The Butterfly Effect: Do Farms Do Harm?

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Michigan State University
HERE Workshop @ University of Illinois
Sept. 28th, 2019 | Champaign, IL

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Kellogg Biological Station
Long-term Ecological Research

Michigan State University
AgBioResearch

Butterfly Populations On the Decline

- Butterflies are a highly-valued group of insects
  - Pollination, aesthetic, cultural value
  - US households' existence value monarchs at **$4.78-$6.65 bill.** per 2012 contingent valuation survey (Diffendorfer et al., 2014)
- Butterfly populations in decline, globally and domestically (Sánchez-Bayo & Wyckhuys, 2019; Wepprich et al., 2019)
  - 53% of species in decline; 1.8% more species in decline annually
  - Ohio populations reduced by 1/3rd in last two decades
- **Pesticide exposure** potentially a driver of butterfly decline (Agrawal & Inamine, 2018; Thomas, 2016)

Sparse Evidence of Pesticide-Pop. Connection

Specific evidence for negative pesticide impacts on butterfly populations for some groups:

Neonicotinoid insecticides

Forister et al., 2016

- Sacramento Valley
- Many Species
- Data from 3 counties since mid-1990s

Gilburn et al., 2015

- United Kingdom
- Many Species
- Data from 1984-2012

Glyphosate herbicides

Saunders et al., 2018

- Illinois
- Monarchs only
- Data from 1994-2013

But past studies have only examined <u>single</u> pesticide groups at a time

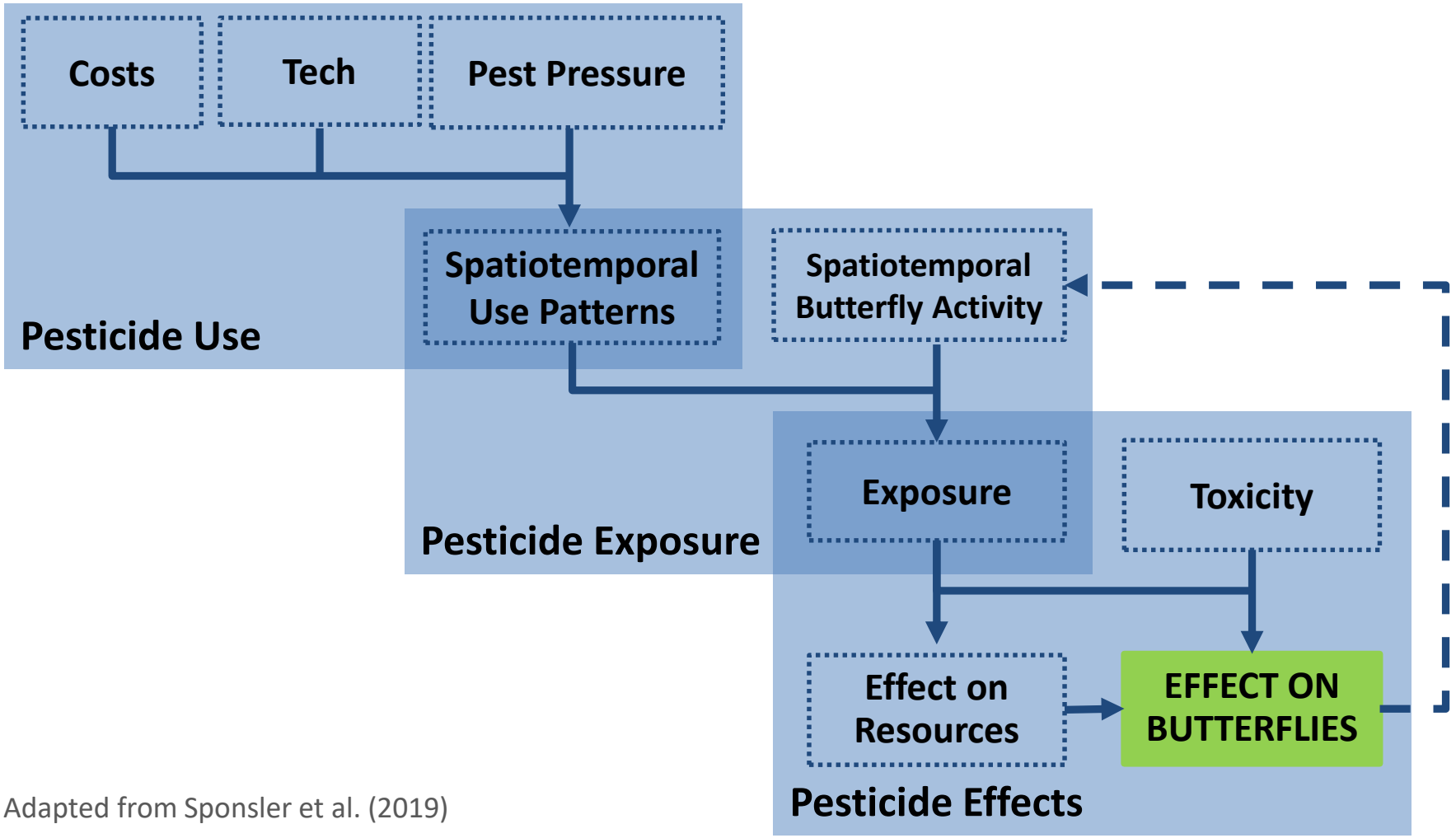
Simultaneously Examining Multiple Pesticides

RQ: How have changes in pesticide use affected Midwestern butterfly abundance?

Contributions

- Use knowledge of substitution effects between pesticides to better inform population models
- Address concerns of omitted variable bias in previous work
- Develop models that can better inform potential policy impacts
  → Substitution under taxes/subsidies

