
4     4 2277.34 2103.42      0 15.38462    2   13 0.0521183 0.473226 296.367
5     5 2347.91 2074.81      0  0.00000    0   13 0.0422267 0.405898 296.785
6     6 2437.21 2086.95      0 16.66667    1    6 0.0417779 0.424769 296.367
```

Model of NDVI in a Boreal System

```r
borModel <- '
NDVI ~ nTot + T61 + Wet
nTot ~ T61'
borFit <- sem(borModel, data=boreal, meanstructure=T)
```

Residuals Might be Spatially Correlated

```r
borRes <- residuals_lavaan(borFit)
```
Calculating a Distance Matrix

1. Distance matrices tell us how close points are in space
   • ape library calculates matrix and Moran’s I

   ```r
   library(ape)
   distMat <- as.matrix(dist(cbind(boreal$x, boreal$y)))
   ```

2. We take the inverse, as closer points have greater similarity
   • The diagonal is 0, as there is no correlation within a point

   ```r
distsInv <- 1/distMat
diag(distsInv) <- 0
   ```

Moran’s I using Residuals

```r
mi.ndvi <- Moran.I(borRes$NDVI, distsInv)
mi.ndvi
$observed
[1] 0.08265236

$expected
[1] -0.001879699

$sd
[1] 0.003985846

$p.value
[1] 0
```

Data is more spatially correlated than expected – need a correction

Adjusting the Effective Sample Size

• Estimate of effective sample size (Fortin & Dale 2005, p. 223, Equation 5.15):

\[
n' = n \cdot \frac{1 - \rho}{1 + \rho} = \frac{n}{\sum_{i=1}^{n} \sum_{j=1}^{n} Cor(x_i, x_j)}
\]

• For first-order autocorrelation \( \rho \) and large \( n \):

\[
n' \approx n \cdot \frac{1 - \rho}{1 + \rho}
\]

Where did that SE Come From?

SE’s calculated as the square root of the variance-covariance matrix of parameters

```r
vcov(borFit)
```

<table>
<thead>
<tr>
<th></th>
<th>NDVI~nT</th>
<th>NDVI~T6</th>
<th>NDVI~W</th>
<th>nT~T61</th>
<th>NDVI~~</th>
<th>nT~~~</th>
<th>NDVI~1</th>
<th>nTot~1</th>
<th>NDVI~nTot</th>
<th>nTot~T61</th>
<th>NDVI~~nTot</th>
<th>nTot~~nTot</th>
<th>NDVI~1</th>
<th>nTot~1</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI~nT</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDVI~T6</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>NDVI~W</td>
<td>0.000</td>
<td>0.000</td>
<td>0.017</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>nT~T61</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.298</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDVI~~NDVI</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
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<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>nTot~~nTot</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>47.113</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDVI~1</td>
<td>0.000</td>
<td>-0.002</td>
<td>0.027</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.448</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>nTot~1</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>-88.329</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Given that \( \text{Var}(x) = \sum[(x-x')^2]/n \), all we need to do is change \( n! \)
Calculating a New Standard Error

```r
#New SE
ndvi.var <- diag(vcov(borFit))[1:3]
ndvi.se <- sqrt(ndvi.err*nrow(boreal)/n.ndvi)

Compare to former SE – new SE is wider
> sqrt(diag(vcov(borFit))[1:3])
  NDVI-nTot NDVI-T61 NDVI-Wet
0.0001701878 0.0022546163 0.1322207383

Z-Tests Show Not All Paths Still ≠ 0
> z <- coef(borFit)[1:3]/ndvi.se
> 2*pnorm(abs(z), lower.tail=F)
  NDVI~nTot      NDVI~T61      NDVI~Wet
5.366259e-02  1.517587e-47 3.404230e-194

Or...do it the easy way
> source("./lavSpatialCorrect.R")
> spatialCorrect(borFit, boreal$x, boreal$y)
```

Morans I
```
$Morans_I
- NDVI
  observed expected sd p.value n.eff
1 0.08265236 -0.001879699 0.0049865846 0 451.6189

$Morans_ISnTot
- observed expected sd p.value n.eff
1 0.3853411 -0.001879699 0.003998414 0 493.4468
...
Or... do it the easy way

\[ T61 \rightarrow nTot \rightarrow NDVI \]

\[ Wet \rightarrow nTot \rightarrow NDVI \]

