Learning-focused decision support for management of *Phragmites* in the U.S. Fish and Wildlife Service Refuge System

*Clinton T. Moore*, *U.S. Geological Survey, University of Georgia, Athens*

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The webinar is listen only. You can listen by phone or through your computer’s speakers.

*We will begin shortly!*
Learning-focused decision support for management of *Phragmites* in the U.S. Fish and Wildlife Service National Wildlife Refuge System

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Georgia Cooperative Fish and Wildlife Research Unit
University of Georgia
Phragmites australis in the U.S. National Wildlife Refuge System

Invasion a widespread concern among northeastern (NE) and northcentral (NC) refuges

Both coastal and inland refuges affected

Millions spent annually to treat Phragmites
  • Efficacy of different treatments is highly uncertain
  • Often done without clear or consistent vision of what is to be achieved
Land managers, program administrators, & research scientists convened to discuss *Phragmites* science and management in the region.

**General conclusions**
- Lack of overarching management guidance principles, shared objectives, and capacity for learning

**Resolutions**
- Management should meet established goals for ecosystem integrity
- Choice of actions should be scientifically based, guided by objectives, and be informative about effectiveness
NWRS Needs

Conservation can’t wait
• Uncertainty is pervasive, but management must occur now

Multi-refuge approach
• How can management be conducted and learning obtained at the regional scale, while providing decision guidance at the scale of a single refuge?
Decision support for *Phragmites* management in NE & NC refuges

Work started in 2011
• Initial focus was NE, then expanded to include NC

We decomposed decision problem into 2 scales:
• *Landscape*: To which patches should actions be directed?
  • GIS tool to assign action priority, given patch spread potential and refuge’s mapped conservation priorities
• *Patch*: What action should be implemented?
  • Monitoring and optimal selection of a sequence of actions to pursue management objectives
Properties of patch-level decision support

1. Condition-based
   • An action is chosen based on current conditions

2. Objective-driven
   • A best action is chosen that is expected to drive the patch to a desired measurable condition

3. Learning-focused
   • Outcome of each action is used to learn how the system responds and how future management should evolve
Property 1: Condition-based

An action is chosen based on current conditions

- “... action”
  - One management option is chosen from a menu of alternatives
- “... current conditions”
  - Patch state: Assignment of the patch to one of 5 component dominance classes, according to monitoring data
Decision context and terms

Patch
- A distinct, pre-action assemblage of *Phragmites*
- The post-action footprint of the same

Timing of decision
- Every other year
- Decisions are *recurrent*: a patch is revisited every 2 years and considered for another action

Action
- A portfolio of individual activities arranged over a 2-year time window
- At each decision opportunity, one action is chosen from a limited menu of actions
Assessing current condition

Monitoring design

- Belt transect arranged on major axis of patch
  - Number of transects scales with size of patch
  - 0.5-m segments along transect are recorded as to which of 5 classes/types dominates
    - *Phragmites*, Desirable, Other undesirable, Bare ground, Water

Property 1: Condition-based
One of 5 component dominance classes, according to monitoring data

- “Dominance” determined by >50% of transect segments with majority cover by the component
- P = *Phragmites*
- D = Desirable species (a refuge-specific list)
- O = Other (non-*Phragmites*) undesirable species
- B = Bare ground
- M = Mixed; no single component dominating

State of the patch
Refuges were asked to identify the kinds of customary activities that could be deployed

- Emphasis on ‘customary’ to increase chance of implementation and to maximize learning across refuges and over time
- Not all customary options were available to all refuges (e.g., burning, some herbicides)
Building the actions menu

Customary activities

- Pre-chemical stress
  - A disturbance activity (cutting, mowing, water manipulation, fire, grazing) intended to stress the plant, to stimulate growth, or enhance uptake of chemical
- Broadcast glyphosate
- Broadcast imazapyr
- Prescribed fire
- Plant or seed native perennials
- No action (rest)
Property 1: Condition-based

Building the actions menu

Activities grouped into 8 portfolios (actions) thought to differentially affect *Phragmites* and desired vegetation
- Activities programmed over two years, and seasons within years