Butterfly-Pesticide System



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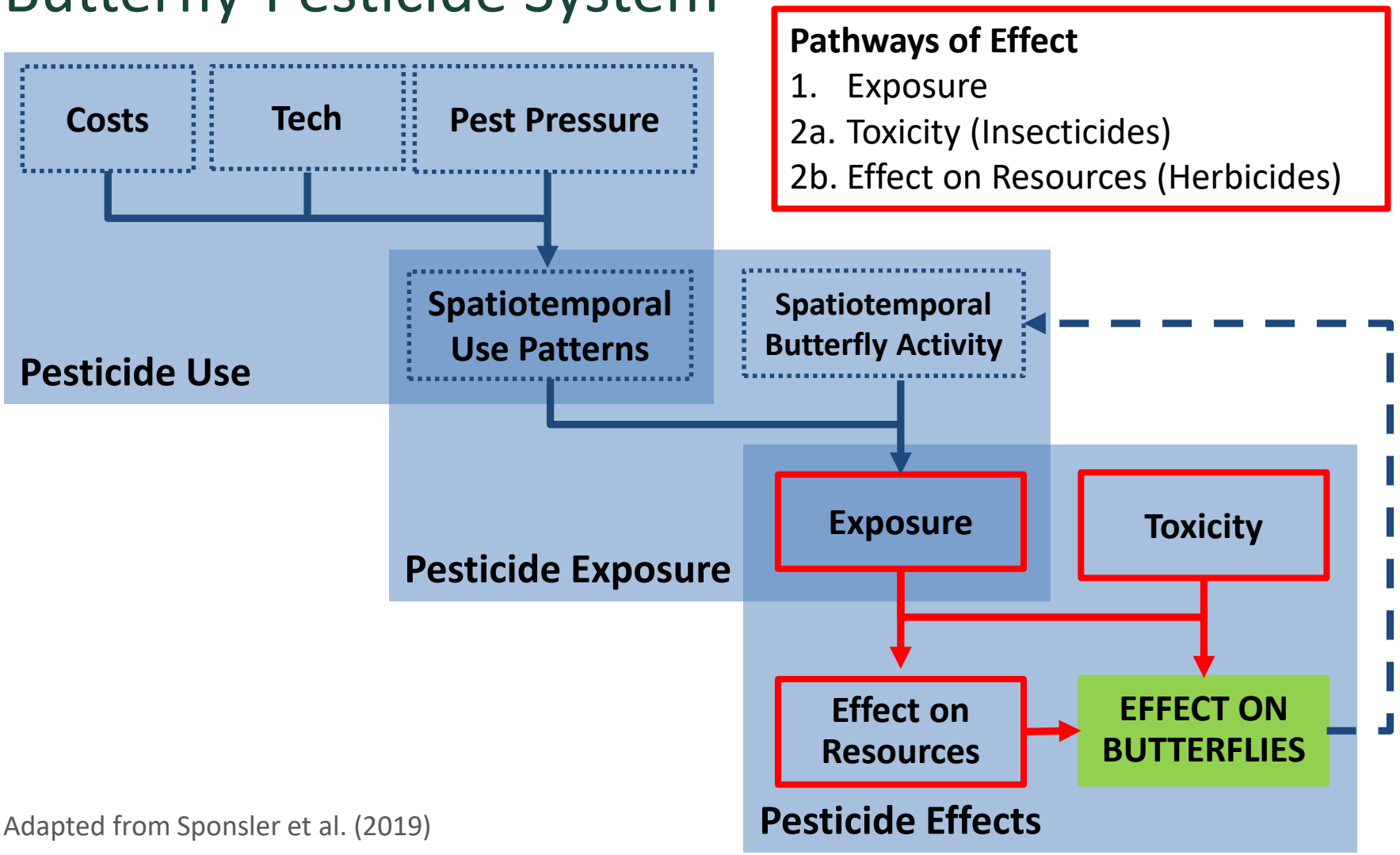

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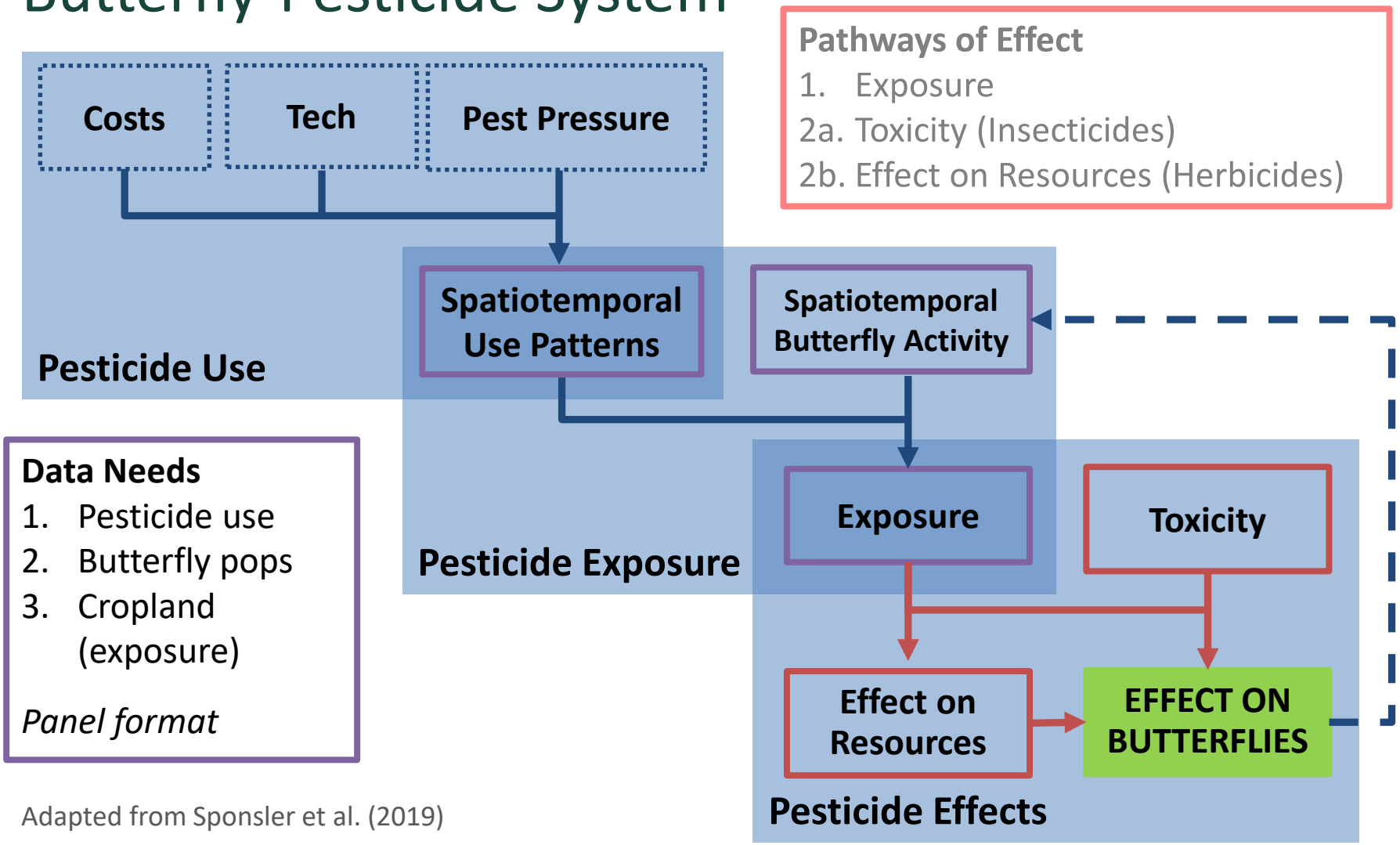

