How cryptic is cryptic diversity? Machine learning approaches to fine scale variation in the morphology of *Emys marmorata*.

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Cryptic diversity

Crytic species are species delimitated via molecular means which were not/cannot be identified via morphology.

How much of cryptic diversity is just a function of sample size and/or method?

Emys marmorata

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Morphological hypothesis

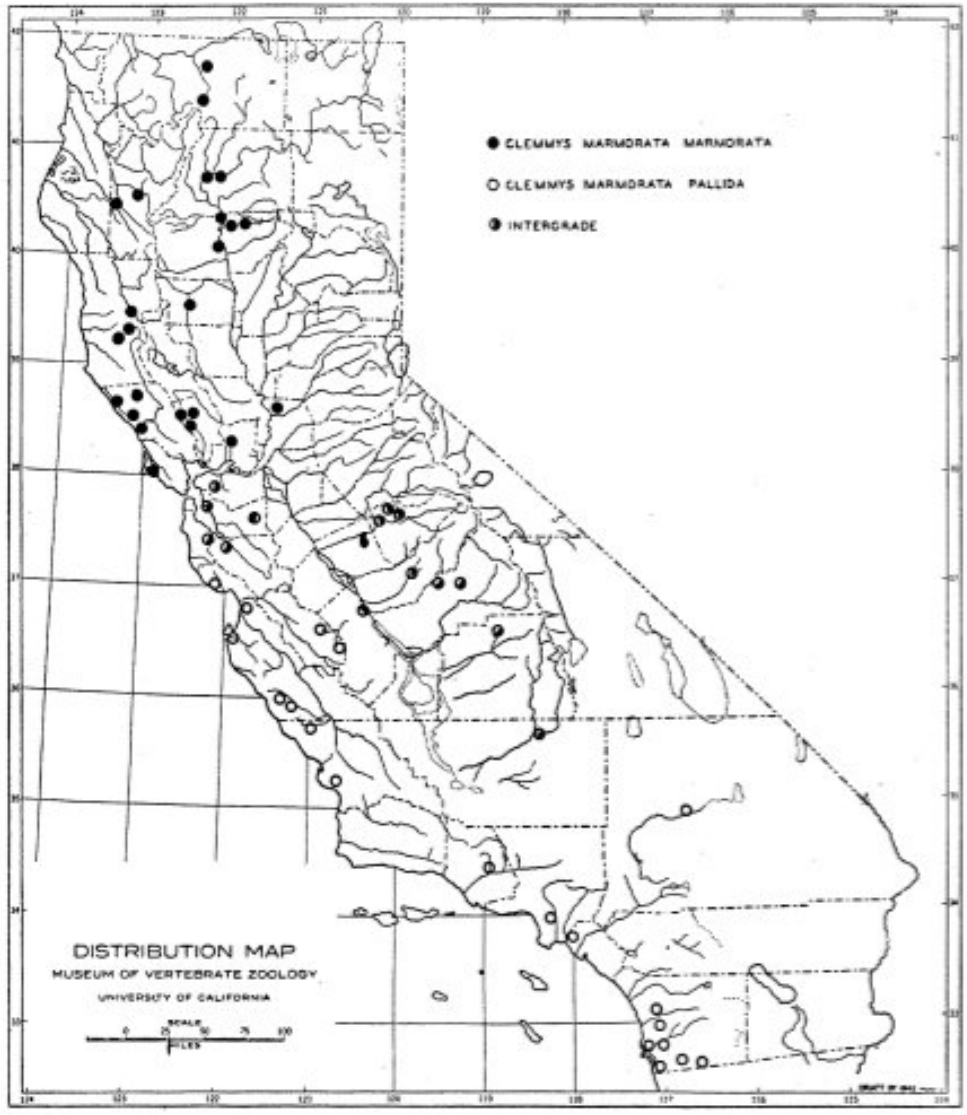
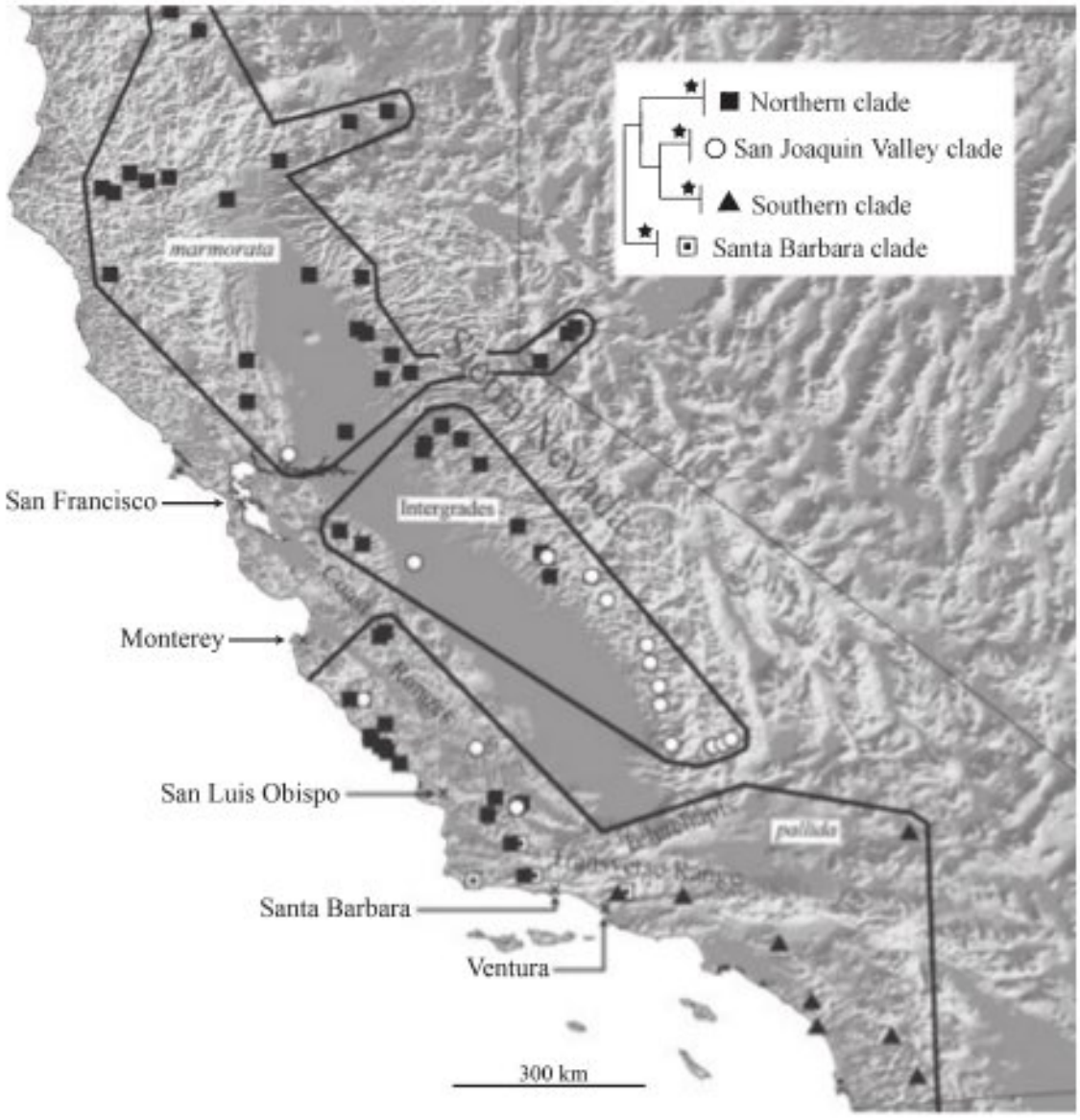


