

Polar Ordination

➤ *Objectives:*

Discuss general approach to this method

Go over settings and results for this method

Polar Ordination – Applications

- Bray-Curtis (POLAR) Ordination arranges samples with respect to “poles” (end or reference points) according to a distance matrix
- The poles (end / reference points) are selected using two samples with the highest ecological distance between them (objective approach), OR using two samples suspected of being at opposite ends of a gradient (subjective approach)
- **Recommendation:** This procedure is especially useful for investigating ecological change (e.g., succession, recovery).

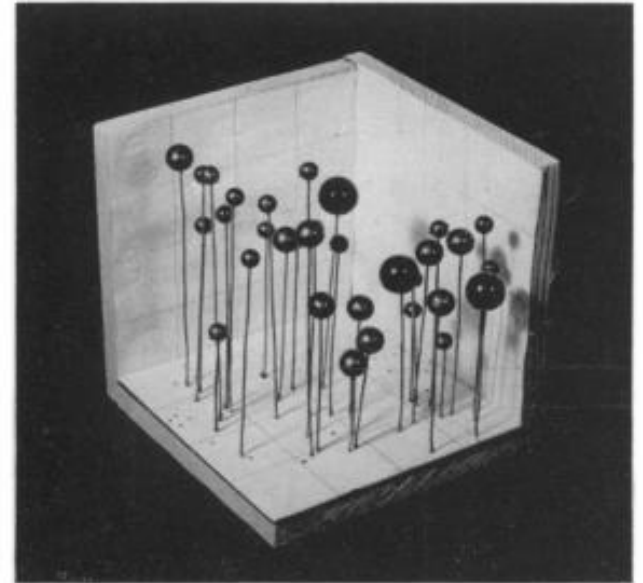


FIG. 7. Three-dimensional model of the dominance behavior of *Quercus borealis* within the ordination. The 3 sizes of spheres indicate the top 3 quartiles of dominance per acre. Stands of the lowest quartile and without the species are represented with holes which appear as dots in the figure. The x axis is on base of model at front from left to right; y axis on base from front to rear; z axis in vertical plane from below to above.

(Bray and Curtis 1957)

Polar Ordination – Pros / Cons

- Polar ordination (PO) arranges samples between endpoints or ‘poles’ according to the distance matrix.
- Endpoints are the two samples with highest ecological (community data) distance between them, *or* two samples which are suspected of being at opposite ends of an important gradient (based on species data in Matrix 1 or environmental data in Matrix 2)
- Thus PO analysis susceptible to subjectivity (biases).
- On the other hand, PO allows testing of hypotheses.

(Bray and Curtis 1957, Beals 1984)

Polar Ordination – Pros / Cons

➤ Advantages:

- Ideal for evaluating problems with discrete “endpoints”:
 - biogeography (arctic sample / tropical sample)
 - succession (after disturbance / “climax community”)
- Ideal for testing specific hypotheses by subjectively selecting the “reference points” (e.g., conditions)

➤ Disadvantages:

- This technique does not provide a general-purpose description of the community; but a biased perspective
- Very sensitive to outliers; by definition – “end points”

Polar Ordination – Example

Table 1.

Importance values of bryophyte species growing on trunks of trees in the Duke Forest, North Carolina (Palmer 1986).

Importance values are a measure of relative abundance.

(Palmer, 1986)

Bryophyte species	BN2	LT1	LT2	PE3	PO2	PT1	PT3	QA1	QR1
<i>Amblystegium serpens</i>	1	0	5	0	0	0	0	3.2	2.3
<i>Anomodon attenuatus</i>	0.9	17.6	26.4	0	41.2	0	0	27.3	22.4
<i>Anomodon minor</i>	2.1	1	5.4	0	9.4	0	0	2.4	0.6
<i>Anomodon rostratus</i>	0	0	1.4	0	4.7	0	0	14	13.6
<i>Brachythecium acuminatum</i>	0	3.1	0	0	0	0	0	5.3	2.9
<i>Brachythecium oxycladon</i>	0.9	1.8	0.8	0	1.6	0	0	1.7	0.5
<i>Bryoandersonia illecebra</i>	1.8	3.7	2	0	0.7	0	0	5.9	1.6
<i>Campylium hispidulum</i>	0.9	1.2	0	0	0	0	0	2.2	2.6
<i>Clasmatodon parvulus</i>	0	1	8.1	0	8.3	0	0	1.1	0.4
<i>Dicranum montanum</i>	1.8	0	0	6.8	0	5.8	9	0	0
<i>Dicranum scoparium</i>	0	0	0	2	0	7.1	0	0	0
<i>Entodon seductrix</i>	0	2.8	5.4	0	0.8	0	0	0	0
<i>Frullania eboracensis</i>	3.7	13.1	10.1	0	7	0	0	7.7	7.5
<i>Haplohymenium triste</i>	0	0.6	0.6	0	2.2	0	0	3.8	1.3
<i>Isopterygium tenerum</i>	16.1	4.6	2.2	30.9	1.4	26.8	18.2	0.6	2.4
<i>Leucobryum albidum</i>	3.1	0	0	44.6	0	35.9	59	0	0
<i>Leucodon julaceus</i>	1.8	5.5	6.7	0	6.8	0	0	7.2	9.7
<i>Lophocolea heterophylla</i>	20.2	0.5	1.4	7.4	0	8.4	0	0	0.9
<i>Platygyrium repens</i>	29.4	5.5	9.5	0	2.1	3.2	0	1.8	2.3
<i>Porella platyphylla</i>	0	1.1	0.6	0	0.7	0	0	2.1	3.2
<i>Radula complanata</i>	0	4	0	0	0.9	0	0	2.3	6.2
<i>Radula obconica</i>	0	6.1	2.5	0	3.5	0	0	2.2	6.1
<i>Sematophyllum adnatum</i>	11	7.9	6.2	6.4	3.9	7.4	6.1	4.6	5.9
<i>Thelia asprella</i>	0	3.3	0	0	0	0	0	0.5	0.9
<i>Thuidium delicatulum</i>	0.9	15.6	1.6	0	0.7	0	0	1.5	0.4

Polar Ordination – Example

Table 2.

Euclidean distance matrix for bryophyte communities of Table 1

(Palmer, 1986)

	BN2	LT1	LT2	PE3	PO2	PT1	PT3	QA1	QR1
BN2	0	42	43	55	57	46	67	50	46
LT1	42	0	22	61	32	53	68	25	23
LT2	43	22	0	63	19	55	70	20	21
PE3	55	61	63	0	70	11	21	65	62
PO2	57	32	19	70	0	64	76	22	26
PT1	46	53	55	11	64	0	27	58	55
PT3	67	68	70	21	76	27	0	71	69
QA1	50	25	20	65	22	58	71	0	10
QR1	46	23	21	62	26	55	69	10	0

Table 3.

Summary of euclidean distances for each sample (n = 8 pairs)

sample	mean	s.d.	median	min	max
BN2	50.8	8.5	48	42	67
LT1	40.8	18.1	37	22	68
LT2	39.1	21.3	32.5	19	70
PE3	51.0	22.2	61.5	11	70
PO2	45.8	23.4	44.5	19	76
PT1	56.5	2.1	56.5	55	58
PT3	70.0	1.4	70	69	76
QA1	40.1	23.5	37.5	10	71
QR1	39.0	21.8	36	10	69

Polar Ordination – Example

Define PT3 and PO2 as endpoints of the first axis.

Assign PT3 (endpoint 1) a score of zero, and PO2 (endpoint 2) a score of 76 (distance from endpoint 1).

NOTE: Distances are relative (where is endpoint 1?)
Assign PO2 (endpoint 1) a score of zero, and PT3 (endpoint 2) a score of 76 (distance from endpoint 1).

Arrange remaining samples along the first axis according to their dissimilarity to PT3 and PO2.

Polar Ordination – Example

Using the following formula:

$$\text{Axis 1 score} = (D^2 + D1^2 - D2^2) / 2D$$

Where D is the distance between the endpoints.

D1 is the distance between the sample and first endpoint.

D2 is the distance between the sample and second endpoint.

Table 4. Polar Ordination Axis scores for the bryophyte data.

Sample	PT3	PE3	PT1	BN2	LT1	QR1	LT2	QA1	PO2
Distance to PT3	0	9	16	46	62	65	68	68	76

Endpoint (pole) 1: PT3 Endpoint (pole) 2: PO2

Correlation with axis 1: 1.000

Polar Ordination – Pros / Cons

Selection of endpoints for second axes is a bit more involved.

Simplest method: choose pair of samples, not including previous endpoints, with maximum distance of separation.