... parameters

| Parameter      | Estimate | n.eff | Std.err | Z-value | P(>|z|)   |
|----------------|----------|-------|---------|---------|----------|
| NDVI~nTot      | -0.0003567484 | 451.6189 | 0.0001848868 | -1.92955 | 5.366259e-02 |
| NDVI~T61       | 0.00246493462  | -14.48453 | 1.517578e-07 | -0.0354776273 | 451.6189 | 0.0024493462 | -14.48453 | 1.517578e-07 |
| NDVI~Wet       | -4.270526589  | 451.6189 | 0.1436405689 | -29.72734 | 3.404230e-194 |
| NDVI~NDVI      | 0.007298286  | 451.6189 | 0.0001131550 | 15.26298 | 4.899505e-51 |
| NDVI~1         | 10.8696158663 | 451.6189 | 0.7267890958 | 14.9582 | 1.470754e-50 |

parameters in Tot

| Parameter      | Estimate | n.eff | Std.err | Z-value | P(>|z|)   |
|----------------|----------|-------|---------|---------|----------|
| nTot~T61       | 1.170661  | 493.4468 | 0.5674087 | 2.06373 | 3.909634e-02 |
| nTot~nTot      | 112.051871 | 493.4468 | 10.707431 | 3.040204e-55 |
| nTot~1         | -322.958937 | 493.4468 | 149.05917 | 1.920334 | 5.679504e-02 |

1. Analysis of Nested Survey Data
2. Multilevel Generalized Piecewise SEM
3. Additional Spatial Techniques
4. Panel Models for Lagged Time Effects
5. Growth Curve Models & Time Series

Problem of Non-Recursive Models

Longitudinal Studies – Time-Step (Panel) Model for Lagged Effects

The Model

Larson and Grace 2004

Differences Between Years: Multigroup?

Larson and Grace 2004

Time-independent dynamics in a Panel Model


An Grouped Outline

1. Analysis of Nested Survey Data
2. Multilevel Generalized Piecewise SEM
3. Additional Spatial Techniques
4. Panel Models for Lagged Time Effects
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Latent Trajectory Models for Timeseries & Repeated Measures with Many Groups


Means Structures: Acquiring Intercepts from SEM!

Means Structures: Acquiring Intercepts from SEM!

$\text{meanMod} \leftarrow \text{\'Giant.Kelp \sim Purple.Urchins'}$

$\text{meanFit} \leftarrow \text{sem(\text{meanMod}, data=kfm, meanstructure=\text{T})}$

| Estimate | Std.err | Z-value | P(>|z|) |
|----------|---------|---------|---------|
| Intercepts: | | | |
| Giant.Kelp | 1.590 | 0.076 | 20.791 | 0.000 |
| Variiances: | | | |
| Giant.Kelp | 0.579 | 0.045 | 12.961 | 0.000 |
Latent Variable Growth Model Simulating a Linear Trend

Latent Variable Growth Model Simulating a Squared Trend

Latent Variable Growth Model Simulating an Exponential Trend

Latent Variable Growth Model Simulating a Linear Trend
Example: Channel Islands Kelp Dynamics

```r
Example:

\[
gMod<-\text{'}
Initial \sim 1*KelpT1 + 1*KelpT2 + 1*KelpT3 + 1*KelpT4
Growth \sim 0*KelpT1 + 1*KelpT2 + 2*KelpT3 + 3*KelpT4
\text{'}
\]
```

```r
gFit<-growth(gMod, data=kelpTseries)
```

Conclusions:
At minimum, no linear trajectory.
At most, kelp densities stay constant with some small variation

R\(^2\)=0.5-0.67

**Intercepts:**
- KelpT1: 0.000
- KelpT2: 0.000
- KelpT3: 0.000
- KelpT4: 0.000

**Estimate**  **Std.err**  **Z-value**  **P(>|z|)**
- Initial: 0.763  0.096  7.976  0.000
- Growth: 0.027  0.032  0.837  0.403

Growth Models and Autoregressive Relationship

\[ a = 0.266 \]

\[ \text{Fit not different} \]
Final Comments on Advanced Topics

1. Often, our concern for spatial and temporal effects is due to our deep ecological fear of pseudoreplication.

2. If you can account for the drivers that create spatial or temporal blocks, you gain information.

3. Many cases are more easily dealt with in a piecewise approach.

4. But, many special cases have techniques in the literature that YOU can now use!