Fig. 4. California localities from which specimens have been examined.

Seeliger 1945 *Copeia*

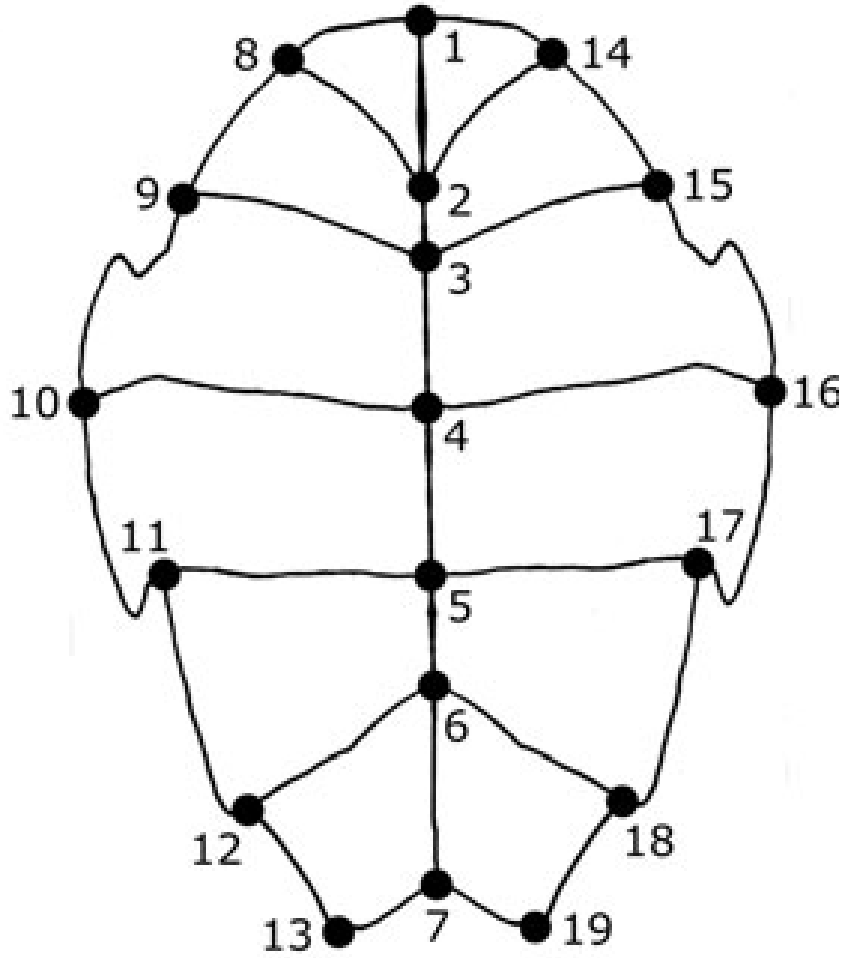
Phylogenetic hypotheses



Spinks *et al.* 2010 *Molec. Ecol*

Methods: morphometrics

- plastral ("belly") shape
- landmarks averaged across bilat axis
- total 13 landmarks, 7 on bilat axis, 6 off
- geographic information known/inferred



Angielczyk *et al.* 2011 *Evolution*

Unsupervised learning

Fancy way of saying clustering or density estimation.

Partitioning around mediods (PAM) compared with “gap” statistic.

Minimize sum of dissimilarities between points and medoids.

“Gap” is analogous to goodness-of-clustering.

Supervised learning

Fancy way of saying classification (and regression).

Features (principal components) predict class (subspecific assignment).

Multinomial logistic regression and random forests.