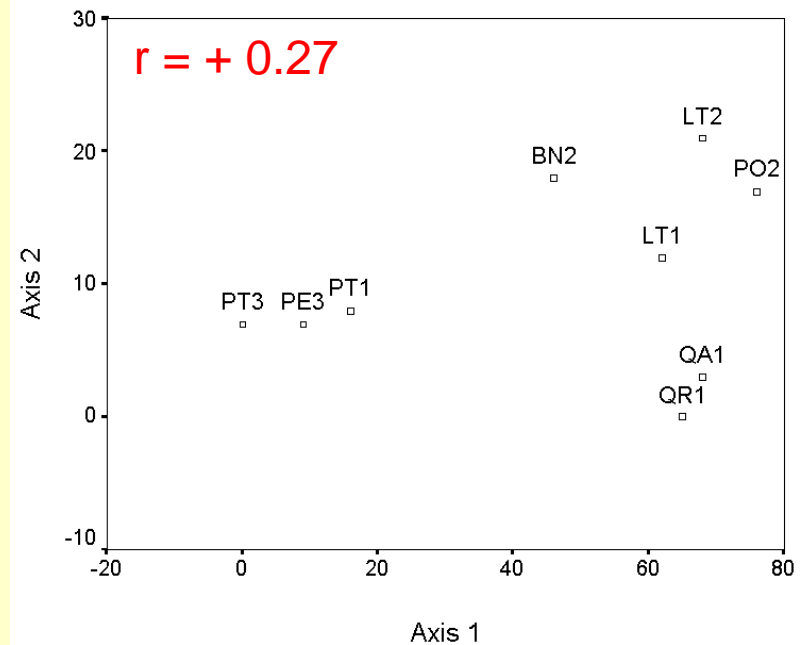
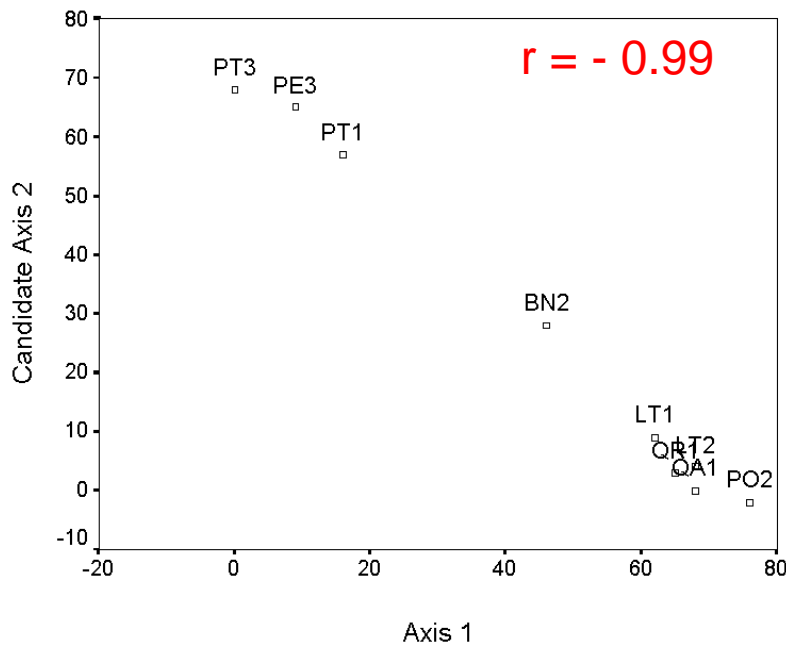
	BN2	LT1	LT2	PE3	PO2	PT1	PT3	QA1	QR1
BN2	0	42	43	55	57	46	67	50	46
LT1	42	0	22	61	32	53	68	25	23
LT2	43	22	0	63	19	55	70	20	21
PE3	55	61	63	0	70	11	21	65	62
PO2	57	32	19	70	0	64	76	22	26
PT1	46	53	55	11	64	0	27	58	55
PT3	67	68	70	21	76	27	0	71	69
QA1	50	25	20	65	22	58	71	0	10
QR1	46	23	21	62	26	55	69	10	0

Polar Ordination – Pros / Cons

However, this criterion selects QA1 and PE3, which results in an axis that has a strong negative correlation with axis 1.

This is undesirable, because the second axis contains little information that is not already contained in axis 1.

Instead, select two samples (QR1 and LT2), which results in an axis with a low correlation with axis 1.



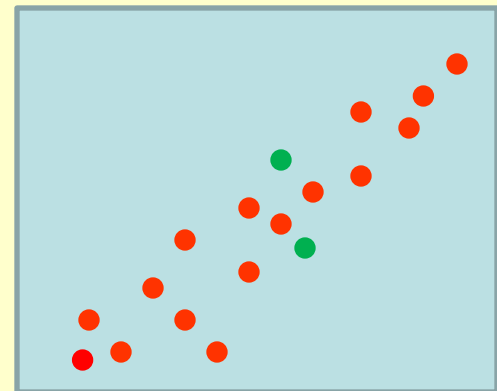
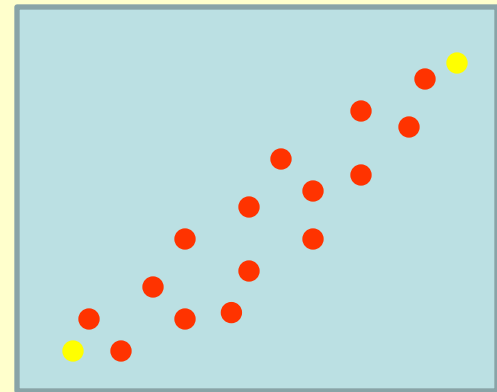
Polar Ordination – Pros / Cons

Beals (1984) extended Bray-Curtis (1957) ordination:

Variance-Regression Method:

Selecting poles by identifying those points (samples) at the edge of the cloud of points (edges of community)

Selection of poles uses an objective approach that maximizes POs ability to capture gradients in the data



Polar Ordination – How it Works

➤ Setting Up:

- Select a distance measure (usually **Sorensen Index**) and calculate matrix of distances (D) between all pairs of points
- Calculate sum of squares of the distances for calculation of the variance represented by each axis
- Select two points, A and B, as reference points for axis 1
- **Define End Points Subjectively OR Use Objective Method**
- **3 Objective Methods:** Variance-Regression is Recommended
 - find point with largest variance in pairwise distances
 - select point which minimizes regression of distances

$$SS_{TOT} = \sum_{i=1}^{N-1} \sum_{j=i+1}^N D_{ij}^2$$

Polar Ordination – How it Works

➤ Selecting Objective End Points:

- Original Approach:

(Bray & Curtis 1957):

Selects outliers by looking for two points with largest distances

(Problematic)

- Variance-Regression:

(Beals 1984)

Selects points at edges of main cloud of points

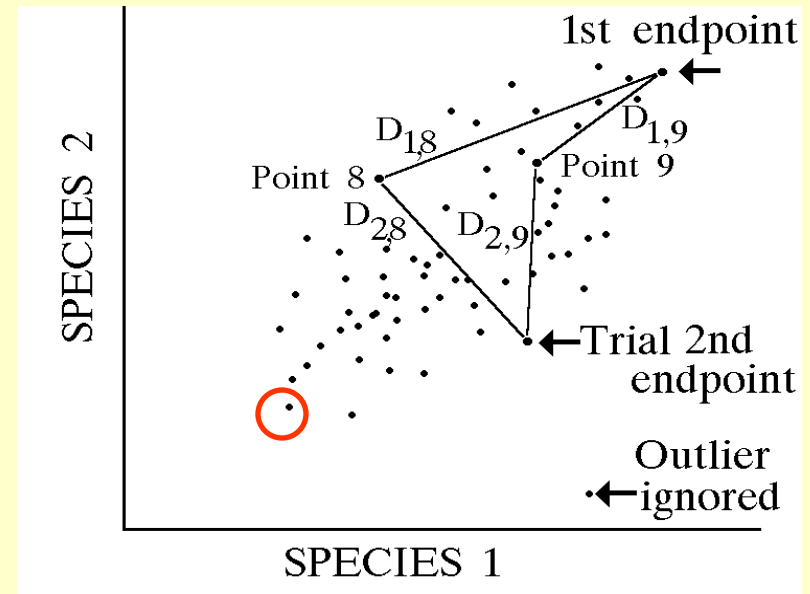
(Recommended)

- Minimum-Centroid (Deviation):

Must pick geometry – subjective, rarely used **(DO NOT USE)**

Why Problematic?

Outliers may not represent “endpoints” of the pattern in the data (e.g., community structure)



Polar Ordination – How it Works

➤ Selecting Objective End Points:

- Original Approach:

Defined first endpoint as sample unit with greatest sum of distances to all other sample units; the second endpoint then had greatest absolute distance to the first endpoint.

Avoid: Often selects outliers as endpoints.

- Variance-Regression:

First pole has greatest variance in distance to other samples.

Second endpoint has lowest regression coefficient among all regressions of distance from each sample unit to first and to the second endpoint, calculated for all possible endpoints.

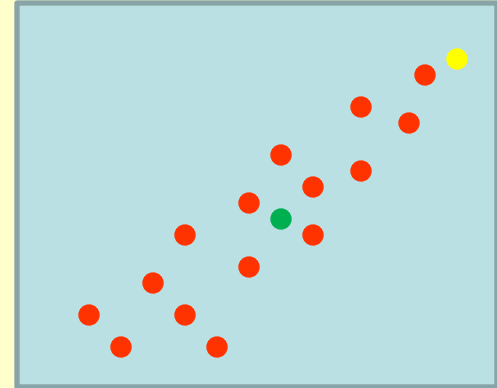
Use: Most commonly used currently.