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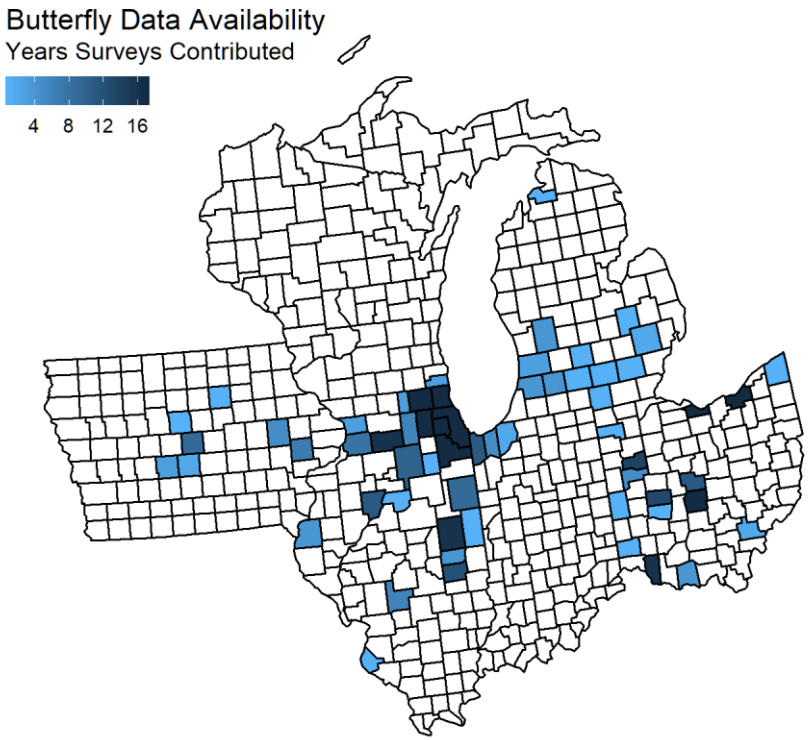
Butterfly Population Data

North American Butterfly Monitoring Network – Butterfly Population Data

- Transact surveys conducted by citizen scientist volunteers
- **56 counties** in Iowa, Illinois, Indiana, Michigan, Ohio, and Wisconsin
- **23 species** including **Monarch**
- Aggregated across summer months to **county x year x species** counts



Pesticide Use Data

Kynetec AgroTrak®

- Field-level application data for **corn** and **soybean** via extensive farmer phone surveys
- Includes sprayed, seed-treated pesticides, and seed traits for every sampled field
- Measured by **acre-treatments**: number of applications per field
  - → Preferred over volume measures because of large differences in application rates
- Aggregated to **county x year x class**

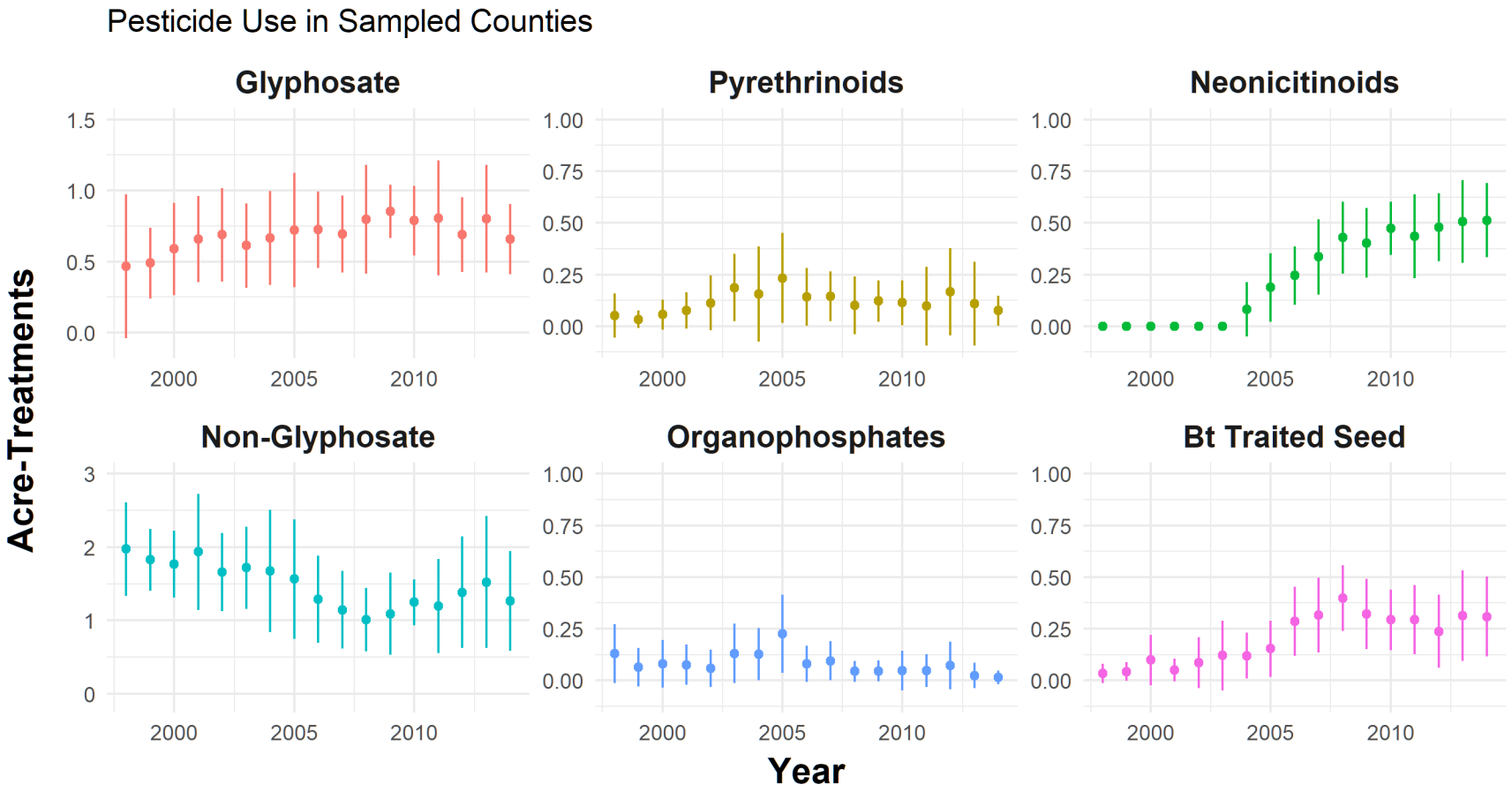
Herbicides
- Glyphosate
- Non-Glyphosate