Model training and selection

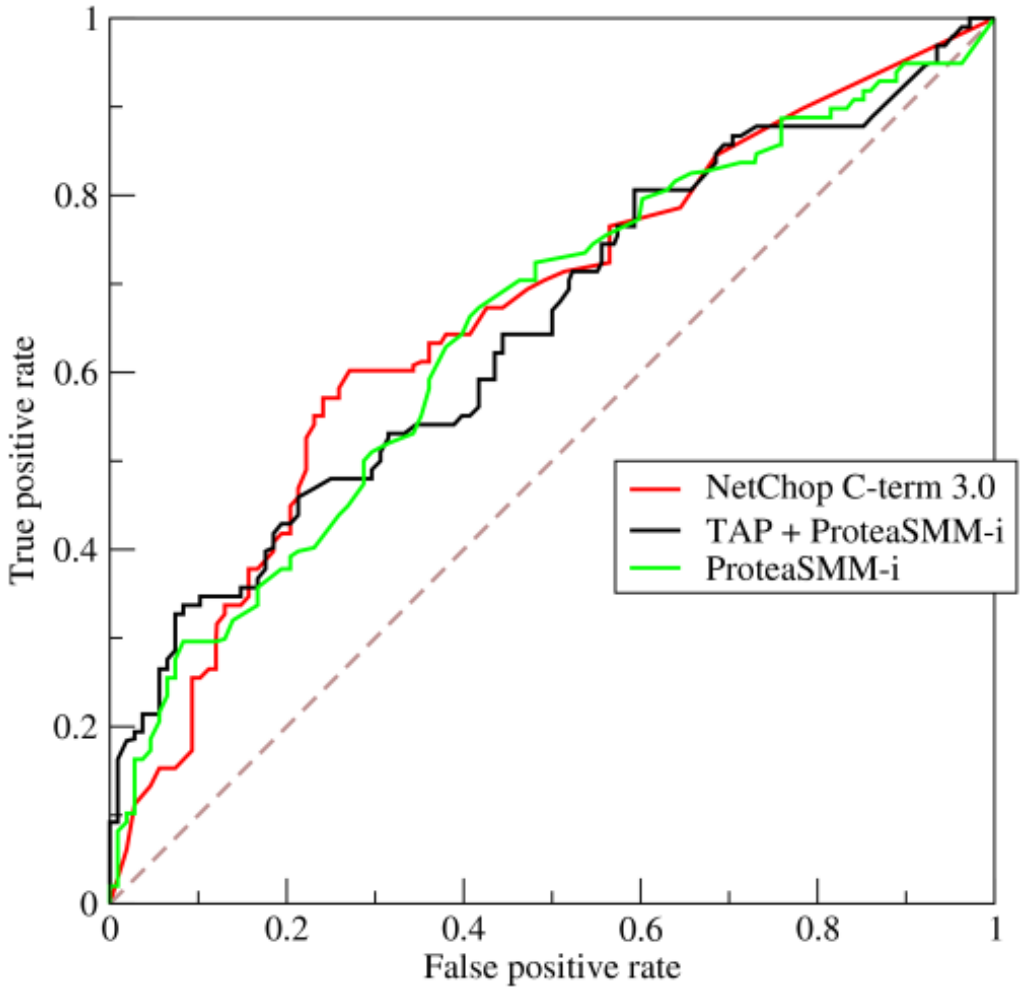
- split into training and testing sets, 75-25.
- tuning parameters via grid-search
- uncertainty via 10-fold CV
- model selection
  - multinomial logistic regression: min AICc
  - random forest: max ROC

ROC and confusion matrices

		Predicted class	
		1	0
Actual class	1	TRUE POSITIVE	FALSE NEGATIVE
	0	FALSE POSITIVE	TRUE NEGATIVE

ROC

- true positive rate or sensitivity: $\frac{TP}{TP+FN}$
- false positive rate or 1 - specificity: $\frac{FP}{FP+TN}$
- multiclass, all-against one (Hand and Till 2001 *Machine Learning*)



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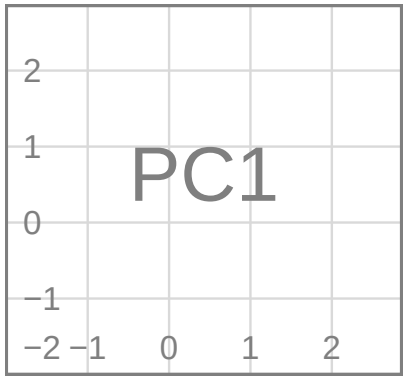
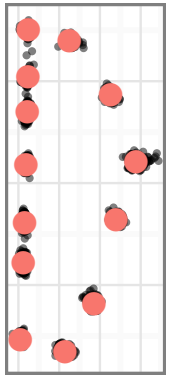
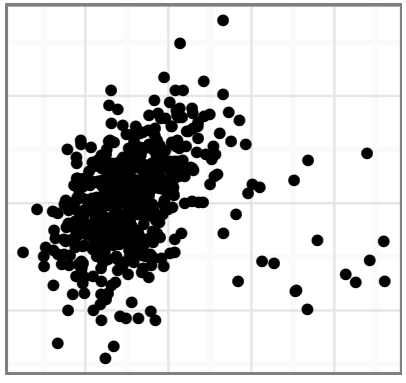
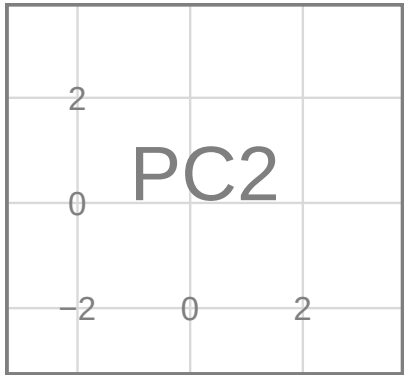
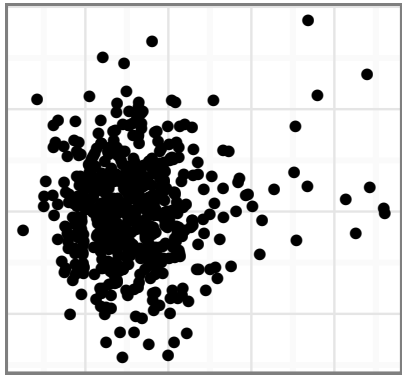
Results: mophometrics