Polar Ordination – How it Works

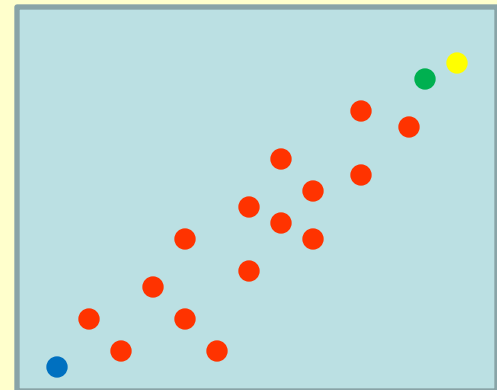
➤ Selecting Objective End Points:

- Variance-Regression:

First endpoint has greatest variance in distances to all other sample units.



Second endpoint has the smallest regression coefficient (negative slope) among the linear fits of the distance from each sample unit to the first and to the second endpoint, calculated for all possible endpoints.

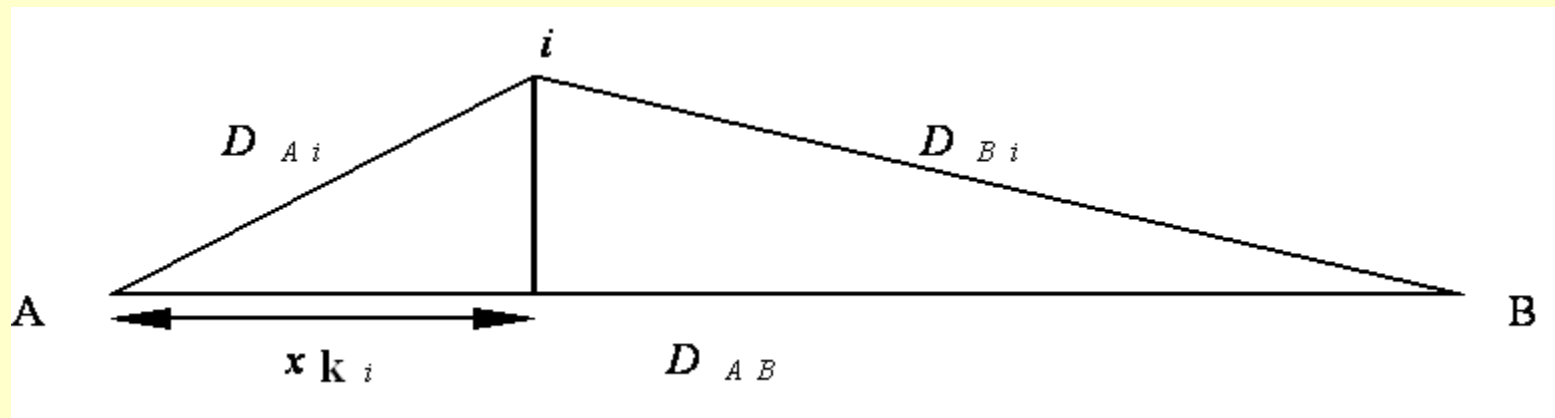


Polar Ordination – How it Works

- The placement of each remaining sample unit between the two endpoints is determined by projecting its position perpendicularly onto the axis defined by the two poles
- Residual distances calculated using the difference of the distances between sample units (in the distance matrix) and the distances between objects (in the ordination axis)
- Amount of variation represented by axis ('% variance explained') calculated as ratio of sum of squares of residual distances to sum of squares in original distance matrix
- When more axes are calculated objectively, placement of sample units on subsequent axes follows same procedure but uses the residual distances from the previous axis

Polar Ordination – How it Works

- Once you have the first axis (k) – linking the two points:
 - Calculate position (x_{ki}) of each point i on the axis g . Point i is projected onto axis k between reference points A and B



- For Reference: Equation for projection onto the axis is:

$$x_{ki} = \frac{D_{AB}^2 + D_{Ai}^2 - D_{Bi}^2}{2D_{AB}}$$

Polar Ordination – How it Works

- Calculate variance represented by axis k as a percentage of the original variance ($V_k \%$). The residual sum of squares has same form as original sum of squares and represents amount of variation from original distance matrix

$$SS_{RESID} = \sum_{i=1}^{N-1} \sum_{h=i+1}^N R_{ij}^2$$

$$\text{Cumulative } V_k \% = 100 \left(1 - \frac{SS_{RESID}}{SS_{TOT}} \right)$$

Polar Ordination – The Good

- Allows user to test a specific “gradient”, in contrast with empirically-derived patterns of variation
- The solution is unique (i.e., you get the same result every time you run it with same options on same dataset)
- Because more information may be explained by an additional objective axis, rather than by the first subjective axis you are testing, subsequent axes sometimes explain a higher percentage of the variance than the first axis
- Residual distances calculated based on the difference in distances between sample units (in distance matrix) – recommend using Sorensen index (robust: joint absences)

Polar Ordination – The Bad

- Requires selection of 2 “endpoints” (i.e., outgroups)
- Does not provide significance tests (p values)
- When objectively selecting endpoints for the an axis, there may be multiple pairs of sample units separated by large distances. Only one pair can be used as endpoints, however, which may obscure ecologically interesting patterns

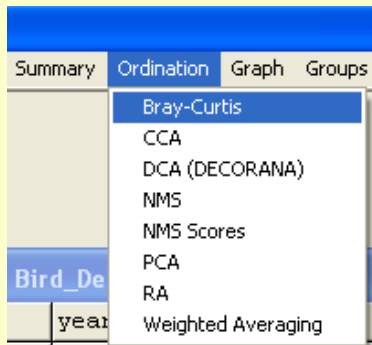
Disclaimer: It is possible that the endpoints you subjectively select *do not end up as the ends* of your ordination axis

This occurs when one or more of the other sample units has a distance to your first chosen endpoint that is greater than the distance to your second chosen endpoint

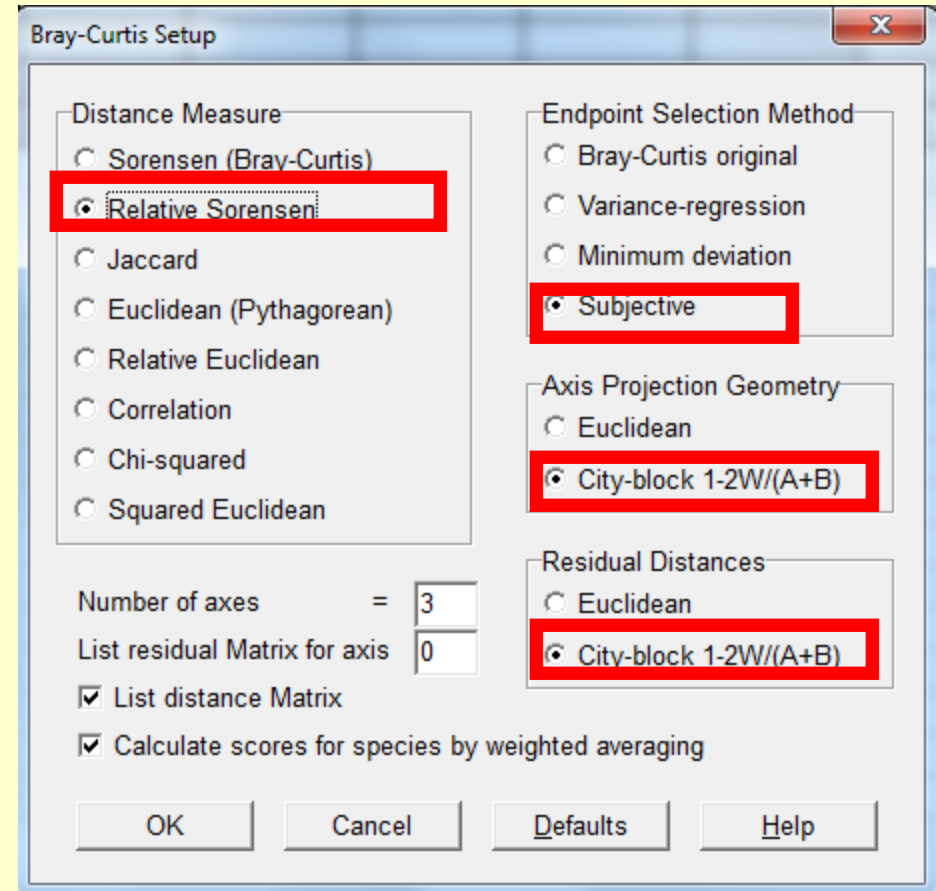
You will still get an ordination, but your subjectively chosen endpoints will not define the ends of the axis

Polar Ordination – Suggested Procedure

(McCune and Grace 2002)