<table>
<thead>
<tr>
<th>Prescrip.</th>
<th>Step 1</th>
<th>Year 1</th>
<th>Step 2</th>
<th>Year 2</th>
<th>Step 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Treat</td>
<td>Time</td>
<td>Treat</td>
<td>Time</td>
<td>Treat</td>
</tr>
<tr>
<td>1</td>
<td>Glyph</td>
<td>Su/F</td>
<td>NA</td>
<td></td>
<td>NA</td>
</tr>
<tr>
<td>2</td>
<td>Imaz</td>
<td>Su/F</td>
<td>NA</td>
<td></td>
<td>NA</td>
</tr>
<tr>
<td>3</td>
<td>Stress*</td>
<td>Sp/Su</td>
<td>Glyph</td>
<td>Su/F</td>
<td>NA</td>
</tr>
<tr>
<td>4</td>
<td>Glyph</td>
<td>Su/F</td>
<td>Burn</td>
<td>Su/F or Sp</td>
<td>NA</td>
</tr>
<tr>
<td>5</td>
<td>Imaz</td>
<td>Su/F</td>
<td>Burn</td>
<td>Su/F or Sp</td>
<td>NA</td>
</tr>
<tr>
<td>6</td>
<td>Stress*</td>
<td>Sp/Su</td>
<td>Glyph</td>
<td>Su/F</td>
<td>Burn</td>
</tr>
<tr>
<td>7</td>
<td>P/S</td>
<td>Sp</td>
<td>NA</td>
<td></td>
<td>NA</td>
</tr>
<tr>
<td>8</td>
<td>Rest</td>
<td></td>
<td>NA</td>
<td></td>
<td>NA</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Year 1</th>
<th>Step 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Glyph Spot</td>
<td>Su/F</td>
</tr>
<tr>
<td>Imaz Spot</td>
<td>Su/F</td>
</tr>
<tr>
<td>Glyph Spot</td>
<td>Su/F</td>
</tr>
<tr>
<td>Glyph Spot</td>
<td>Su/F</td>
</tr>
<tr>
<td>Imaz Spot</td>
<td>Su/F</td>
</tr>
<tr>
<td>Glyph Spot</td>
<td>Su/F</td>
</tr>
<tr>
<td>P/S</td>
<td>Sp/F</td>
</tr>
<tr>
<td>Rest</td>
<td></td>
</tr>
</tbody>
</table>
Building the actions menu

Depending on activity constraints, full menu of 8 actions may not be available to a refuge.

<table>
<thead>
<tr>
<th>Able to apply Imazapyr?</th>
<th>Able to burn?</th>
<th>Able to pre-stress?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>Yes</td>
<td>1,2,3,4,5,6,7,8</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>1,2,3,7,8</td>
</tr>
<tr>
<td>No</td>
<td>Yes</td>
<td>1,3,4,6,7,8</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>1,3,7,8</td>
</tr>
</tbody>
</table>
Property 2: Objective-driven

A best action is chosen that is expected to drive the patch to a desired measurable condition

- “... best action”
  - A formal comparison of alternative actions to determine the one most likely to achieve objectives
- “... expected to drive”
  - An action leads to an expected outcome according to a predictive model
- “... desired measurable condition”
  - A specific condition target that has value to the manager
Managers participated in an exercise to elicit “satisfaction” levels

- Structured to focus on one aspect of issue at a time
- Region-specific preferences: Results kept separate for NE and NC managers
- Resulted in scores (scaled 0-1) about level of satisfaction in
  (a) achieving a specific patch state
  (b) cost of achieving that state
<table>
<thead>
<tr>
<th>Action</th>
<th>Starting State</th>
<th>Desirable</th>
<th>Bare</th>
<th>Mixed</th>
<th>Other</th>
<th>Phragmites</th>
</tr>
</thead>
<tbody>
<tr>
<td>R - Rest</td>
<td>Desirable</td>
<td>0.90</td>
<td>0.64</td>
<td>0.48</td>
<td>0.20</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>Bare</td>
<td>0.93</td>
<td>0.68</td>
<td>0.52</td>
<td>0.25</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>Mixed</td>
<td>0.95</td>
<td>0.71</td>
<td>0.55</td>
<td>0.28</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td>0.99</td>
<td>0.75</td>
<td>0.60</td>
<td>0.34</td>
<td>0.26</td>
</tr>
<tr>
<td></td>
<td>Phragmites</td>
<td>1.00</td>
<td>0.76</td>
<td>0.61</td>
<td>0.36</td>
<td>0.28</td>
</tr>
<tr>
<td>SGF - Stress Glyph Fire</td>
<td>Desirable</td>
<td>0.65</td>
<td>0.44</td>
<td>0.30</td>
<td>0.07</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>Bare</td>
<td>0.68</td>
<td>0.47</td>
<td>0.34</td>
<td>0.12</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>Mixed</td>
<td>0.69</td>
<td>0.49</td>
<td>0.37</td>
<td>0.16</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td>0.72</td>
<td>0.53</td>
<td>0.41</td>
<td>0.21</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>Phragmites</td>
<td>0.72</td>
<td>0.54</td>
<td>0.43</td>
<td>0.23</td>
<td>0.17</td>
</tr>
</tbody>
</table>

- Trade-off between desirability of outcome and cost to get it
- Values express *degrees of satisfaction* only; they do not express chance that a particular action achieves a particular outcome!
Property 2: Objective-driven

Model

Model tells us what response to expect given an action taken

Candidate actions

Current state

Transition probabilities

Possible outcome states

Phrag

Desirable

Bare

Mixed

Other

Phrag
Model development

We lacked data to parameterize a model
• Conducting research was not an option
• Literature only partly helpful

Transition probabilities may differ by system
• Freshwater vs brackish vs saline

Best recourse:
1. Ask experts
2. Commit to updating knowledge as decisions are made and responses tracked
Property 2: Objective-driven

Expert elicitation

Reached out to experts in NWRS and GLPC network

Respondents considered scenarios of applying specific actions to 10 identical patches
• How many of the 10 resulted in *Phragmites*-dominated, Desirable-dominated, etc.?