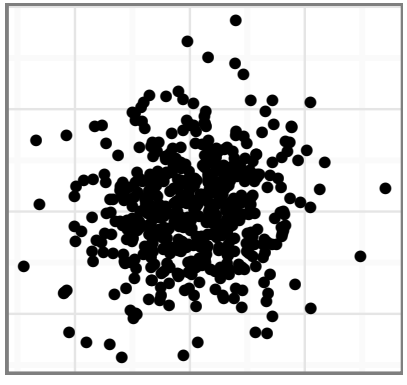


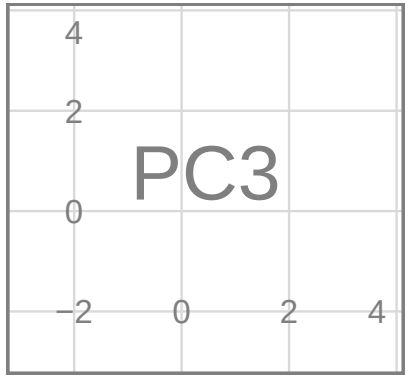




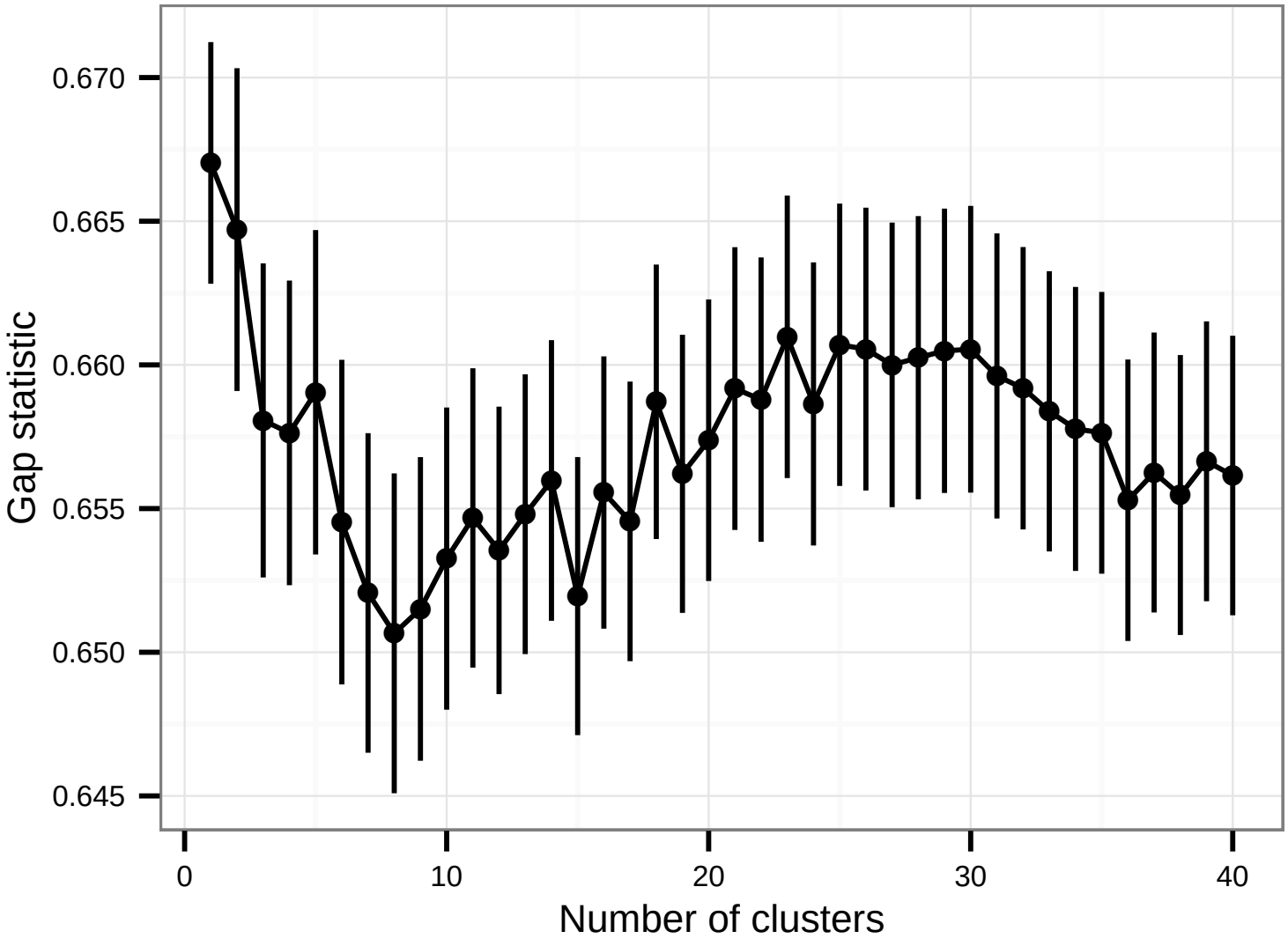




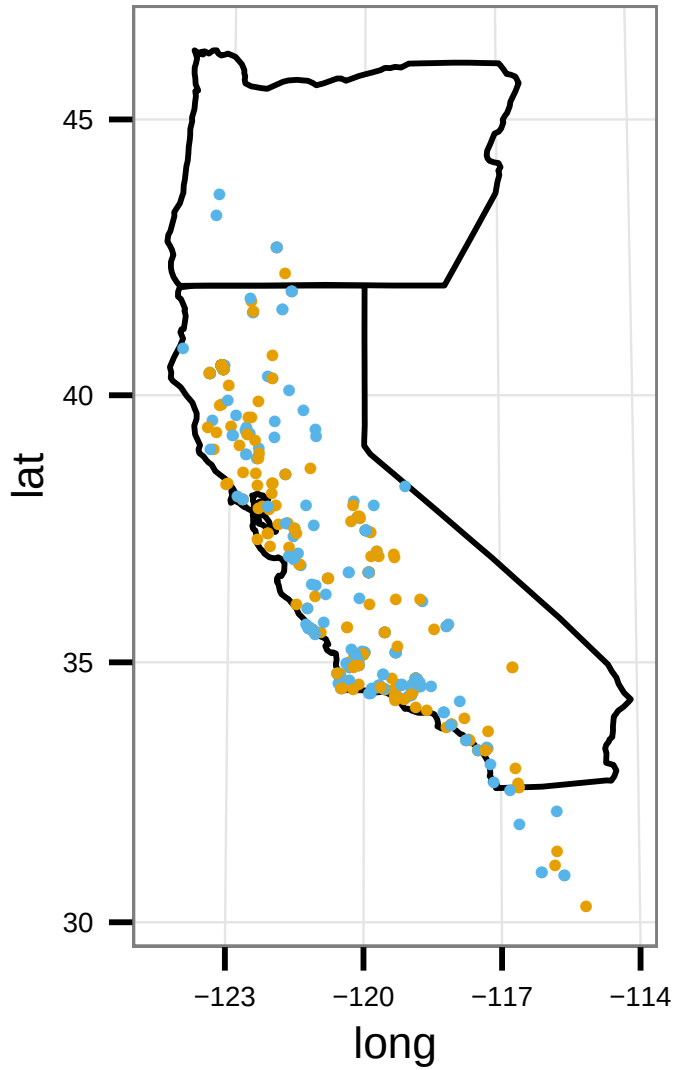




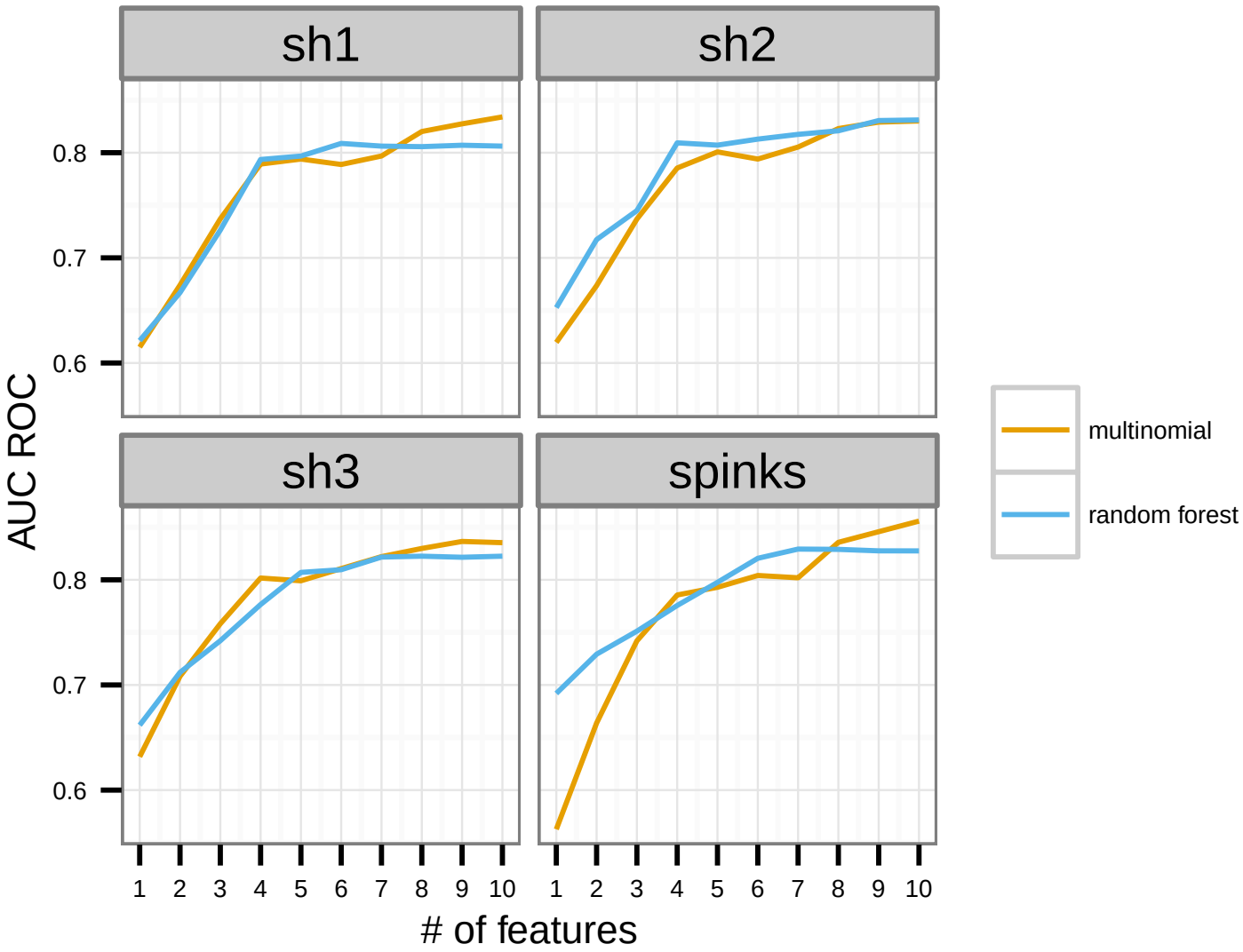