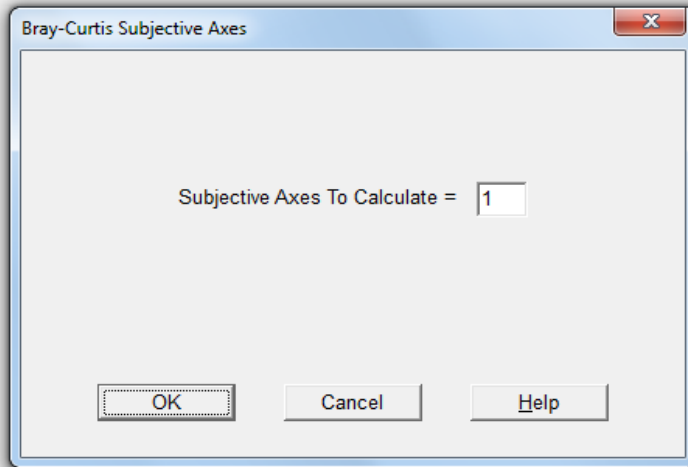
- First: Distance Measure
 - For species data: **Sorensen**
- Second: Select End Points
 - Try **Subjective**
- Third: Geometry / Residuals
 - Recommend **City-Block**



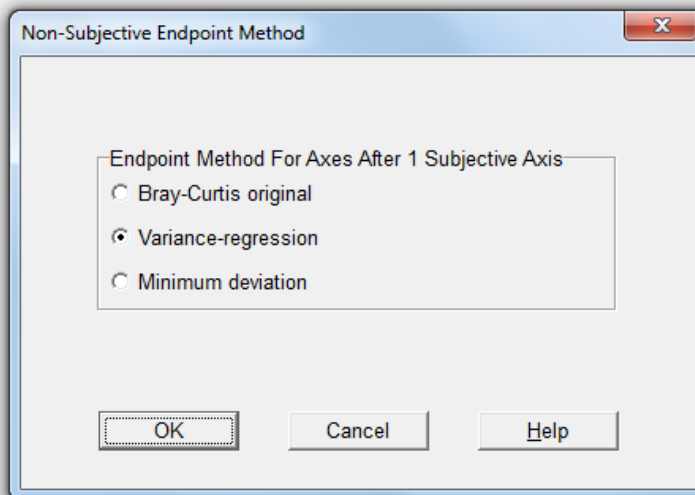
NOTE: # Axes only changes reported results – not solution.
Always try more than 1. Set List Residual Matrix = 0

Polar Ordination – Suggested Procedure

➤ Next, pick number of subjective axes



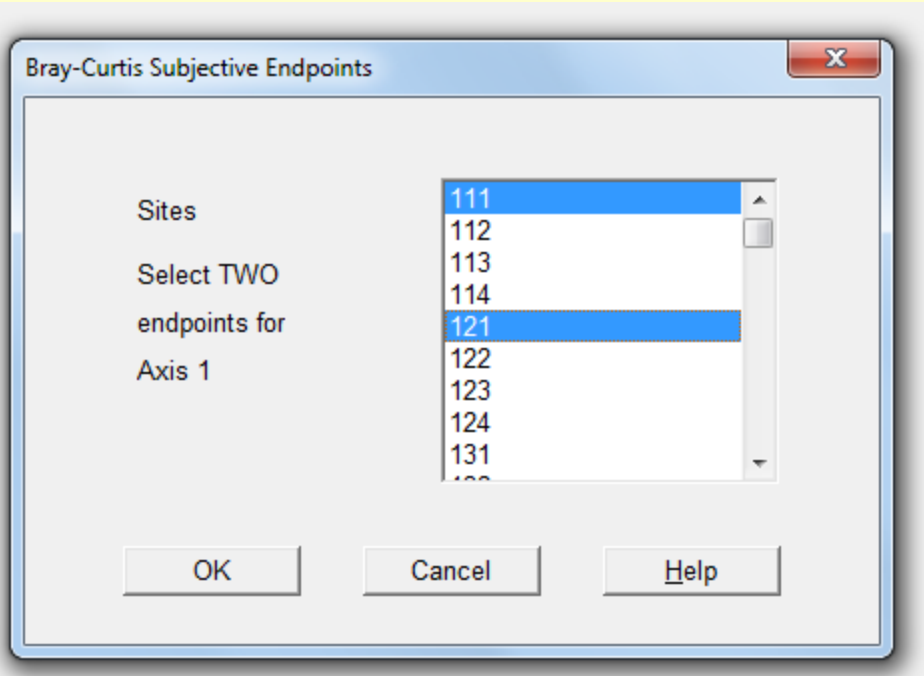
- **Note:** Possible that “objective” axes capture more variation than the “subjective” axis selected



- Method for determining the (remaining) objective axes

Polar Ordination – Suggested Procedure

- Next, pick subjective axes end points



- **Note:**

To select two samples:

Use CONTROL key to toggle and select second end point, with first end point already selected

Polar Ordination – Results

➤ Examine Results.txt file: Settings / Options

The following options were selected:

```
Distance measure = Relative Sorensen
Endpoint selection = Subjective ends
Endpoint selection for axes after 1 = Var.-Regression
Projection geometry = City-block
Calculation of residuals = City-block
```

Output options selected:

```
* Write distance matrix
* Write axes 1 through 3
  Write no residual distance matrix
```

➤ Ordination axes in order of variance explained – showing endpoints chosen and sample scores

```
Endpoints for axis 1: plot1 plot8
Distances (ordination scores) are from plot1
```

```
Sum of squares of non-redundant distances
in original matrix = .893973E+02
```

```
Axis 1 extracted 49.28% of the original distance matrix
Cumulative: 49.28%
Sum of squares of residual distances remaining = .453427E+02
```

Variance:

49.28 %

Polar Ordination – How it Works

- Once you have the first axis (k) – linking the two points:
 - Calculate position (x_{ki}) of each point i on the axis k . Point i is projected onto axis k between reference points A and B

Ordination scores on axis 1

Seq.	Name	Score	Seq.	Name	Score	Seq.	Name	Score	Seq.	Name	Score
1	plot1	0.000	2	plot2	0.384	3	plot3	0.451	4	plot4	0.537
5	plot5	0.732	6	plot6	0.938	7	plot7	0.783	8	plot8	1.000
9	plot9	0.638	10	plot10	0.645	11	plot11	0.517	12	plot12	0.504
13	plot13	0.517	14	plot14	0.510	15	plot15	0.508	16	plot16	0.348

Plot 1

Plot 8

Distance = 0

Distance = 1

- **NOTE:** Direction is arbitrary, but all distances are positive (Because of Relative Sorensen, distances bounded: 0 to 1)

Polar Ordination – Results

- Examine performance of axes 2 and 3: Results.txt file

```
Endpoints for axis 2: plot13    plot4
Distances (ordination scores) are from plot13

Regression coefficient for this axis =          -6.41
Variance in distances from the first endpoint =          1.26

Axis 2 extracted  34.26% of the original distance matrix
Cumulative:  83.54%
Sum of squares of residual distances remaining = .147185E+02
```

End Points: 13 & 4

Variance: 34.26 %

```
Endpoints for axis 3: plot3    plot11
Distances (ordination scores) are from plot3

Regression coefficient for this axis =          -0.25
Variance in distances from the first endpoint =          0.90

Axis 3 extracted   9.70% of the original distance matrix
Cumulative:  93.24%
Sum of squares of residual distances remaining = .604461E+01
```

End Points: 3 & 11

Variance: 9.70 %

Comparison NMDS and PO Results

- Examine selection of NMDS axes: Only 3 requested

STRESS IN RELATION TO DIMENSIONALITY (Number of Axes)

Axes	Stress in real data 100 run(s)			Stress in randomized data Monte Carlo test, 999 runs			p
	Minimum	Mean	Maximum	Minimum	Mean	Maximum	
1	19.589	26.792	51.889	29.487	48.085	54.005	0.0010
2	8.055	9.559	19.664	12.502	21.640	36.582	0.0010
3	4.005	4.499	7.419	5.350	12.165	26.473	0.0010

p = proportion of randomized runs with stress < or = observed stress
i.e., $p = (1 + \text{no. permutations} \leq \text{observed}) / (1 + \text{no. permutations})$

Best Answer: 2 Axes (Real distance variance: 67.3%)

R 2 (Explained Variance)

Axis	Inc.	Cum.
1	0.391	0.391
2	0.282	0.673

Comparison of NMDS and PO Results

- Examine NMDS correlations with axes

<u>Tau Correlations</u>	<u>Axis1</u>	<u>Axis2</u>
longitude	-0.150	-0.433
latitude	-0.750	-0.200
wind_speed	+0.143	+0.329
SST	-0.762	-0.142
CHL	+0.559	+0.017
Depth	-0.683	-0.167
CV_depth	+0.483	+0.300

Orthogonality

<u>Axis pair</u>	<u>r</u>	<u>%</u>
1 vs 2	0.039	99.8

Comparison of NMDS and PO Results

- Examine PO axis correlations with matrix 2

<u>Tau Correlations</u>	<u>Axis1</u>	<u>Axis2</u>	<u>Axis3</u>
longitude	-0.283	-0.444	+0.034
latitude	-0.850	-0.192	-0.237
wind_speed	+0.262	+0.212	+0.206
SST	-0.828	-0.160	-0.306
CHL	+0.492	+0.221	+0.155
Depth	-0.517	-0.259	-0.356
CV_depth	+0.383	+0.393	+0.356

Orthogonality

<u>Axis pair</u>	<u>r</u>	<u>%</u>
1 vs 2	0.197	96.1
1 vs 3	0.040	99.8
2 vs 3	0.236	94.4

R² (% Real Variance)

<u>Axis</u>	<u>Inc.</u>	<u>Cum.</u>
1	0.212	0.212
2	0.210	0.422
3	0.150	0.573

Polar Ordination – Next Steps

How to tease apart influence of cross-correlated variables?

