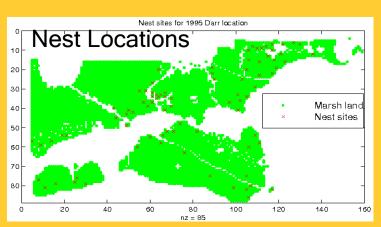
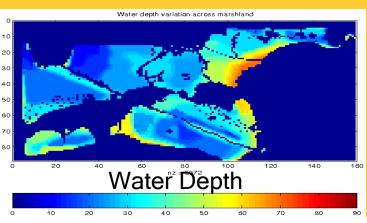
Learning Objectives

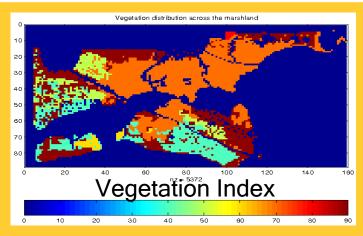
- After this segment, students will be able to
 - Compare traditional & location prediction models
 - Contrast Linear Regression & Spatial Auto-Regression

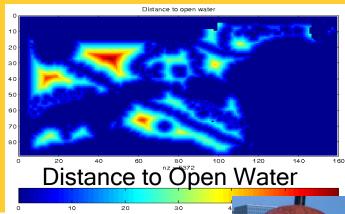


Illustration of Location Prediction Problem





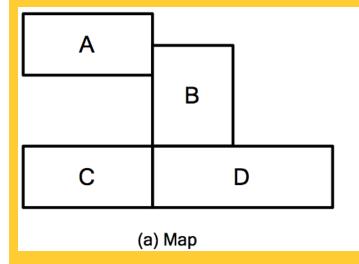


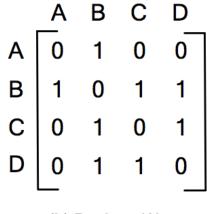


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Neighbor Relationship: W Matrix





(c) Row-normalized W



Location Prediction Models

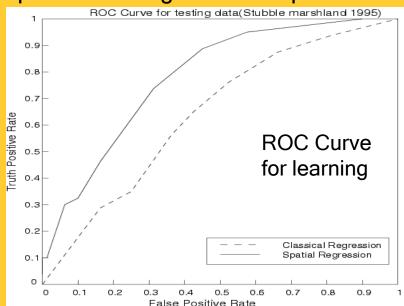
- Traditional Models, e.g., Regression (with Logit or Probit),
 - Bayes Classifier, ...
- Spatial Models
 - Spatial autoregressive model (SAR)
 - Markov random field (MRF) based Bayesian Classifier

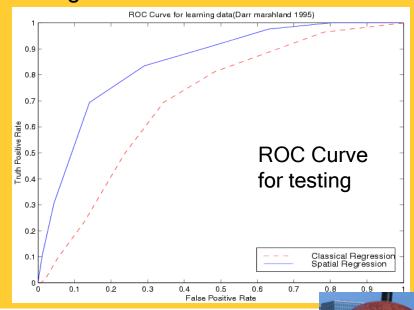
Spatial
$y = \rho W y + X \beta + \varepsilon$
$Pr(c_i \mid X, C_N) = \frac{Pr(C_i) Pr(X, C_N \mid c_i)}{Pr(X, C_N)}$



Comparing Traditional and Spatial Models

- Dataset: Bird Nest prediction
- Linear Regression
 - Lower prediction accuracy, coefficient of determination,
 - Residual error with spatial auto-correlation
- Spatial Auto-regression outperformed linear regression



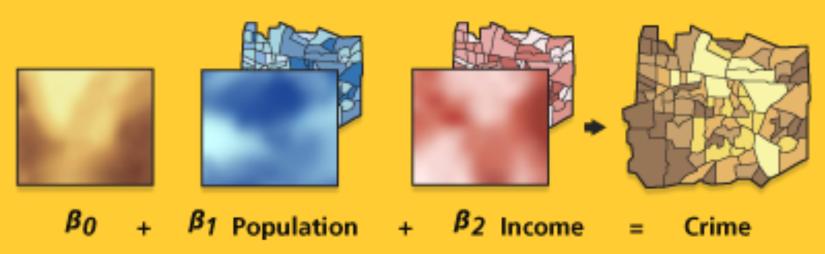


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Modeling Spatial Heterogeneity: GWR

- Geographically Weighted Regression (GWR)
 - Goal: Model spatially varying relationships
 - Example: $y = X\beta + \varepsilon$ Where β and ε are location dependent

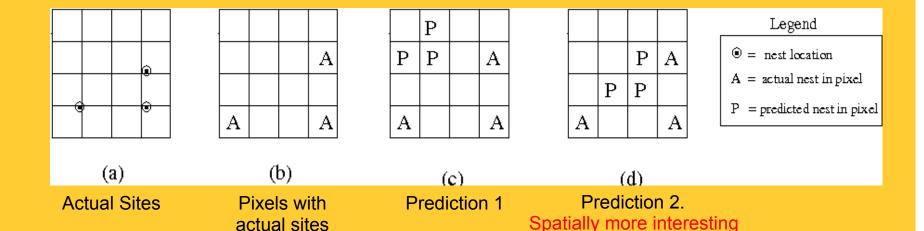


Source: resources.arcgis.com



Research Needs for Location Prediction

- Spatial Auto-Regression
 - Estimate W
 - Scaling issue $\rho Wy \text{ vs. } X\beta$
- Spatial interest measure
 - e.g., distance(actual, predicted)



than Prediction 1

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