Insecticides

Sprayed
- Pyrethroids
- Organophosphates

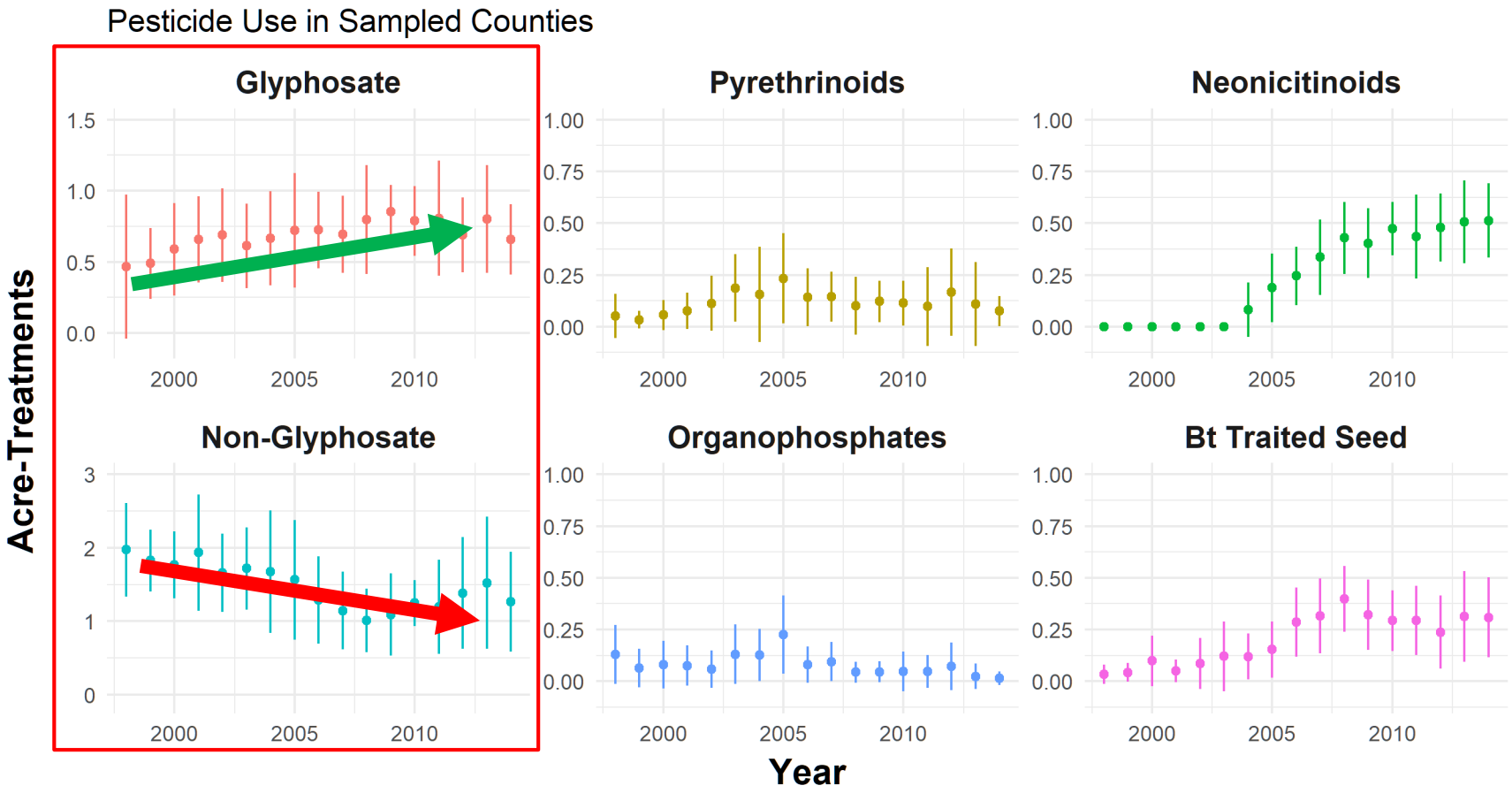
Systemic
- Neonicotinoids
- BT Seed

Contemporaneous Changes in Pesticide Use



Vertical lines represent standard deviations.

Contemporaneous Changes in Pesticide Use



Glyphosate substitutes for **Non-Glyphosate**

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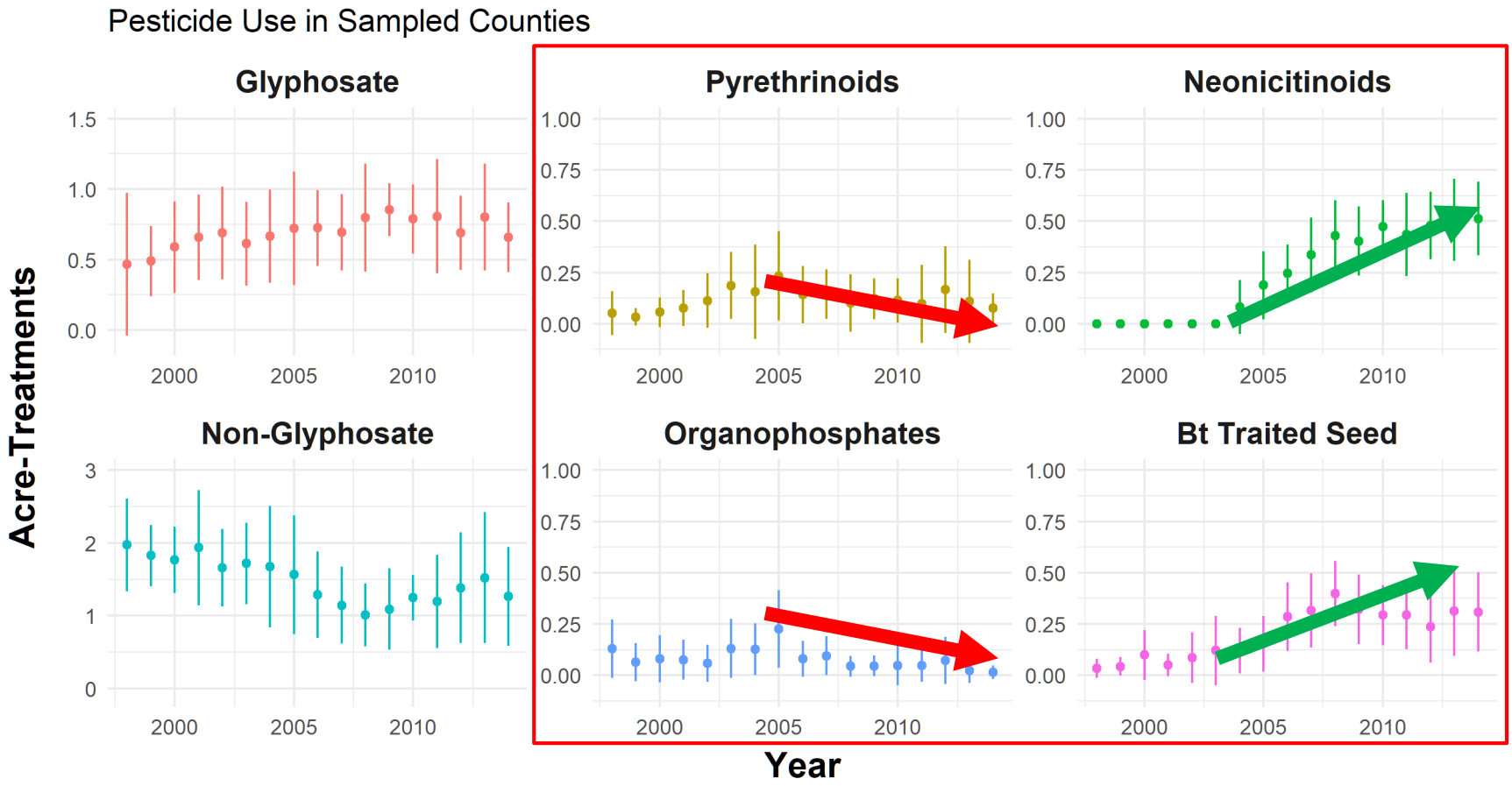