- Examine PO axis: based on SST
- Examine PO axis: based on CHL
- Examine PO axis: based on Depth

Polar Ordination – A Subjective Approach

➤ Approach:

Allows the ordering of sample units between two “poles” (outgroup samples) based on patterns of co-occurrence in the species response data.

Frequently overlooked, although it is the only ordination tool that allows users to subjectively determine gradient endpoints, and has been shown to work well on heterogeneous datasets.

➤ Application:

Especially useful for investigating 1-D change / gradients (e.g., succession).

Succession / Gradient



But...

Selecting the “poles”
is a major limitation

Selecting Robust Poles

➤ Question?

How can we work around the problem of selecting poles?

➤ Here is an Idea:

Use two reference samples from a different study?

➤ For example:

- The “reference” / “end point” samples can arise from other data (published – historical)
- What was the community like before impact happened? (e.g., pre-fishery fish community data, pre-fire plant data)

Polar Ordination – What to Report

- Distance Metric Used (Sorensen / Relative Sorensen)
- Method for selecting End Points – What are they
Use subjective for axis 1
Select “City block” Distance / Residuals – similar to NMS
Use Variance-Regression method for additional axes
- Number of dimensions considered
Always use more than 1 (consider objective axes)
- % variance explained by axes (r^2): ordination / real space
- Bi-plot ordination plots
- Correlations of env. data / species with axes (Tau)
- Orthogonality of axes: May be lower than NMS / PCA
- **NOTE: No Randomization Tests (p values).**

References

Bray, J.R., and J.T. Curtis. 1957.

An ordination of the upland forest communities of southern Wisconsin. *Ecological Monographs* 27:325-349.

Beals, E.W. 1984.

Bray-Curtis ordination: an effective strategy for analysis of multivariate ecological data. *Advances in Ecological Research* 14:1-55

Palmer, M.W. 1986.

Pattern in corticolous bryophyte communities of the North Carolina piedmont: Do mosses see the forest or the trees? *Bryologist* 89:59-65

Indian Ocean Birds: Analysis by Danielle McKay

➤ Data files:

Raw.matrix1.wk1 (main matrix)

16	samples									
22	species									
	Q	Q	Q	Q	Q	Q	Q	Q	Q	Q
	WCPT	WISP	SPPT	YNAL	LISH	LTJA	SOSH	BBAL	SOAL	GWPT
sample1	0	0	0	0	0	0	0	0	0	0
sample2	0	0	0	0	12.5	0	0	0	0	0

Raw.matrix2.wk1 (second matrix)

16	samples						
7	variables						
	Q	Q	Q	Q	Q	Q	Q
	longitude	latitude	wind_speed	SST	CHL	Depth	CV_depth
sample1	54.88	-23.23	19	27.15	0.06	4086.5	7.47
sample2	54.21	-29.07	15	24.45	0.07	4982.5	3.07

- 17 Indian Ocean bird species (cosmopolitan and tropical)
- 16 sampling sites and 7 environmental variables.
- Variables: latitude at transect midpoint (negative, South Hemisphere), longitude, wind speed (knots), sea surface temperature (°C), chlorophyll concentration (g chl/m³), depth (meters), and CV (s.d./mean) of depth (m).

Dataset Processing

- **Number of species discarded: 5**
 - Discarded species found in only one sampling location.
 - Outlier species according PC-ORD: GWPT
- **Final sample size used:** 16 samples, 17 species (both tropical and cosmopolitan), and 7 environmental variables (environmental variables are all quantitative)
- **Skewness:** Skewness in this data is high ($\gg 1$ for all but one species) because there are so many zeros. Some of the environmental variables also have high skewness.

I analyzed the dataset with NMS which is well suited for non-normal data with lots of zeros.

I did not manipulate or transform the data before running NMS.

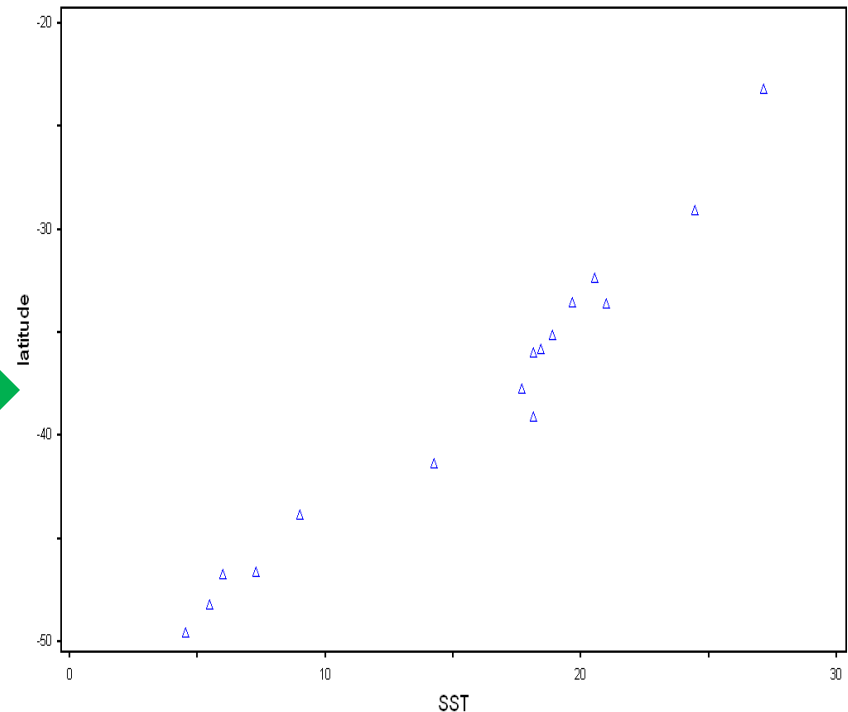
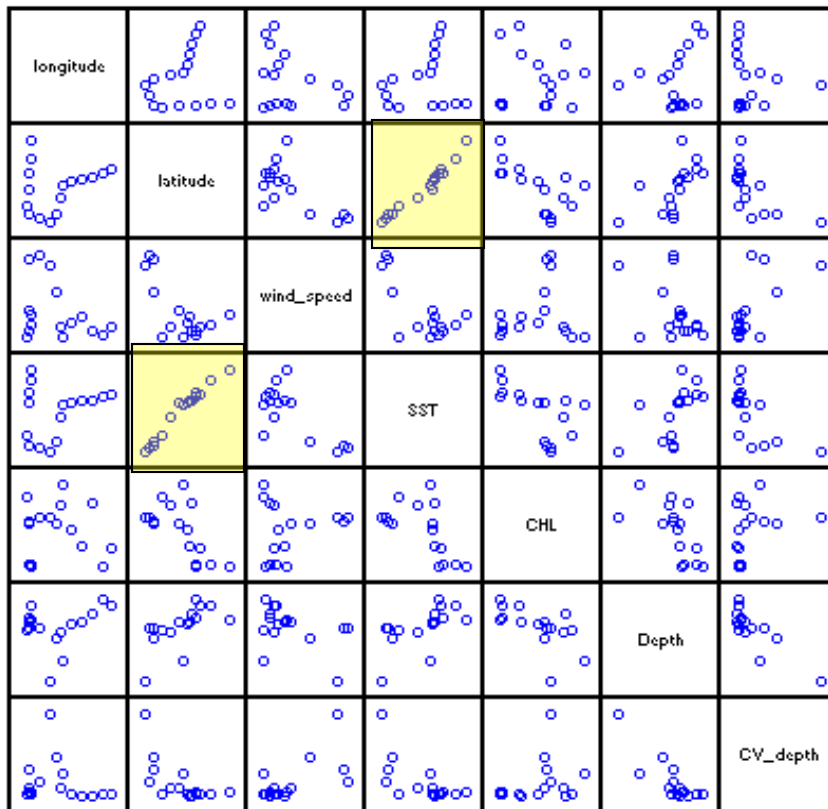
Dataset Exploration

- Scatterplot of pair-wise environmental variables revealed a case of co-linearity

Latitude / SST have a strong positive correlation.

