# Assessing the Risk of Cucurbit Downy Mildew Outbreak in the Eastern United States

P.S. Ojiambo

Department of Entomology & Plant Pathology
North Carolina State University

NC STATE UNIVERSITY

College of Agriculture and Life Sciences

Cucurbit Downy Mildew (*Pseudoperonospora cubensis*)

- ## Global distribution
  - World-wide; where cucurbits are found
  - Warm and humid weather

- ## Status of CDM in the U.S.
  - Mainly in eastern region
  - Resurgence on cucumber since 2004
  - California since 2007

- ## Control options
  - No resistant cultivars
  - Reliance on fungicides
  - Prediction and forecasting important

Cucumber

Squash

Sporangium

Cantaloupe
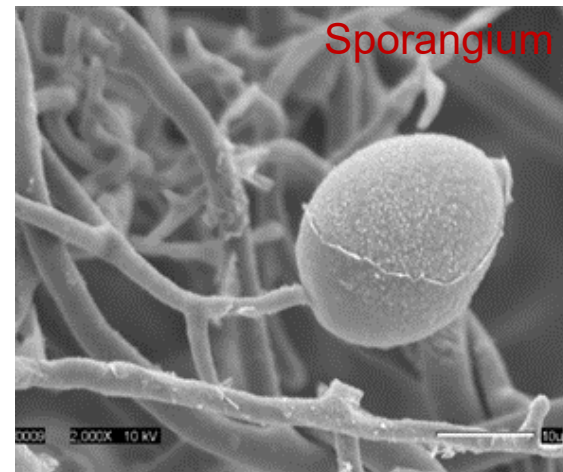
Seasonal Spread of Cucurbit Downy Mildew in the Eastern U.S.

- Disease exhibits annual extinction and recolonization cycles

- Determine risk of disease outbreak at landscape level:
  1. Bayesian modeling of time to disease outbreak
  2. Joint modeling of time to disease outbreak and epidemic duration

NC STATE UNIVERSITY
College of Agriculture and Life Sciences

1. Bayesian Modeling CDM Risk in eastern US

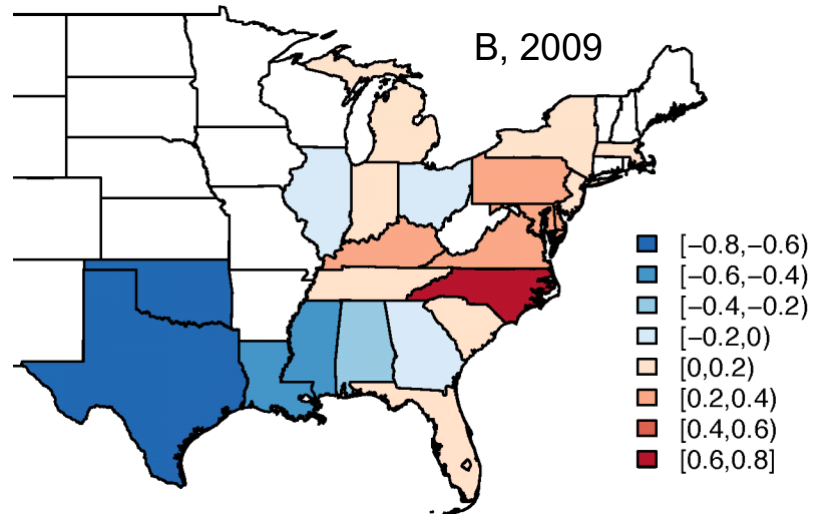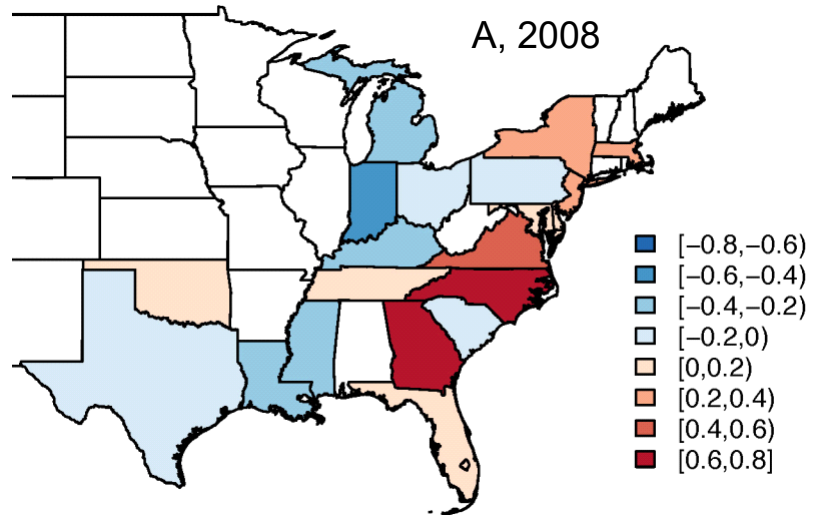- ## Hierarchical Bayesian model
  - Combines survival, spatial and Bayesian approaches

$$\begin{cases} \text{Data model: } \rho_{ij}^{\rho-1} \exp(\boldsymbol{\beta}^T \cdot \boldsymbol{X}_{ij} + \mathbf{W}_i) \\ \text{Process model: } \mathbf{W}|\lambda \sim \text{CAR}(\lambda); \ \lambda = 1/\sigma^2 \\ \text{Parameter model: } \beta \to \text{flat prior } (0 \ to \ \infty) \\ \qquad\qquad\qquad\quad \rho, \lambda \to \text{gamma prior } (1, 10^4) \end{cases}$$