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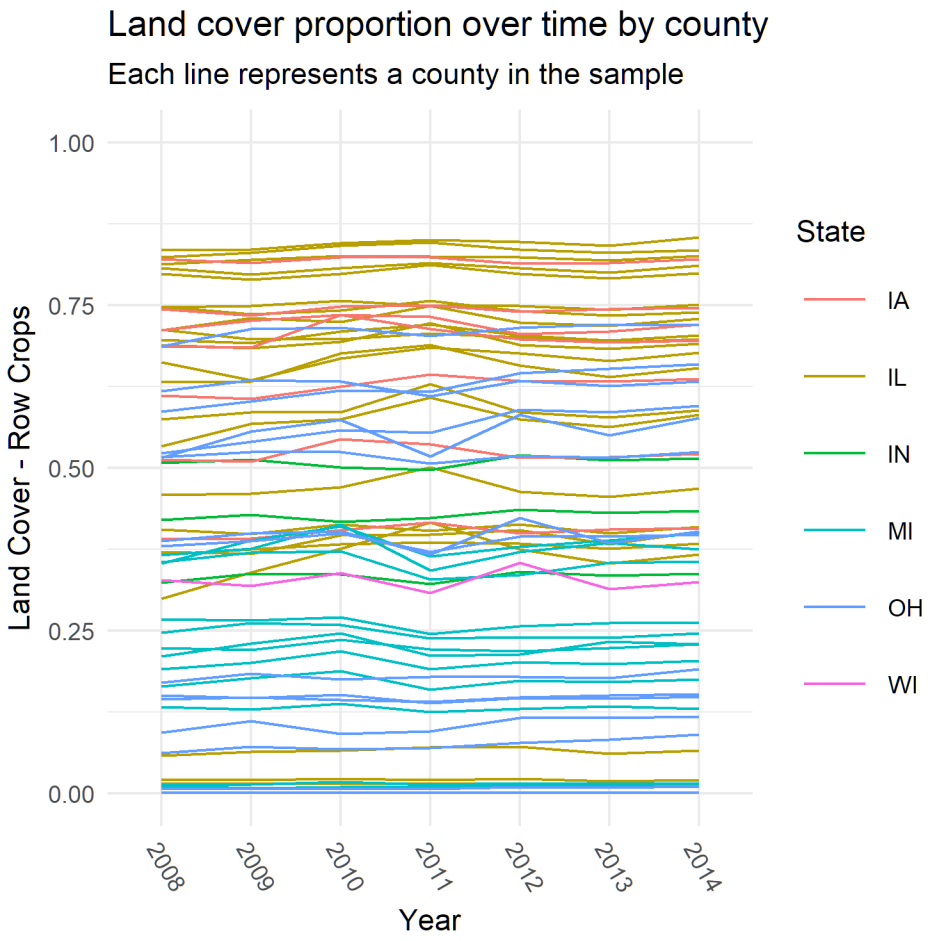
Systemic Insecticides substitute for **Sprayed Insecticides**

Land Use Data

Cropland Data Layer

- Land cover at **30m resolution** across region based on satellite data
- Available consistently **since 2008**
- Calculate *share* of land under **corn** and **soybeans** for each county
- Very little interannual variation within county
  - → Average over available years to create static measure and apply to county-years where CDL is unavailable

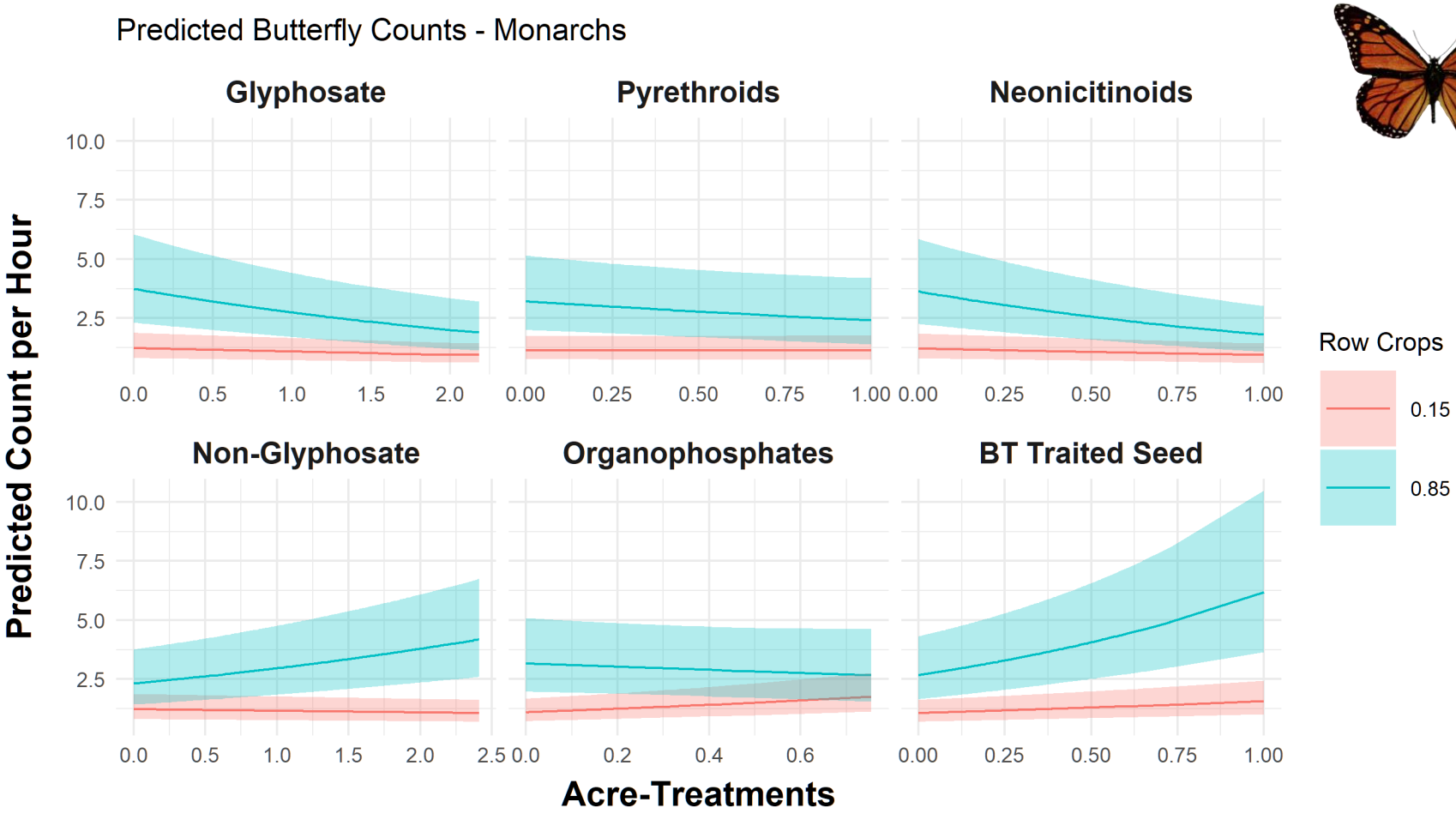


Modeling Counts as a Function of Pesticides

Poisson model with crossed random intercepts

- Dependent variable: # of **monarchs** observed
  - Offset for sampling effort (minutes) so interpreted as rate
- Covariates include…
  1. Pesticide measures
  2. Row crop land cover
  3. Pesticide measures **X** row crop land cover
  4. Climate variables (early, mid, and late season)
     - Temperature (butterfly growing degree days)
     - Precipitation (mm)
- Random intercepts for **county** and **year**
- **370 county-year** observations

Preliminary Results Suggest Possible Impacts



Shaded regions indicate 95% c.i.'s based on sandwich s.e.'s.