(As latitude gets more negative traveling south, temperature decreases)

Otherwise, no strong correlation between any of the other variables



Dataset Analysis

Ordination of samples in species space. 16 samples 17 species

The following options were selected:

ANALYSIS OPTIONS

1. SORENSEN = Distance measure
2. 6 = Number of axes (max. = 6)
3. 500 = Maximum number of iterations
4. RANDOM = Starting coordinates (random or from file)
5. 1 = Reduction in dimensionality at each cycle
6. 0.20 = Step length (rate of movement toward minimum stress)
7. USE TIME = Random number seeds (use time vs. user-supplied)
8. 250 = Number of runs with real data
9. 250 = Number of runs with randomized data
10. YES = Autopilot
11. 0.000000 = Stability criterion, standard deviations in stress
 over last 10 iterations.
12. THOROUGH = Speed vs. thoroughness

OUTPUT OPTIONS

13. NO = Write distance matrix?
 14. NO = Write starting coordinates?
 15. NO = List stress, etc. for each iteration?
 18. NO = Plot stress vs. iteration?
 17. NO = Plot distance vs. dissimilarity?
 16. NO = Write final configuration?
 19. UNROTATED = Write varimax-rotated or unrotated scores for graph?
 20. YES = Write run log?
 21. NO = Write weighted-average scores for species ?
-

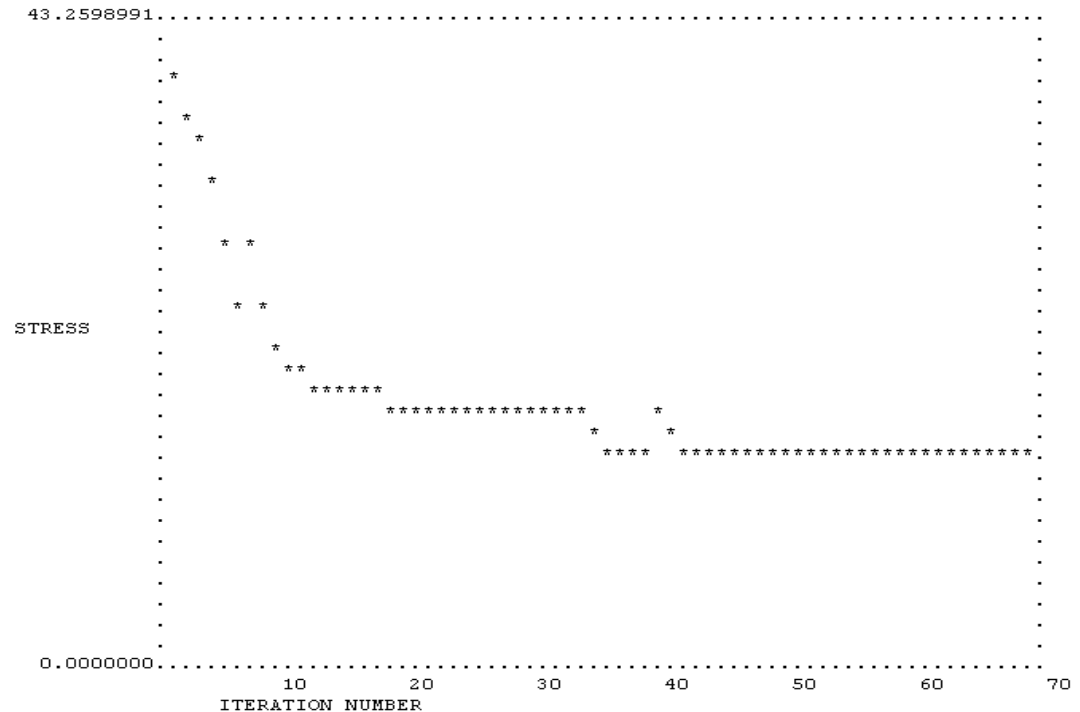
Dataset Analysis

➤ Final stress / instability / iterations for the best solution :
2-Dimensions

```
12.42224 = final stress for 2-dimensional solution  
0.00000 = final instability  
68 = number of iterations
```

Stress

PLOT OF STRESS V. ITERATION NUMBER
(to prevent wrapping of wide plots when printing, use small font)



Results Interpretation

➤ Criteria for selection of number of axes

Criterion 1: Decline in Stress with added axis at least 5

Criterion 2: P value < 0.05

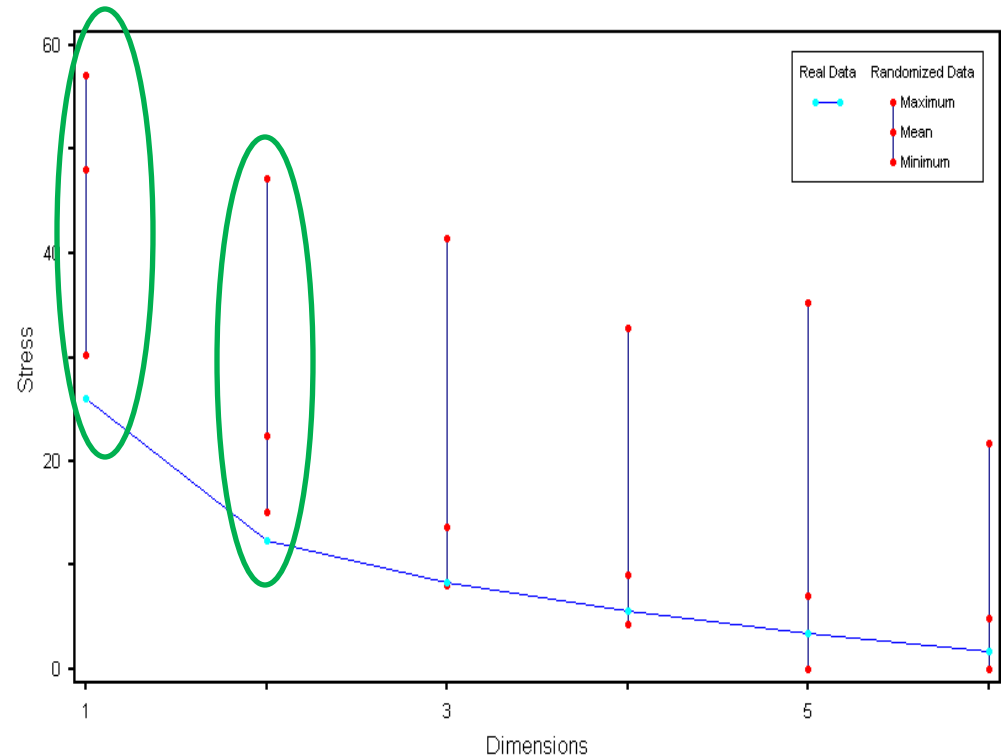
STRESS IN RELATION TO DIMENSIONALITY (Number of Axes)

Axes	Stress in real data 250 run(s)			Stress in randomized data Monte Carlo test, 250 runs			p
	Minimum	Mean	Maximum	Minimum	Mean	Maximum	
1	26.082	43.714	56.524	30.196	48.038	57.121	0.0040
2	12.422	15.837	36.573	15.141	22.383	47.130	0.0040
3	8.304	9.272	26.473	8.000	13.679	41.447	0.0159
4	5.546	6.262	20.691	4.386	9.023	32.744	0.0438
5	3.492	4.138	23.875	0.000	7.102	35.270	0.0438
6	1.710	1.950	13.534	0.000	4.936	21.738	0.0637

p = proportion of randomized runs with stress < or = observed stress
i.e., $p = (1 + \text{no. permutations} \leq \text{observed}) / (1 + \text{no. permutations})$

Results Interpretation

- **NMS Scree Plot**
- Computer chose 2D result, with lowest stress.
- Adding a dimension, would not change stress by > 5 , even though it is significant (p value < 0.05)



```
12.42224 = final stress for 2-dimensional solution
0.00000 = final instability
68 = number of iterations
```

Results Interpretation

Coefficient of Determination (% of Variance): for both axes together

Coefficients of determination for the correlations between ordination distances and distances in the original n-dimensional space:

Axis	R Squared	
	Increment	Cumulative
1	.252	.252
2	.431	.684

68.4% of the variance explained by two axes

➤ Orthogonality

Axis pair	r	Orthogonality, % = $100(1-r^2)$
1 vs 2	0.266	92.9

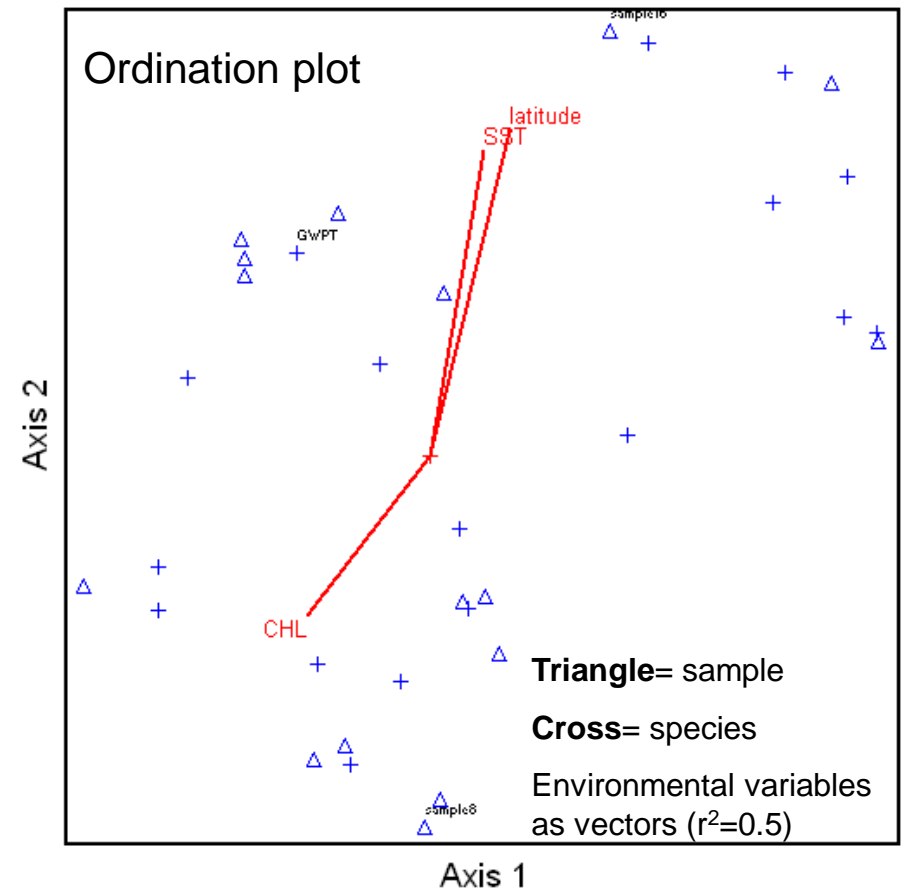
the two axes are independent

Results Interpretation

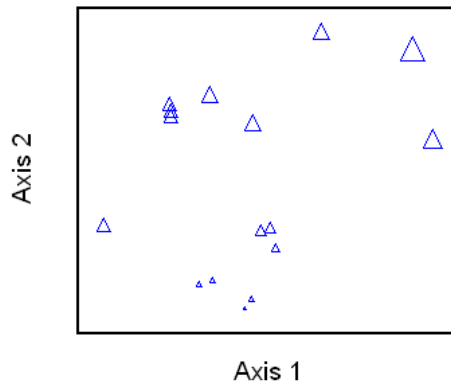
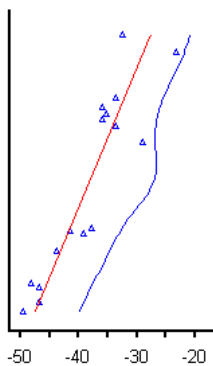
Showing the two most important axes with species and samples labeled as points, environmental variables as vectors. **Axis two is best represented by latitude and SST (which vary together), CHL has a slight negative correlation with axis 1 and axis 2.**

According to Clarke's Rule of Thumb:
A final stress of 10-20 produces a useable picture although values at the upper end suggest a potential to mislead.

12.42224 = final stress for 2-dimensional solution
0.00000 = final instability
68 = number of iterations



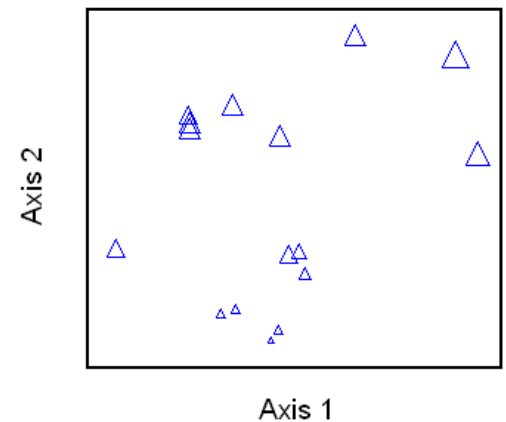
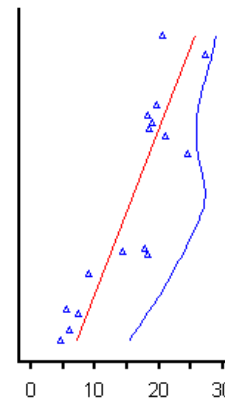
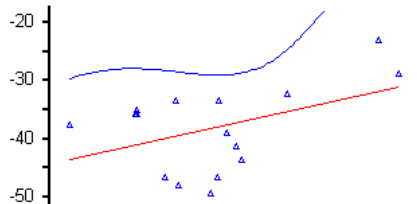
Results Interpretation



← Latitude correlations with axes 1 and 2.

High tau (0.75) indicates a strong positive relationship with Axis 2

latitude
 Axis 1
 $r = .448$ $\tau = .217$
 Axis 2
 $r = .905$ $\tau = .750$

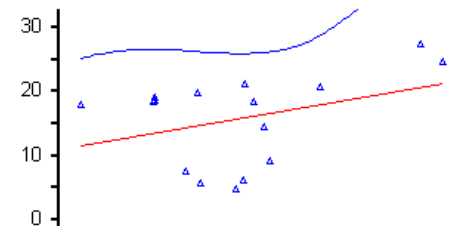


Sea surface temperature correlations with axes 1 and 2.

High tau (0.695) indicating strong positive relationship with Axis 2



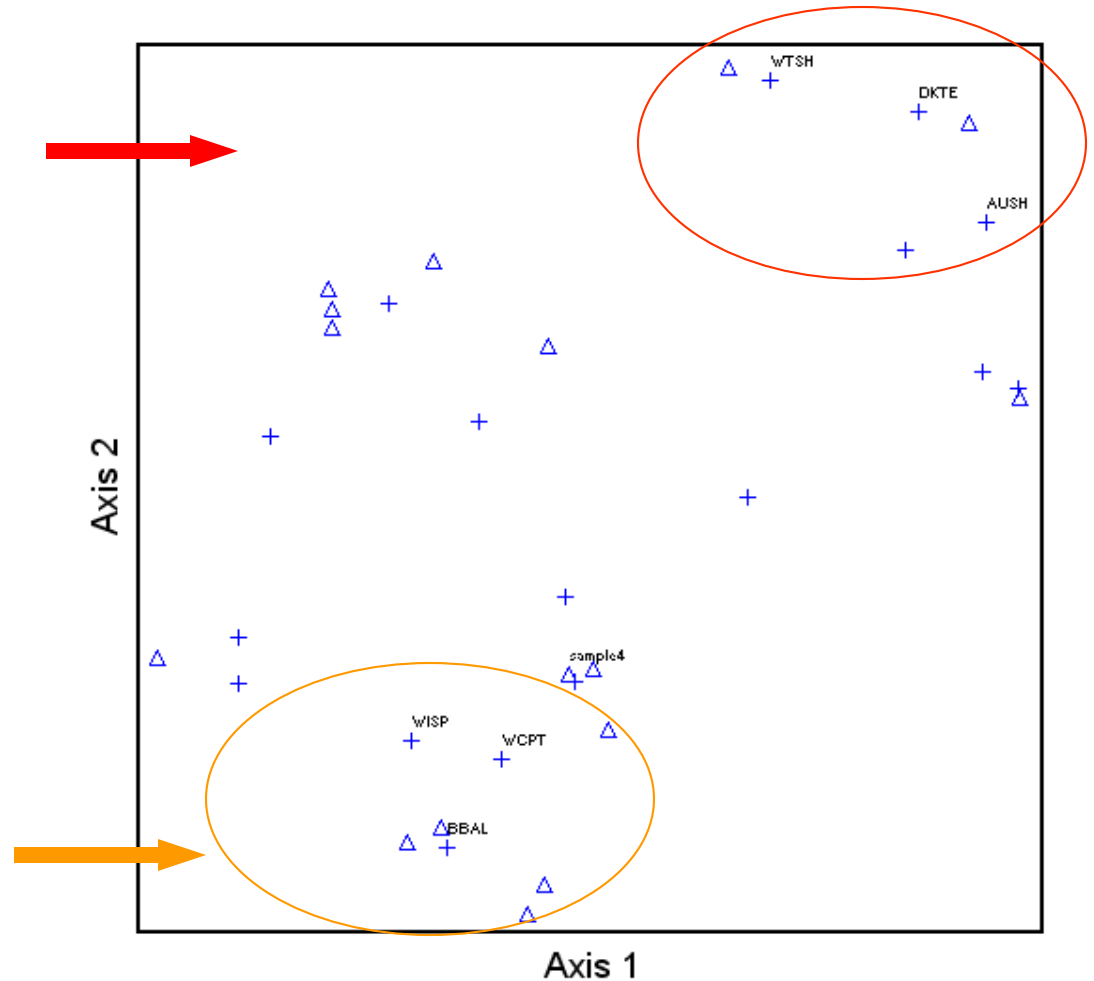
SST
 Axis 1
 $r = .369$ $\tau = .243$
 Axis 2
 $r = .875$ $\tau = .695$



Results Interpretation

WTSH, DKTE, and AUSH
(found at the top of axis #)
are all tropical species

WISP, WCPT, and BBAL
(found at the bottom of axis 2)
are all cosmopolitan species.