Respondents indicated their region and system type (freshwater, brackish, saline)
Scenario 1: Treatment "G": Glyphosate broadcast followed by glyphosate spot treatment

System:

Treatment description/structure:

<table>
<thead>
<tr>
<th>Year</th>
<th>Step</th>
<th>Treatment</th>
<th>Timing</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>Glyphosate broadcast</td>
<td>Late summer/fall</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>Glyphosate spot treatment</td>
<td>Late summer/fall</td>
</tr>
</tbody>
</table>

Scenario 1A: Today, all 10 patches are in the Phragmites dominance class. Two years after this treatment, how many patches are in class:

<table>
<thead>
<tr>
<th>Phragmites</th>
<th>Other Undesirable</th>
<th>Desirable</th>
<th>Bare Ground</th>
<th>Mixed</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>

Property 2: Objective-driven

Expert elicitation
Property 2: Objective-driven

‘Starting point’ model

Responses averaged to get provisional model
• Over time, we can update these values

Candidate actions

Current state

Desirable
Bare
Mixed
Other
Phrag

Glyph-Fire

Transition probabilities

0.55
0.02
0.14
0.06
0.23
We have the necessary ingredients:

- A current condition (patch state)
- **Value**: Desirability of outcome weighed against cost of action
- **Model**: Chance of the outcome under the action

*Dynamic programming* finds optimal actions over time to maximize accumulated value
### Optimal decision policies (examples)

<table>
<thead>
<tr>
<th>Patch State</th>
<th>R5 Freshwater</th>
<th>R5 Saline</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Phragmites</em></td>
<td>Stress + Glyphosate</td>
<td>Stress + Glyphosate + Fire</td>
</tr>
<tr>
<td>Other Undesirable</td>
<td>Stress + Glyphosate</td>
<td>Glyphosate Broadcast</td>
</tr>
<tr>
<td>Desirable</td>
<td>Rest (No Action)</td>
<td>Rest (No Action)</td>
</tr>
<tr>
<td>Bare</td>
<td>Glyphosate Broadcast</td>
<td>Glyphosate Broadcast</td>
</tr>
<tr>
<td>Mixed</td>
<td>Stress + Glyphosate</td>
<td>Imazapyr Broadcast</td>
</tr>
</tbody>
</table>

**Recommendations may change through time...**
- When probabilities of transition are revised
- If managers reassess their satisfaction values
Outcome of each action is used to learn how the system responds and how future management should evolve

• “Outcome of each action ...”
  • Monitoring is a necessary requirement for learning
  • “... to learn how the system responds”
  • Monitoring data are used to modify the provisional model
  • “... how future management should evolve”
  • A new decision policy is computed each cycle, using modified model
Property 3: Learning-focused

**Model updating**

**Example**
- Average of 20 expert responses about outcome state given action ‘X’ applied to patch in state ‘P’

<table>
<thead>
<tr>
<th>Desirable</th>
<th>Bare</th>
<th>Mixed</th>
<th>Other</th>
<th>Phrag</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.08</td>
<td>0.28</td>
<td>0.43</td>
<td>0.11</td>
<td>0.10</td>
</tr>
</tbody>
</table>

- Outcome of action ‘X’ applied to a single patch in state ‘P’:

<table>
<thead>
<tr>
<th>Desirable</th>
<th>Bare</th>
<th>Mixed</th>
<th>Other</th>
<th>Phrag</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- Updated probabilities:

<table>
<thead>
<tr>
<th>Desirable</th>
<th>Bare</th>
<th>Mixed</th>
<th>Other</th>
<th>Phrag</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.08</td>
<td>0.27</td>
<td>0.46</td>
<td>0.10</td>
<td>0.09</td>
</tr>
</tbody>
</table>
Property 3: Learning-focused

Model updating

Recurrent process, using each cycle’s data to modify model predictions from cycle before

Relative influence of expert judgment vs field observation
Property 3: Learning-focused

Translating data into decisions and learning

Web-based data entry portal combined with Access database to perform analyses

- Field managers enter data through SharePoint for data capture and value checking
- Project coordinator uses automated controls in Access database to
  - Apply updates to models
  - Compute new decision policies
Decision guidance is local, but learning takes place across organization.

Values and science both drive decision making: important to separately consider them.

Informed decision making is possible despite lack of research data.

Learning occurs even if guidance isn’t followed.

Approach does not preclude side experimentation.

Critical roles of monitoring.
Sponsors: USFWS and USGS

Collaborators

- Chicago Botanic Garden
  - Eric Lonsdorf, Vicky Hunt, Sarah Jacobi
- USFWS
  - **Region 5**: Laura Eaton-Poole, Kelly Chadbourne, David Bishop, John Gallegos, Laura Mitchell, Sue Adamowicz, Nancy Pau, Linda Ziemba, Kevin Holcombe, Nate Carle, Jan Taylor, Hal Laskowski
  - **Region 3**: Sean Blomquist, Kathy Huffman, Ron Huffman, Michelle Vander Haar
- USGS
  - Kurt Kowalski

GLPC network members who participated in our survey

Photo credits: Leslie Mehrhoff
Q & A

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THANK YOU!

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