Results: gap clustering



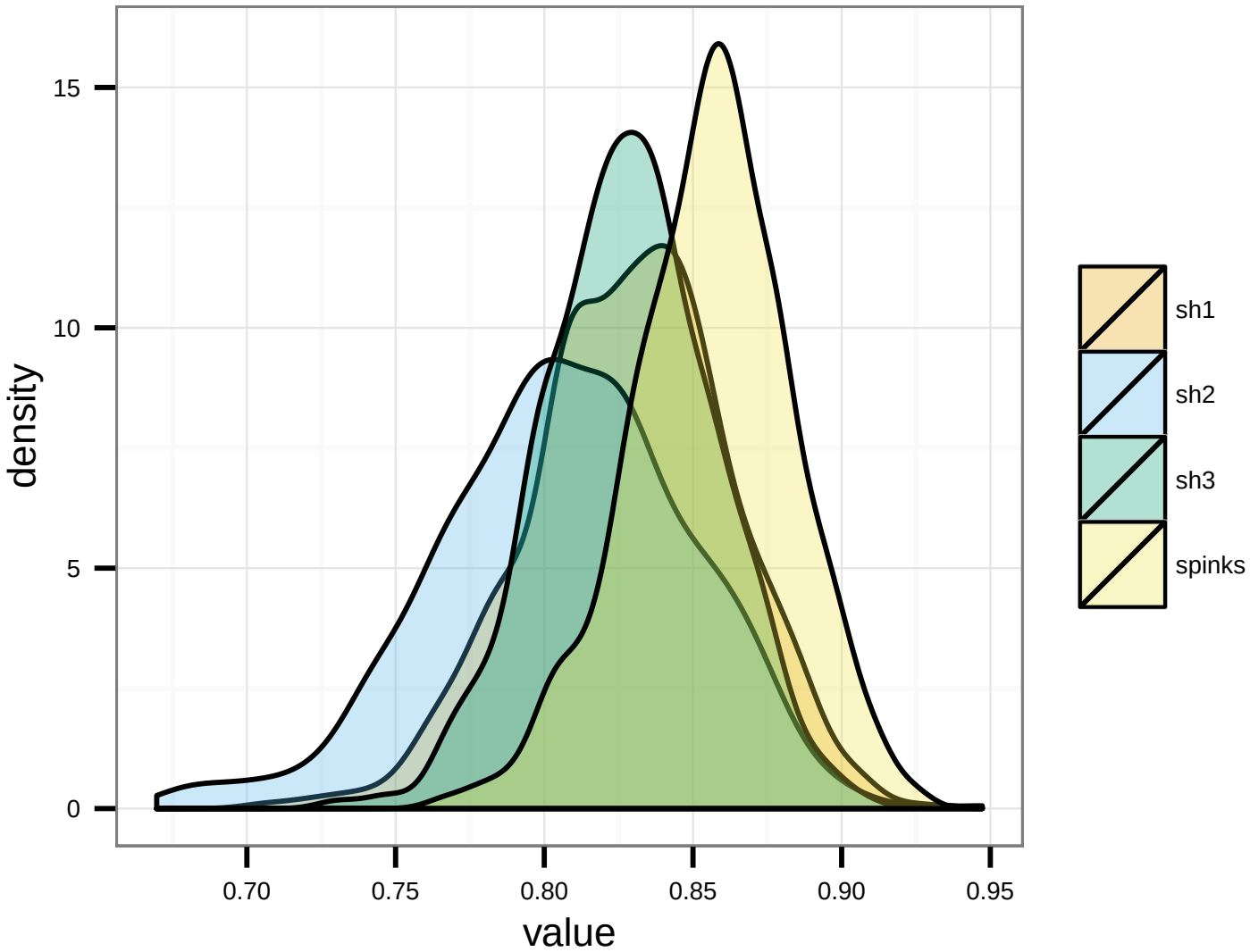
Second best cluster



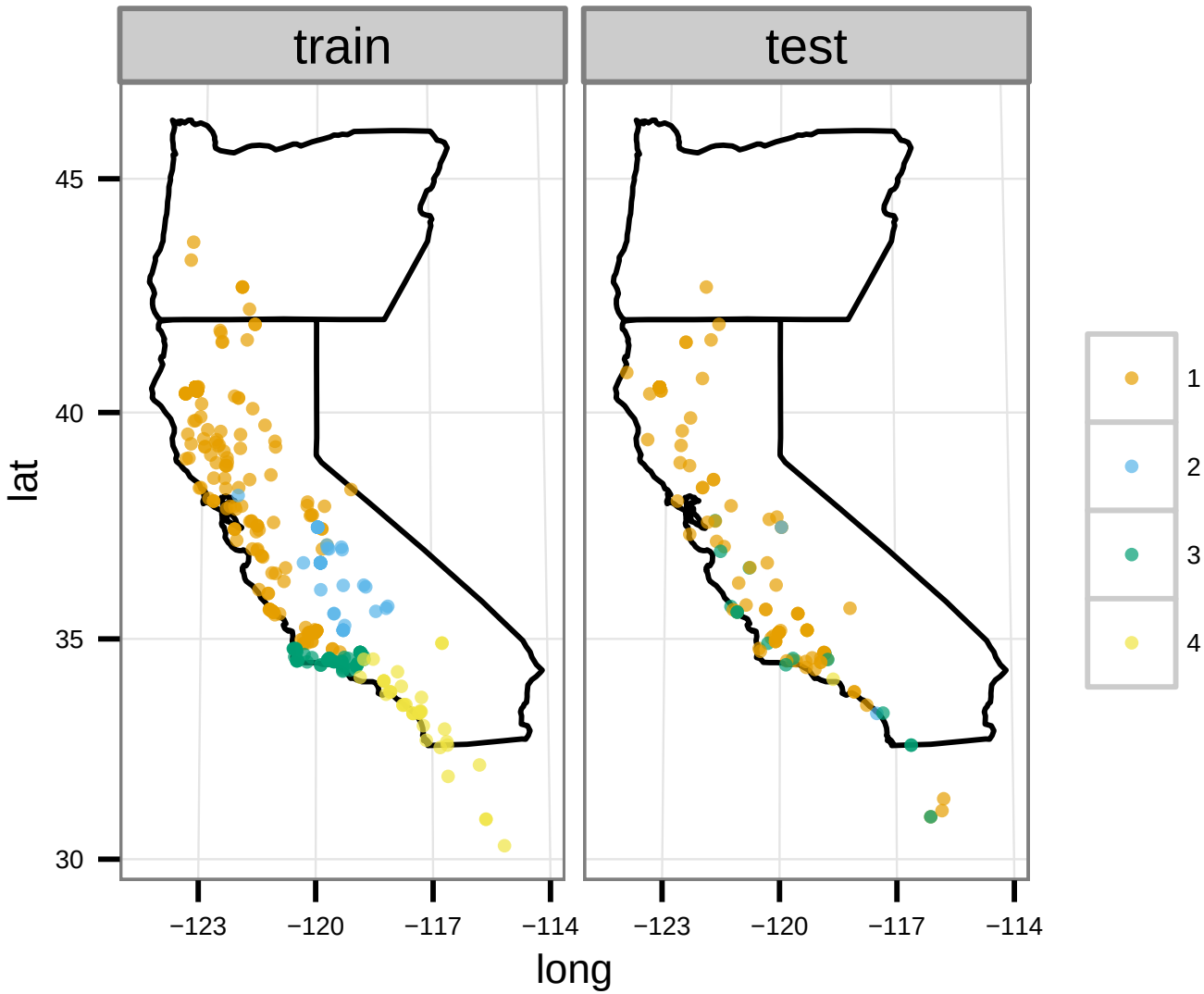
Model selection via ROC



Generalize using best random forest model

