Learning from others: Modeling the growth and spread of CWD in an emergent area

Jonathan Cook, Dr. David Williams, Dr. Sonja Christensen, Dr. William Porter

Boone and Crockett Quantitative Wildlife Center
Michigan State University
Chronic wasting disease

• Fatal, neurodegenerative disease
Chronic wasting disease

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- Reduced herd health leading to population declines
Chronic wasting disease

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• Management response has been aggressive, but limited success
Chronic wasting disease

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• Reduced herd health leading to population declines
• Deer are valuable
• Management response has been aggressive, but limited success
• Early detection, rapid response
CWD discovered in Michigan

- 58 positives across 6 counties since 2015
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CWD discovered in Michigan

- 58 positives across 6 counties since 2015
- 47 cases in western cluster, Kent and Montcalm counties
- Need to understand extent of disease in order to engage management efforts
- Prediction using a single year of data not possible
Learn from others

- Wisconsin has a long history of CWD
- Generated a lot of powerful data
- Sophisticated techniques for modeling spread and growth of CWD
Can we apply an existing modeling framework to predict the extent of CWD in western Michigan using a 1 year of data?
Spatiotemporal Effect

\[
\frac{\partial}{\partial t} u(s,t) = \left( \frac{\partial^2}{\partial s_1^2} + \frac{\partial^2}{\partial s_2^2} \right) [\mu(s)u(s,t)] + \lambda(s)u(s,t)
\]

Reference: Hefley et al. 2017

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Spread of Disease
\[ \log(\mu(s)) = \text{Intercept} + \text{Landscape Covariates} \times \alpha \]

Growth of Disease
\[ \lambda(s) = \text{Intercept} + \text{Landscape Covariates} \times \gamma \]

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**Individual Effect**
\[ y_i \sim \text{Bernoulli}(p_i) \]
\[ \Pr(\text{Infection}) = u(s, t) e^{(\text{Sex and Age} \times \beta)} \]

Reference: Hefley et al. 2017

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**Spread of Disease**

\[ \log(\mu(s)) = \text{Intercept} + \text{Landscape Covariates} * \alpha \]

**Growth of Disease**

\[ \lambda(s) = \text{Intercept} + \text{Landscape Covariates} * \gamma \]

**Spatiotemporal Effect**

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Year 1

Pr of Infection
High
Low
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Year 1

Year 5

Year 10

Pr of Infection
High
Low
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Objectives

1) Identify the most likely starting point of disease
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1) Identify the most likely starting point of disease

2) Evaluate sensitivity of predictions to landscape covariate effects
Objective 1: Identify the most likely starting point of disease
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What can the current distribution of positives tell us about where to initiate the model?

\[
\max [ L(\theta \mid x_1, \ldots, x_n ) ]
\]
where,
\[
\theta = \text{starting location}
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\[
x_n = \Pr(\text{Infection}) \text{ at locations of disease}
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Model Performance

Year 5 Post Introduction

Distance From Truth (meters)

Number of Simulated Positives

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Model Performance

- After 5 years median distance = $5414 \pm 2300$ m
After 5 years median distance = 5414 ± 2300 m
After 10 years median distance = 7606 ± 3800 m
Objective 1: Identify the most likely starting point of disease

Finding: With 47 disease detections and a single year of data, we can predict the point of introduction to $5.4 \pm 2.3$ km after 5 years, $7.6 \pm 3.8$ km after 10 years.
Objective 2: Evaluate sensitivity of predictions to landscape covariate effects
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Spread of Disease

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Reference: Hefley et al. 2017
Spread of Disease =

\[ \text{Intercept} + \]

\[ \text{River} \times \alpha_1 + \]

\[ \text{Forest} \times \alpha_2 + \]

\[ \text{Development} \times \alpha_3 \]
Spread of Disease =

Intercept +

River * $\alpha_1$

Forest * $\alpha_2$ +

Development * $\alpha_3$

Reference: Hefley et al. 2017
Spread of Disease =

\[ \text{Intercept} + \]

\[ \text{River} \times \triangle 10\% (\alpha_1) + \]

\[ \text{Forest} \times \text{Mean}(\alpha_2) + \]

\[ \text{Development} \times \text{Mean}(\alpha_3) \]

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Spread of Disease =

\[ \text{Intercept} + \]
\[ \text{River} \times \Delta 10\% (\alpha_1) + \]
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67 Different Combinations of Values

Reference: Hefley et al. 2017

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<table>
<thead>
<tr>
<th>Year</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Uncertainty (Pr &gt;.01)</th>
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Cook | Modeling Emergent Disease
Minimum

Year 1

Minimum

Maximal

Year 5

Maximum

Uncertainty (Pr > .01)

Year 10

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Minimum

Year 1

Pr of Infection
Value
High : 0.16
Low : 0.01

Maximum

Year 5

Year 10

Uncertainty (Pr >.01)

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Minimum

Maximum

Uncertainty (Pr > .01)

Year 1

Year 5

Year 10

Cook | Modeling Emergent Disease
Minimum

Year 1

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Year 5

Uncertainty (Pr > .01)

Year 10

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Minimum

Year 1

Maximum

Year 5

Uncertainty (Pr > .01)

Year 10

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Sensitivity to Covariate Effects
Sensitivity to Covariate Effects
Sensitivity to Covariate Effects

- Model results most sensitive to changes in effect size for spread of disease in forested landscapes
Objective 2: Evaluate sensitivity of predictions to landscape covariate effects

**Finding 1:** The predicted spatial extent of disease is robust to changes in effect sizes.

**Finding 2:** Predicted $Pr(\text{Infection})$ most sensitive to the spread of disease in forested habitat.
Conclusions

Can we apply an existing modeling framework to predict the extent of CWD in western Michigan using 1 year of data?
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• Used to confirm extent of proposed management zone in MI.
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- Findings support a cautious application of WI CWD model to MI.

- Used to confirm extent of proposed management zone in MI.

- Disease research is adaptive: Additional data, updated predictions.
Thank You!

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