Year	Model	DIC	ΔDIC
2008	No frailty	2,537	23
	Unstructured	2,520	7
	Structured	2,513	--
2009	No frailty	2,428	18
	Unstructured	2,417	7
	Structured	2,410	--

- ## Models implemented in WinBUGS using MCMC methods
  - Data (time to disease outbreak) from disease monitoring network
  - Standard survival analysis model (no random effects)
  - Frailty model: structured or unstructured random effects

- ## Best model selection
  - DIC and ΔDIC
  - Frailty model with structured random effects

Ojiambo and Kang (2013). Phytopathology 103:216-227

Risk of Disease Outbreak: Hierarchical Bayesian Frailty Model

A, 2008

[−0.8,−0.6)
[−0.6,−0.4)
[−0.4,−0.2)
[−0.2,0)
[0,0.2)
[0.2,0.4)
[0.4,0.6)
[0.6,0.8]

B, 2009

[−0.8,−0.6)
[−0.6,−0.4)
[−0.4,−0.2)
[−0.2,0)
[0,0.2)
[0.2,0.4)
[0.4,0.6)
[0.6,0.8]

- High risk of disease in North Carolina, Virginia

- Cluster of low disease risk around the Great Lakes in 2008 and 2009

- Cluster of low disease risk in southern states; TX, MS, LA, AL

- Disease control: states in the mid-Atlantic region

2. Joint Modeling of Time to Disease Outbreak and Epidemic Duration

- **Rationale:** Time to disease outbreak is associated with epidemic duration; Goal: understand the nature of association of these two components on disease risk

- Joint Bayesian hierarchical model with spatial random effects
  - Parametric Weibull model for time to disease outbreak: $h(t_{ji}|x_{1ij}) = \rho t_{ij}^{\rho-1} \exp(x_{1ij}'\beta_1 + \phi_{1i})$
  - Zero-truncated Poisson distribution for epidemic duration:

$$p(y_{ij}|\lambda_{ij}) = \begin{cases} 0, & \text{if } y_{ij} = 0 \\ \dfrac{\lambda_{ij}^{y_{ij}} \exp(-\lambda_{ij})}{y_{ij}!(1-\exp(-\lambda_{ij}))}, & \text{if } y_{ij} = 1, 2, \ldots \end{cases}$$

  - Process model: 4 competing model; Spatial: GMCAR and UniCAR; Non-spatial: IndNormal and MvNorm)
  - Parameter model: prior distributions for all parameters specified
  - Best model identified using: DIC, LOOIC

NC STATE UNIVERSITY
College of Agriculture and Life Sciences

Model Performance and Risk Assessment

- Model performance
   - GMCAR had the smallest DIC and LOOIC
    - GMCAR selected as process model

	GMCAR	UniCAR	MvNorm	IndNorm
p_D	33.3	35.6	38.9	38.0
DIC	3677	3678	3678	3679
LOOIC	3756	3760	3762	3766

- Risk of CDM (2009)
    - High risk in states along the mid-Atlantic region (NY, PA, NC)
    - High risk along the great lakes region (MI, OH)
    - Low risk in southwest US (TX, MS, LA)

- Implications for monitoring and control
    - Immediate control in high risk states
    - Disease monitoring should concentrate in high risk area
    - Use network analysis to identify high risk locations

NC STATE UNIVERSITY
College of Agriculture and Life Sciences
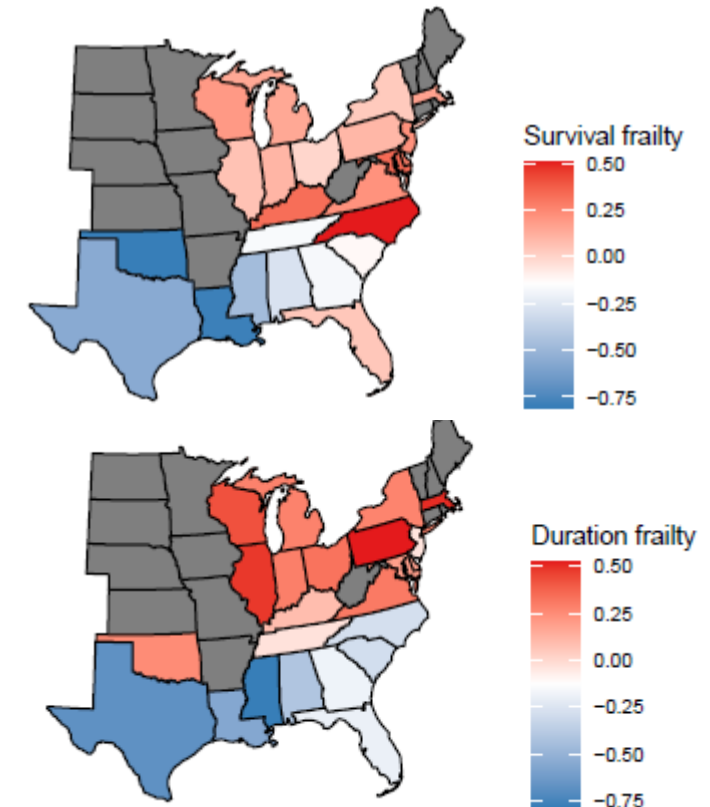
Acknowledgements

- Emily Kang (Univ. of Cincinnati)

- Jieyan Zhang (Graduate student, Univ. of Cincinnati)

- CDM ipmPIPE team
  - Wendy Britton
  - Collaborating institutions

- Funding sources
  - Univ. of Cincinnati Res Council
  - Charles Taft Res Center
  - USDA PIPE Program