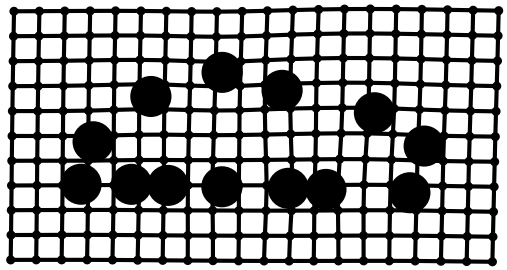


Best classification scheme via RF model results



Mean shape of classes

1



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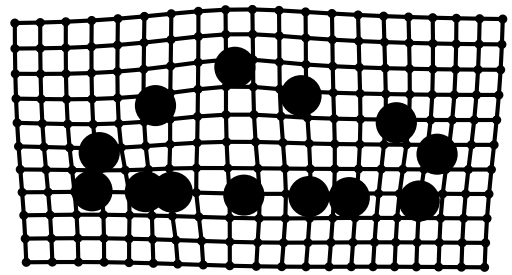

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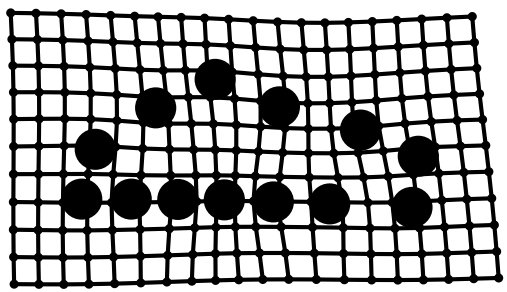
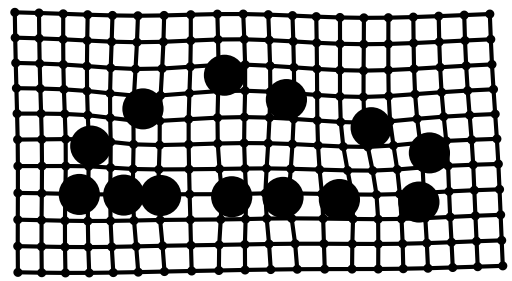
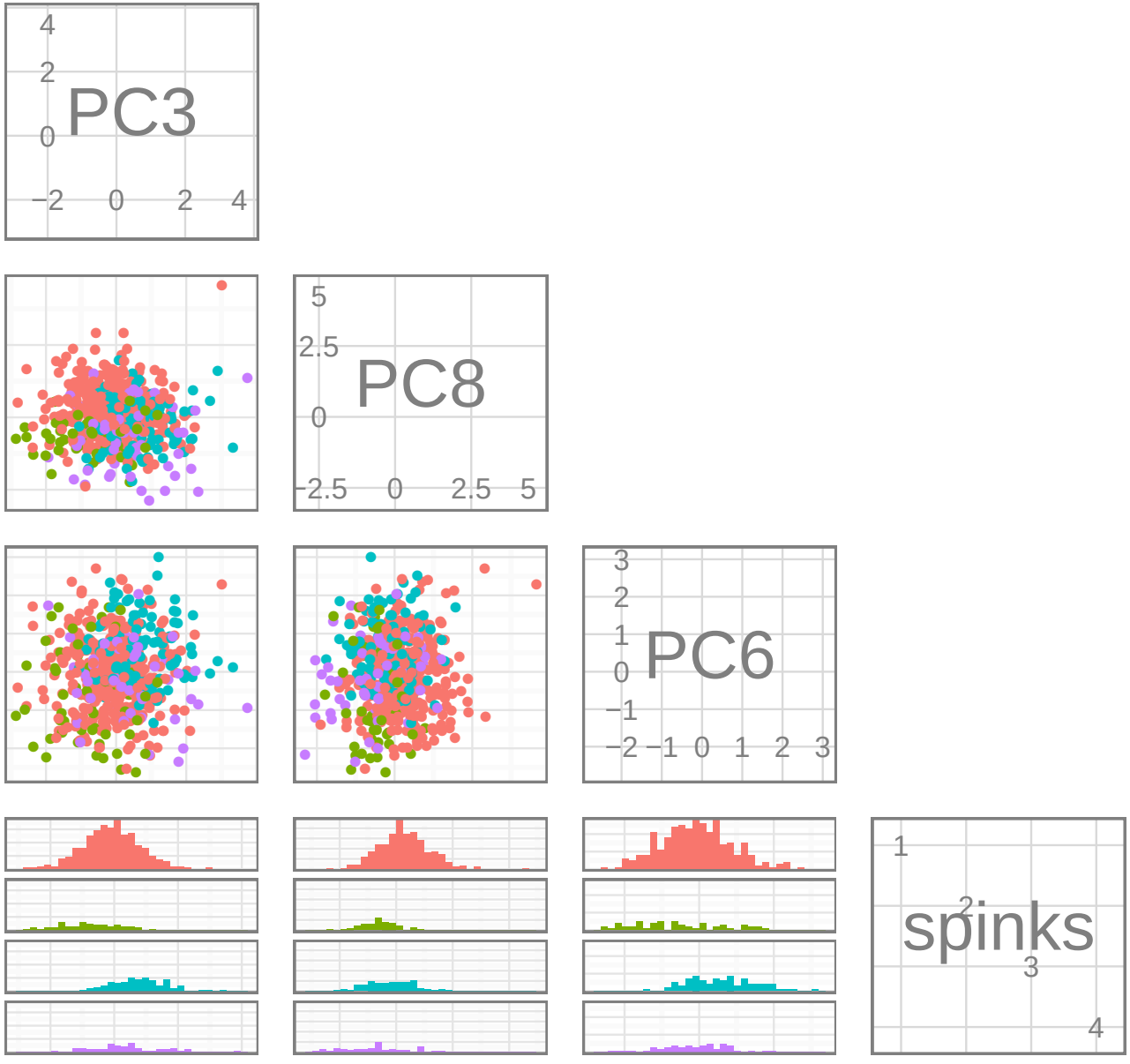