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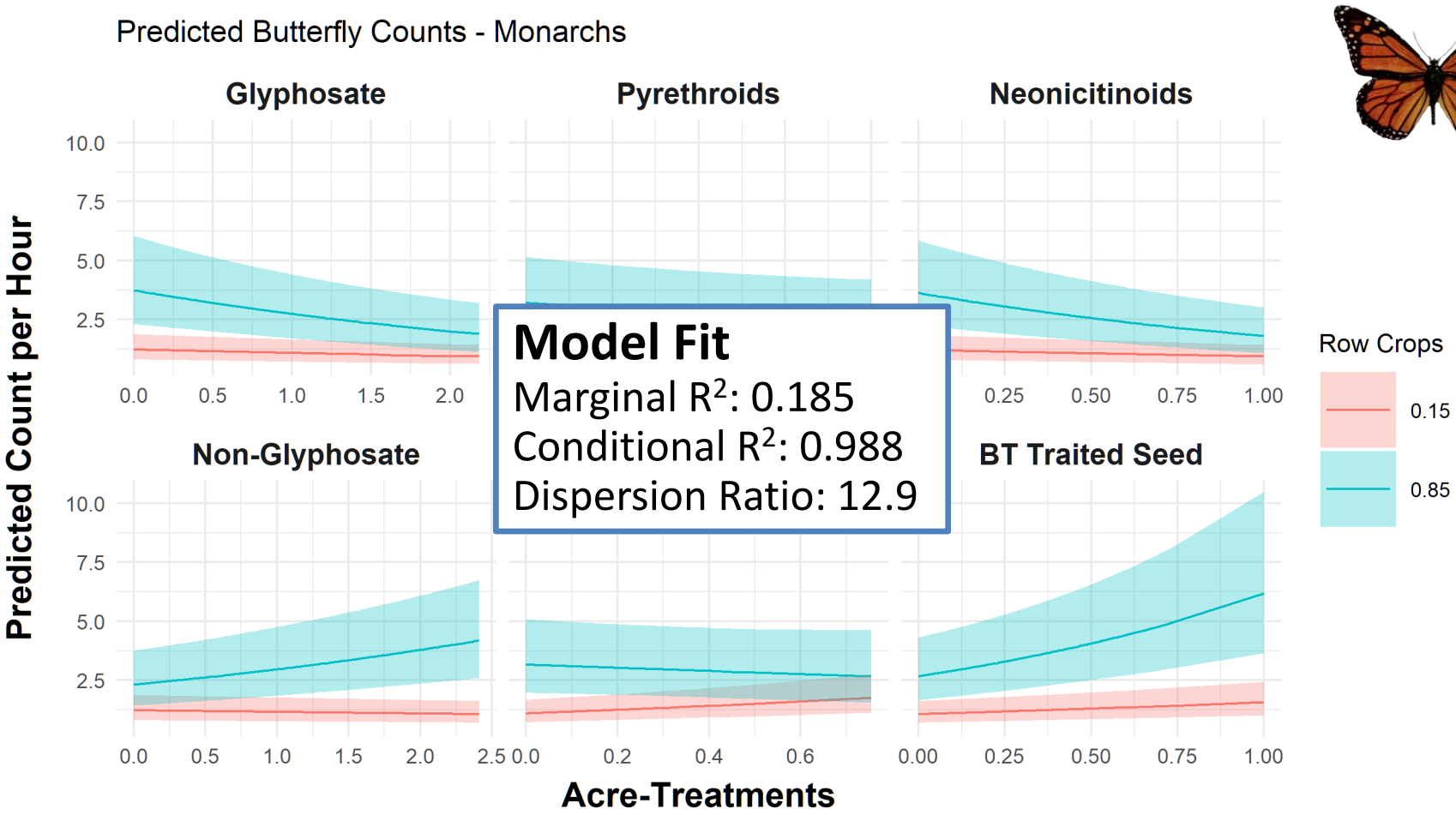

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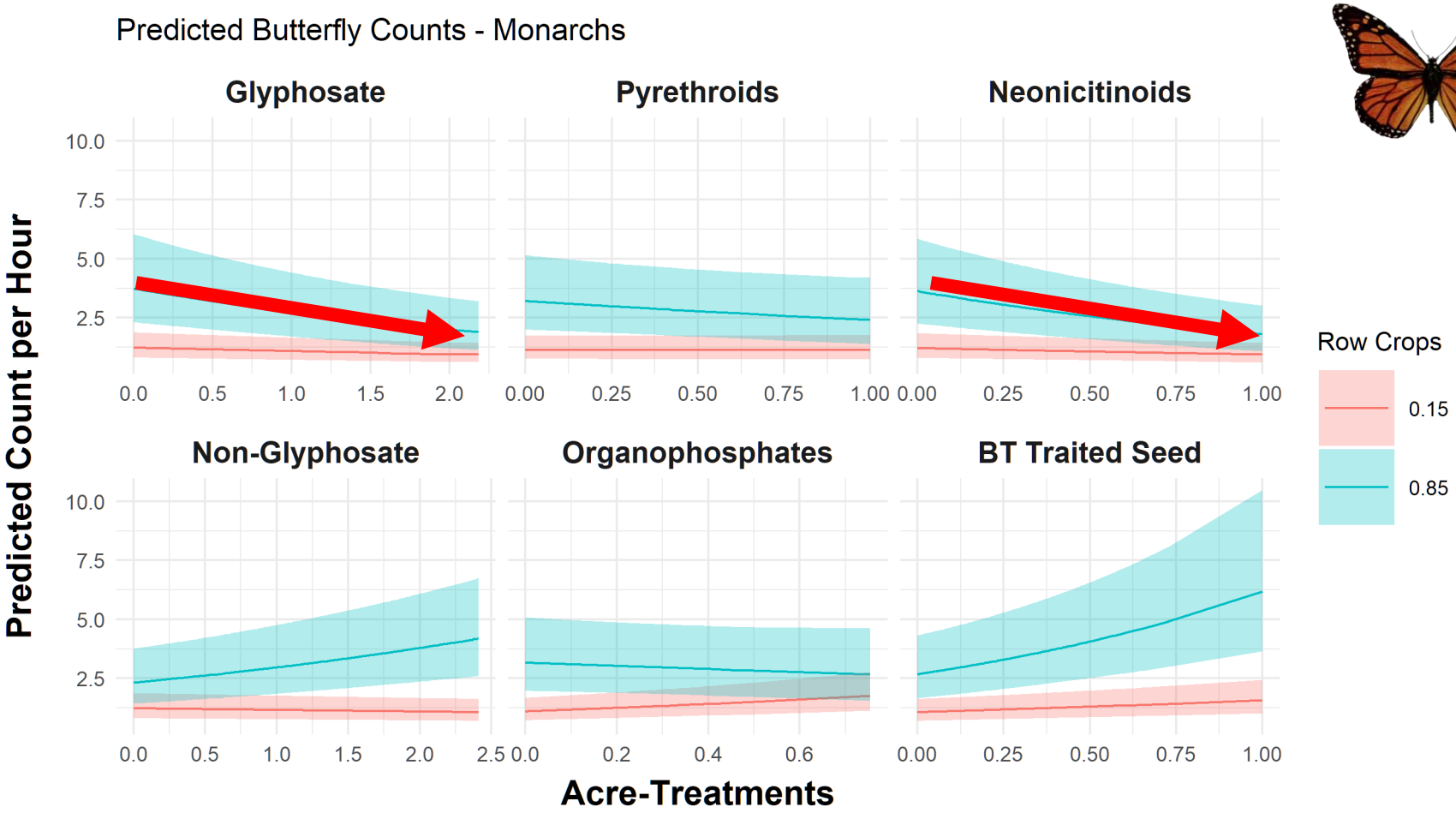

