Method of predicting reference condition biota affects the performance and interpretation of ecological indices

Charles P. Hawkins\textsuperscript{1}, Yong Cao\textsuperscript{1}, & Brett Roper\textsuperscript{2}

\textsuperscript{1}Department of Watershed Sciences
Utah State University, Logan, UT

\textsuperscript{2}Fish and Aquatic Ecology Unit
Forestry Sciences Lab, USDA Forest Service
Logan, UT 84321
Desirable Index Properties

1. Relevant – e.g., biological integrity.
2. Interpretable
3. Accurate - responds to ecosystem alteration in expected ways.
4. Precise enough to detect ecologically significant departures from reference conditions.
Ecological Assessments Depend on Two Coupled Elements

- Quantification of the biota
- Prediction of the reference state

Inference regarding condition of the biota
Previous Evaluations of Index Performance

Index Type & Prediction Method were usually confounded
What to do?

- Common Data Set
  - Classify Sites Regions / Typologies
  - Model Natural Biota-Env Relationships
- Identify and Calibrate Indices
  - Apply to Managed Sites and Simulated Data
  - Compare Performance
PIBO Project:

94 high-quality reference sites.

255 managed sites.

Targeted riffle collections.

300 count samples.
Compared Two Index Types

1. MMIs: based on 37 candidate metrics previously used in the region.

2. O/E: proportion of expected taxa
8 Index-Prediction Combinations

1. MMIs:
   A. 1 class (null – same prediction everywhere)
   B. Multiple Linear Regression of MMI A
   C. MLR on individual metrics
   D. Classification and Regression Trees (CART) on metrics
   E. Random Forests regression on metrics

2. O/E:
   A. Null - same prediction everywhere
   B. Discriminant Functions model – traditional
   C. Random Forests model
Assessing Performance

1. Precision:
   A. Standard deviation (SD) of reference site values.
   B. 10\textsuperscript{th} percentile of reference site values.

2. Accuracy
   A. $R^2$ of Random Forests regressions of post-index reference site values on environmental gradients.
   B. Response to known (simulated) alteration of 13 reference sites.

3. Responsiveness:
   A. Mean index value of managed sites.
   B. Student’s $t$ value for $t$-test between reference and managed sites.

4. Sensitivity:
   A. % of managed sites with index values < 10\textsuperscript{th} percentile of reference site values.
MMI Development

• If metrics modeled, use regression residuals as response ‘metric’.

• Quantify discrimination of reference and test sites.

• Select most discriminatory of correlated metrics.

• Standardize MMIs by dividing by reference site means (i.e., standardized reference mean = 1).
### MMIs and Natural Variation
(14 natural environmental factors)

<table>
<thead>
<tr>
<th>Index</th>
<th># metrics</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>MMI-A (null)</td>
<td>13</td>
<td>NA</td>
</tr>
<tr>
<td>MMI-B (MMI-A &amp; MLR)</td>
<td>13</td>
<td>0.15</td>
</tr>
<tr>
<td>MMI-MLR</td>
<td>12</td>
<td>0 - 0.27</td>
</tr>
<tr>
<td>MMI-CART</td>
<td>8</td>
<td>0 - 0.49</td>
</tr>
<tr>
<td>MMI-RF</td>
<td>9</td>
<td>0 - 0.16</td>
</tr>
</tbody>
</table>
Simulating Impairment

1. 13 reference quality sites with large collections (up to 2300 individuals).
2. \( Y_i = X_i[1-C(1-tv_i)] \).
   A. \( X_i = \) number of individuals of taxon \( i \) in unaltered sample.
   B. \( C = \) level of stress (9 levels, 0 to 3.2).
   C. \( tv_i = \) tolerance value of taxon \( i \) (0 to 10/6.5).
   D. \( Y_i = \) number of individuals of taxon \( i \) in stressed sample.
3. Sampled 300 individuals from each large collection following stress and estimate MMI and O/E values.
Characterizing Ecological Truth


2. Similarity of the stressed big sample assemblage to the reference one:
   A. log abundance data.
   B. Bray-Curtis index (0-1).

3. Hypotheses:
   A. O/E will track taxa loss best.
   B. MMI will track Bray-Curtis best.
## Performance Metrics

<table>
<thead>
<tr>
<th></th>
<th>Reference Samples</th>
<th>Managed Samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Index</td>
<td>SD</td>
<td>10th %</td>
</tr>
<tr>
<td>MMI-A (null)</td>
<td>0.14</td>
<td>0.76</td>
</tr>
<tr>
<td>MMI-A (MLR)</td>
<td>0.13</td>
<td>0.82</td>
</tr>
<tr>
<td>MMI-MLR</td>
<td><strong>0.11</strong></td>
<td>0.88</td>
</tr>
<tr>
<td>MMI-CART</td>
<td>0.14</td>
<td>0.80</td>
</tr>
<tr>
<td>MMI-RF</td>
<td>0.12</td>
<td>0.84</td>
</tr>
<tr>
<td>O/E-null</td>
<td>0.17</td>
<td>0.76</td>
</tr>
<tr>
<td>O/E-DFM</td>
<td>0.13</td>
<td>0.85</td>
</tr>
<tr>
<td>O/E-RF</td>
<td><strong>0.11</strong></td>
<td><strong>0.94</strong></td>
</tr>
</tbody>
</table>
Index sensitivity as a joint function of precision and responsiveness
Stress differentially affected each of the 13 reference sites.
An NMDS ordination shows decreasing similarity with increasing stress.
All MMIs exhibited a plateau effect in response to stress. O/E indices showed a linear response across the entire stress gradient.
Concluding Remarks

- **GOOD** - Modeling improves assessments and allows us to avoid ‘one-size-fits-all’ numerical criteria.

- **CAUTION** - How we develop indices affects their specific behaviors, and we need to understand the implications of those behaviors.

- **BAD** - The ‘plateau’ behavior of all MMIs was troubling. Perhaps calibrating with a stress gradient will help (sensu Leska Fore and colleagues).

- **TRADE OFFS** - Modeling greatly improves index sensitivity but it is not “easy”. What are implications for watershed groups, consulting firms, etc.?