4

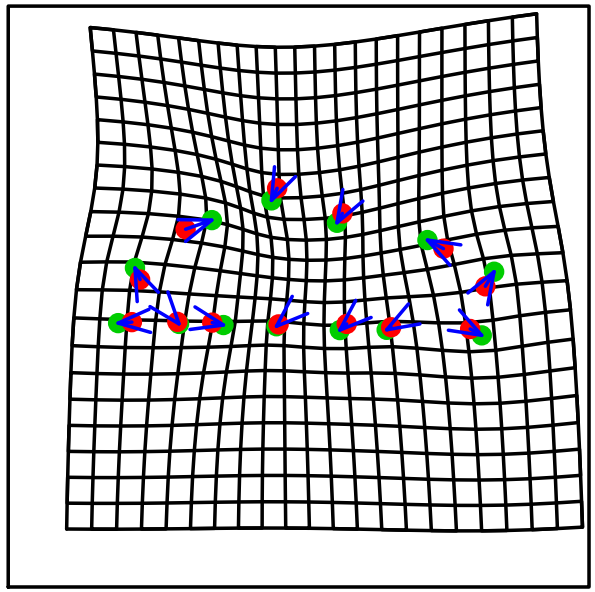


Variable importance of random forest model

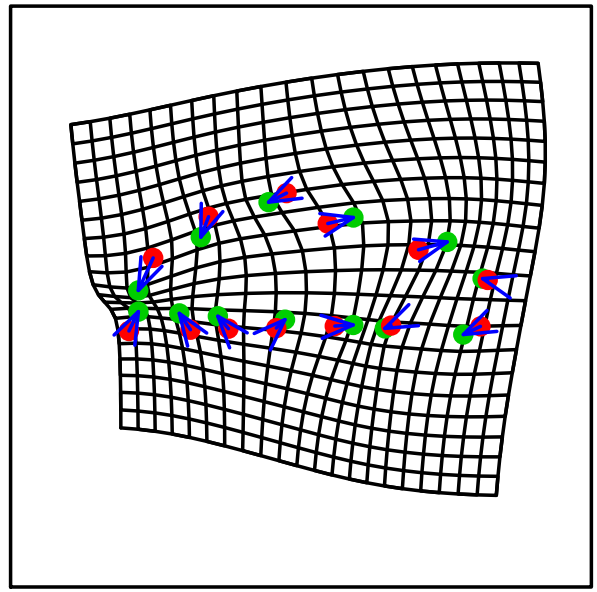


Shape across PC3

min observed

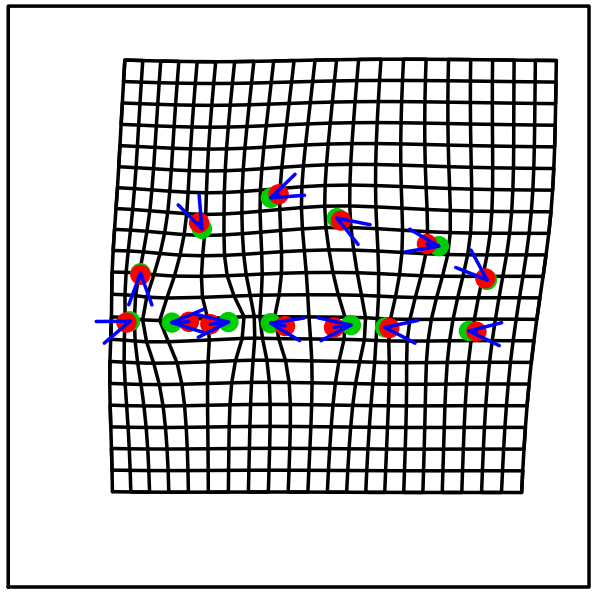


max observed

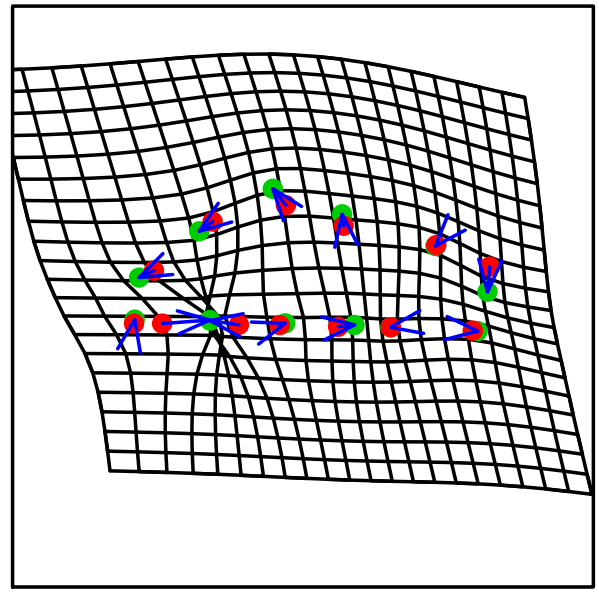


Shape across PC8

min observed



max observed



Future

- illustration of morphological validation of previously cryptic variation
  - the concordance is remarkable
  - large sample sizes can be difficult
- utility of large data, machine learning methods
- unsupervised methods for when no explicit hypothesis – nonparametric Bayes
- cause of interclass variation – local adaptation? pure isolation?

Acknowledgements

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