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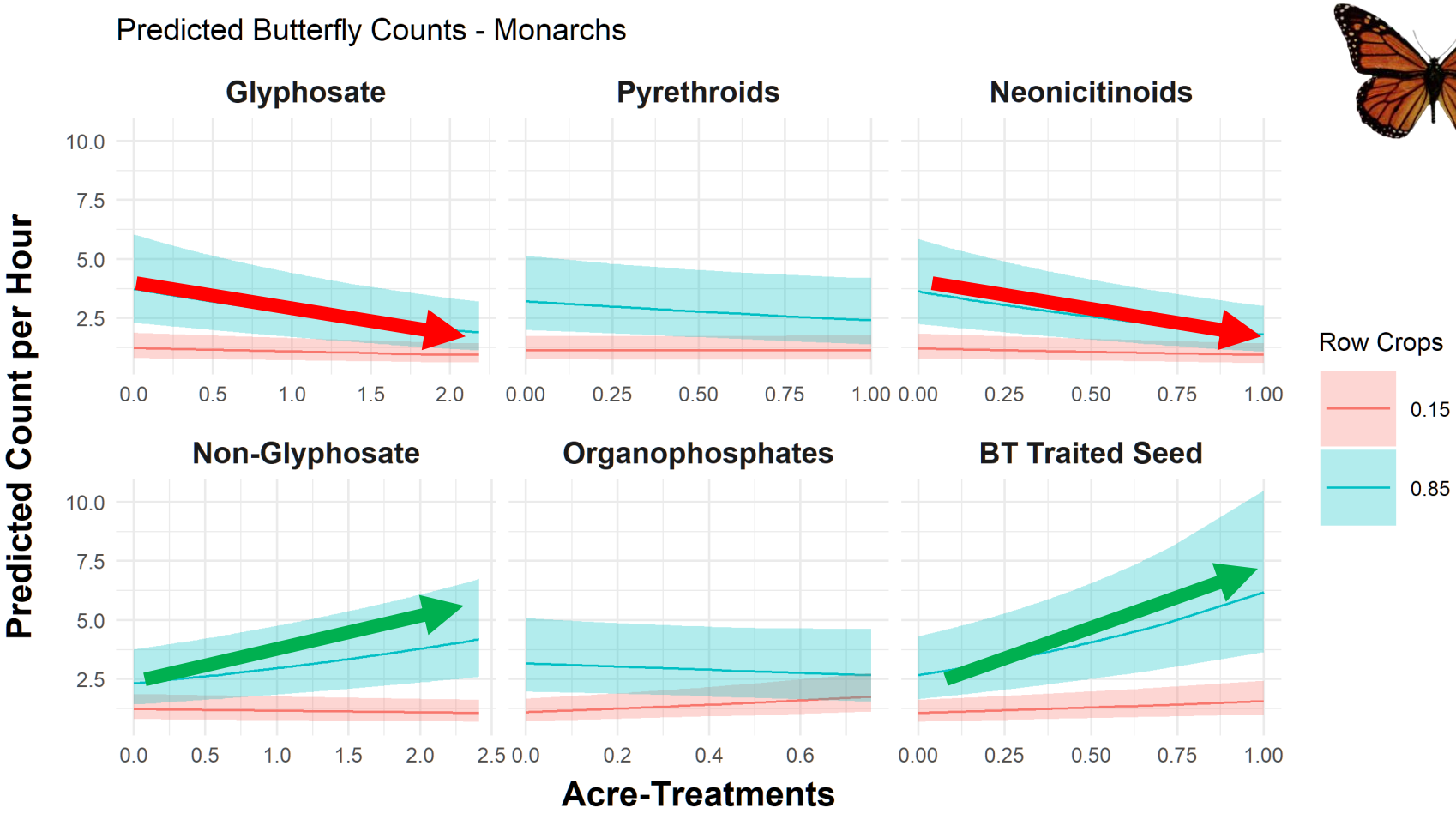

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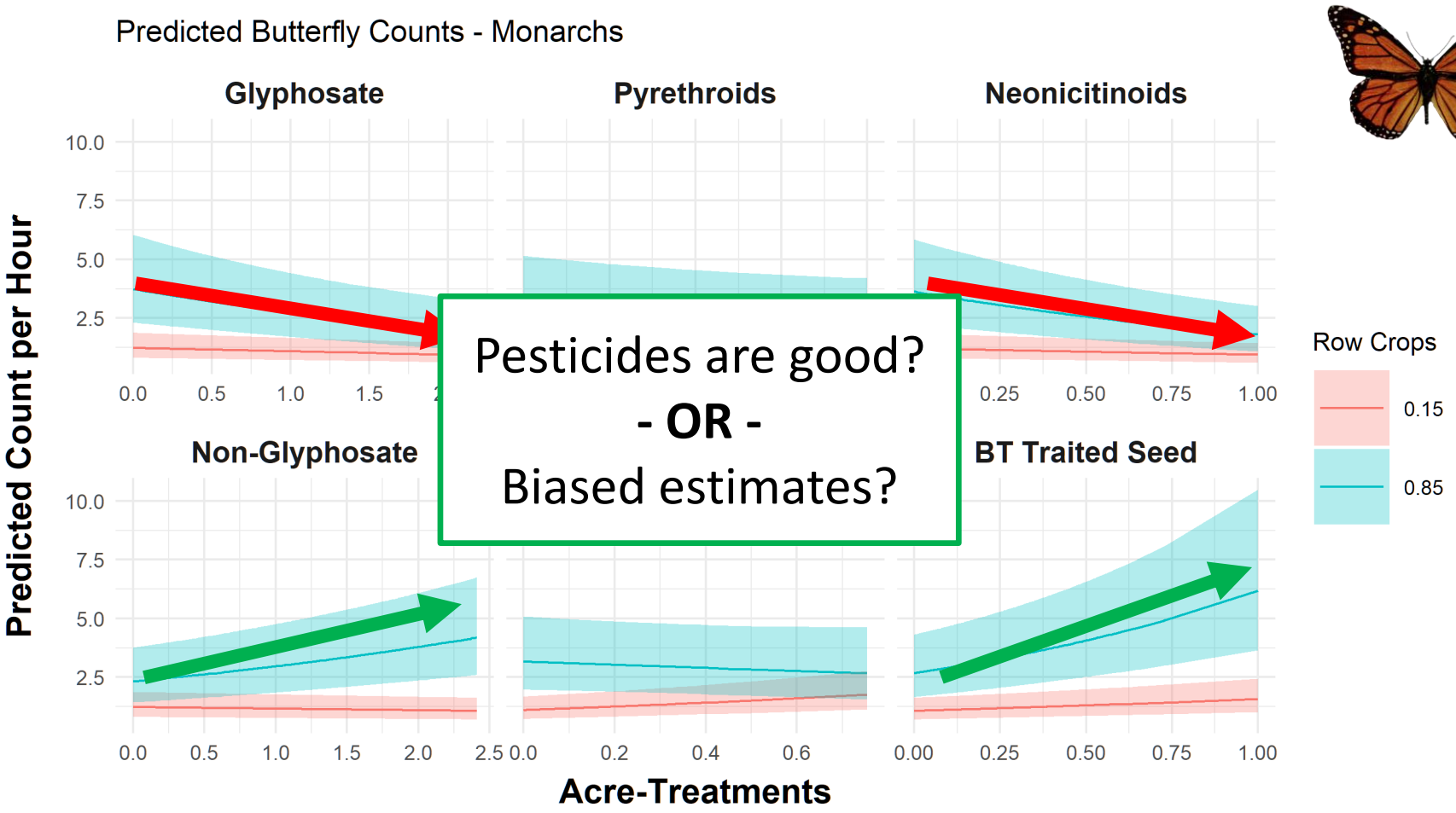