Re-analysis with Polar Ordination

- ★ I used the **Sorensen distance** metric, and chose Latitude as the environmental variable I was interested in.
- ★ To select **endpoints** I used:
 - subjective for axis one (which allowed me to choose)
 - variance-regression for the other axis
- ★ I selected **city-block distance / residuals** so my results would be comparable to NMS.
- ★ To look at the **latitude gradient** I chose the northernmost (**-23.23°S**) and southernmost (**-49.59°S**) sites in the dataset.
 - sample 1 as the first endpoint
 - sample 8 as the last endpoint.
- ★ I considered **2 dimensions** in my analysis since NMS gave me 2-D as the best solution.

Re-analysis with Polar Ordination

★ The proportion explained by each axis (r^2):

Coefficients of determination for the correlations between ordination distances and distances in the original n-dimensional space:

Axis	R Squared	
	Increment	Cumulative
1	.197	.197
2	.235	.432

The r^2 values are much lower in P.O. than what I got with NMS

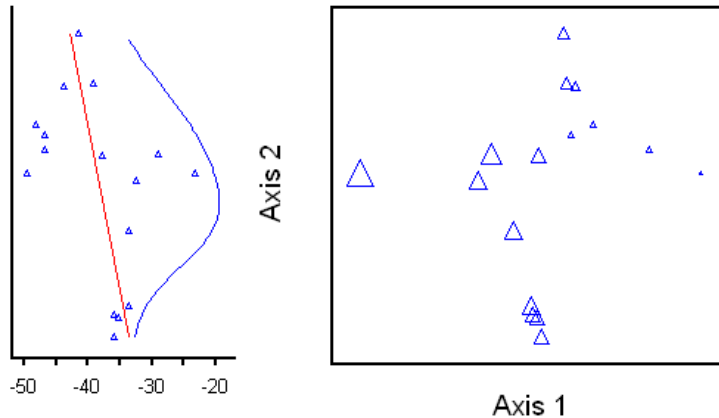
★ Orthogonality:

Increment and cumulative R-squared were adjusted for any lack of orthogonality of axes.

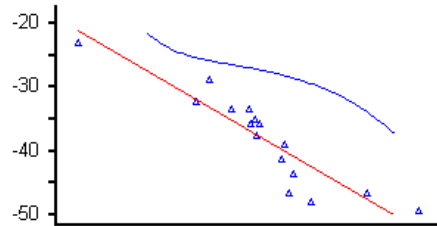
Axis pair	r	Orthogonality, % = $100(1-r^2)$
1 vs 2	0.192	96.3

Orthogonality - still good!

Re-analysis with Polar Ordination



latitude
Axis 1
 $r = -.914$ $\tau = -.867$
Axis 2
 $r = -.384$ $\tau = -.243$

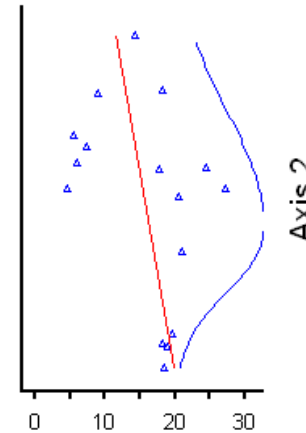


High tau (-0.867) indicates a strong negative relationship with Axis 1

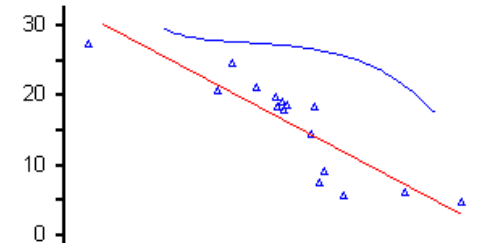
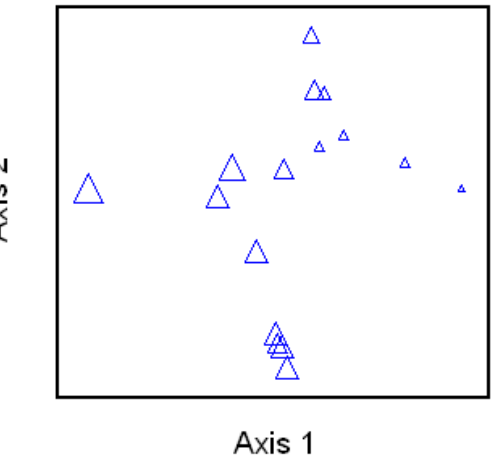
The relationship was strong before, but now it is stronger and negative

High tau (-0.845) indicating strong negative relationship with Axis 1

The relationship was strong before, but now it is stronger and negative



SST
Axis 1
 $r = -.870$ $\tau = -.845$
Axis 2
 $r = -.363$ $\tau = -.227$



Re-analysis with Polar Ordination

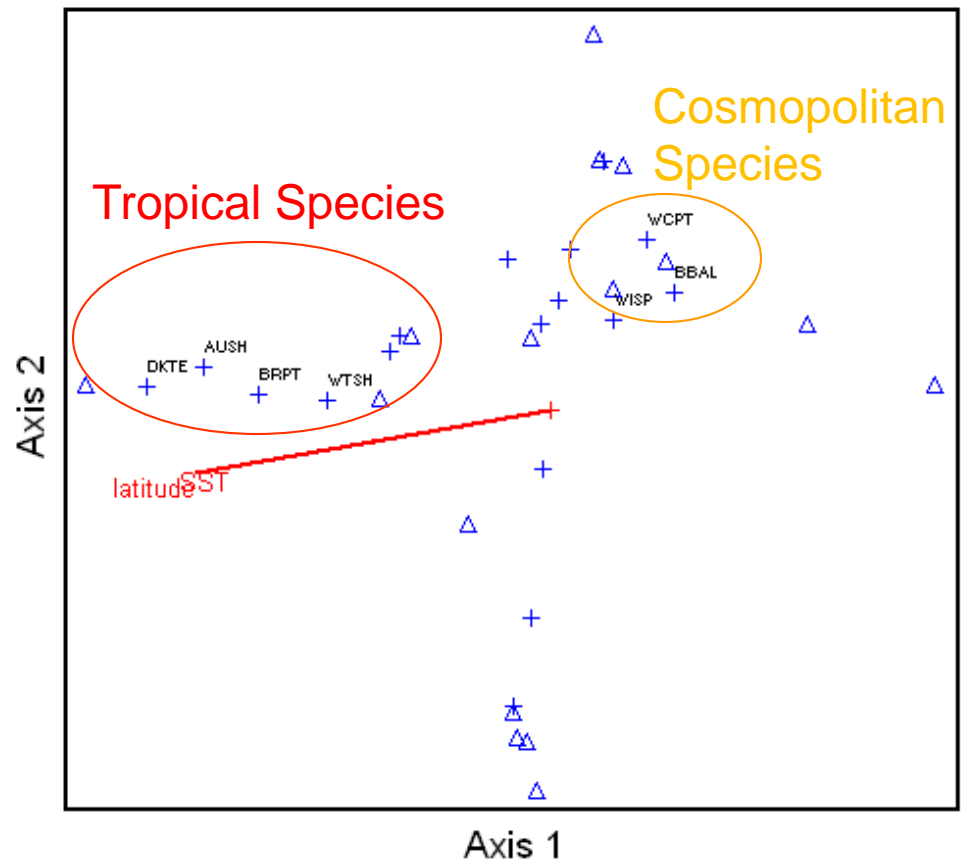
Polar Ordination bi-plot, environmental variables (with $r^2 > 0.500$) as vectors.

I chose the same 0.500 threshold I used in the NMS, and the same environmental variables showed up (latitude and SST).

★ The same species that were found at the ends of axis 2 (representing high and low latitude and SST) in NMS are now at the ends of axis 1. This is great!

Tropical species found at the beginning of the axis (samples with largest latitude / SST)

Cosmopolitan species were found at the other end (samples with lowest latitude / SST).



NMS vs. Polar Ordination

I found better variance explained using the NMS analysis than the Polar Ordination (PO), 68.4% cumulative for Axis 1 and 2 with NMS, only 43.2% cumulative for both axes with PO. The orthogonality was pretty good for both analyses (92.9 in NMS and 96.3 in PO). It is surprising that the orthogonality was higher with PO, as usually it tends to be lower than in NMS. It was good to see in the correlations of environmental data and species with the axes that tau was very strong for both latitude and SST in PO, as it was in NMS. In fact, the tau values were higher in PO but negative, while they were positive in NMS. Latitude and SST best represented axis 2 in NMS, in PO they represented axis 1 (the one that I chose endpoints for).

In NMS I used an r^2 cutoff of 0.500, I did the same in PO, hoping to find the same vectors. The strongest vectors were still there in PO, SST and temperature, but chlorophyll did not show up as it did in NMS. Finally, since I knew that axis 1 would be representing latitude in my Polar Ordination as axis 2 did in NMS, I wanted to look at the species found at the top and bottom of this axis (the southern and northernmost boundaries). I found in NMS the species found closest to the equator were found at one end of axis 2 while the species found closest to the south pole were found at the other end of the axis. The same pattern was found in the ordination plot generated from PO, the same tropical species were found at one end of axis 1, while the same cosmopolitan species were found at the other end of the axis. Great!