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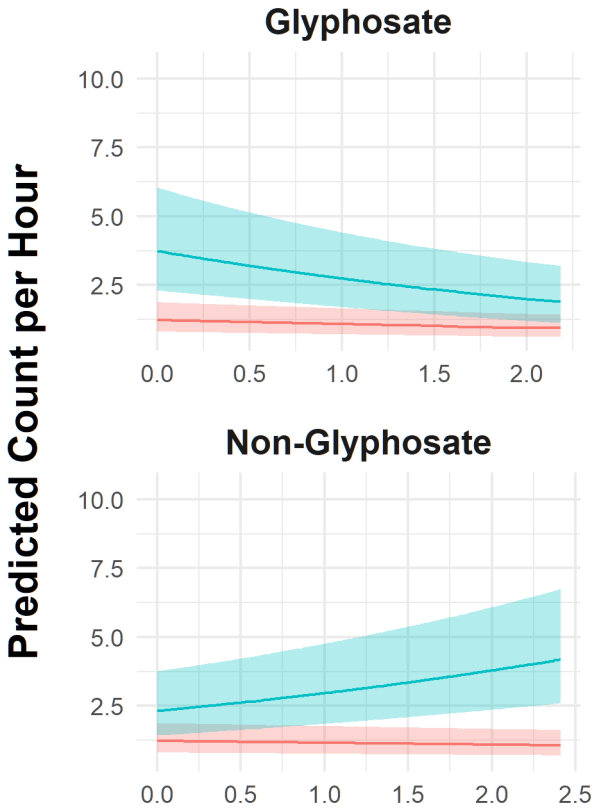
Possible Interpretation of Biased Estimates?

Using substitution patterns observed in the literature…



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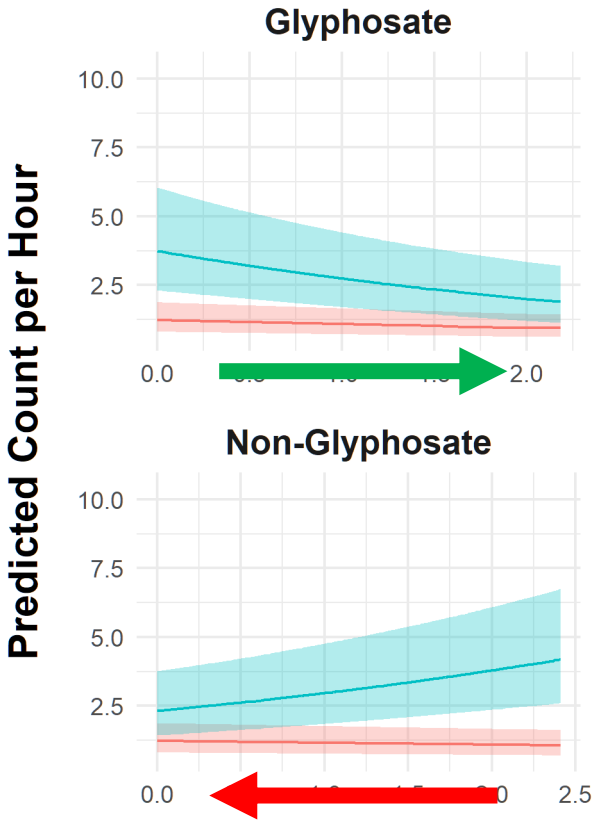

- Between 1998-2011 GT seed adopters used on average…
  - ↑ 0.9 lbs/ac **more glyphosate**
  - ↓ 0.6 lbs/ac **less non-glyphosate**

(Perry et al., 2016)

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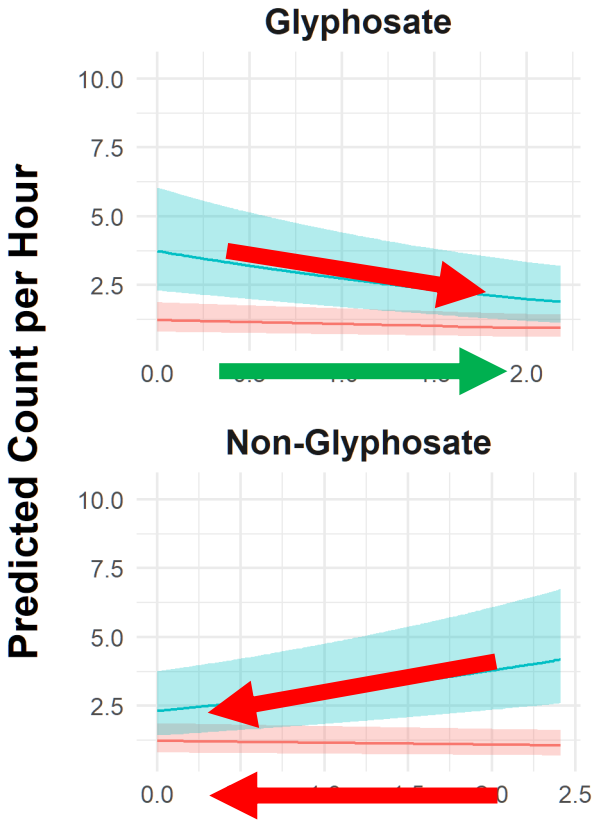

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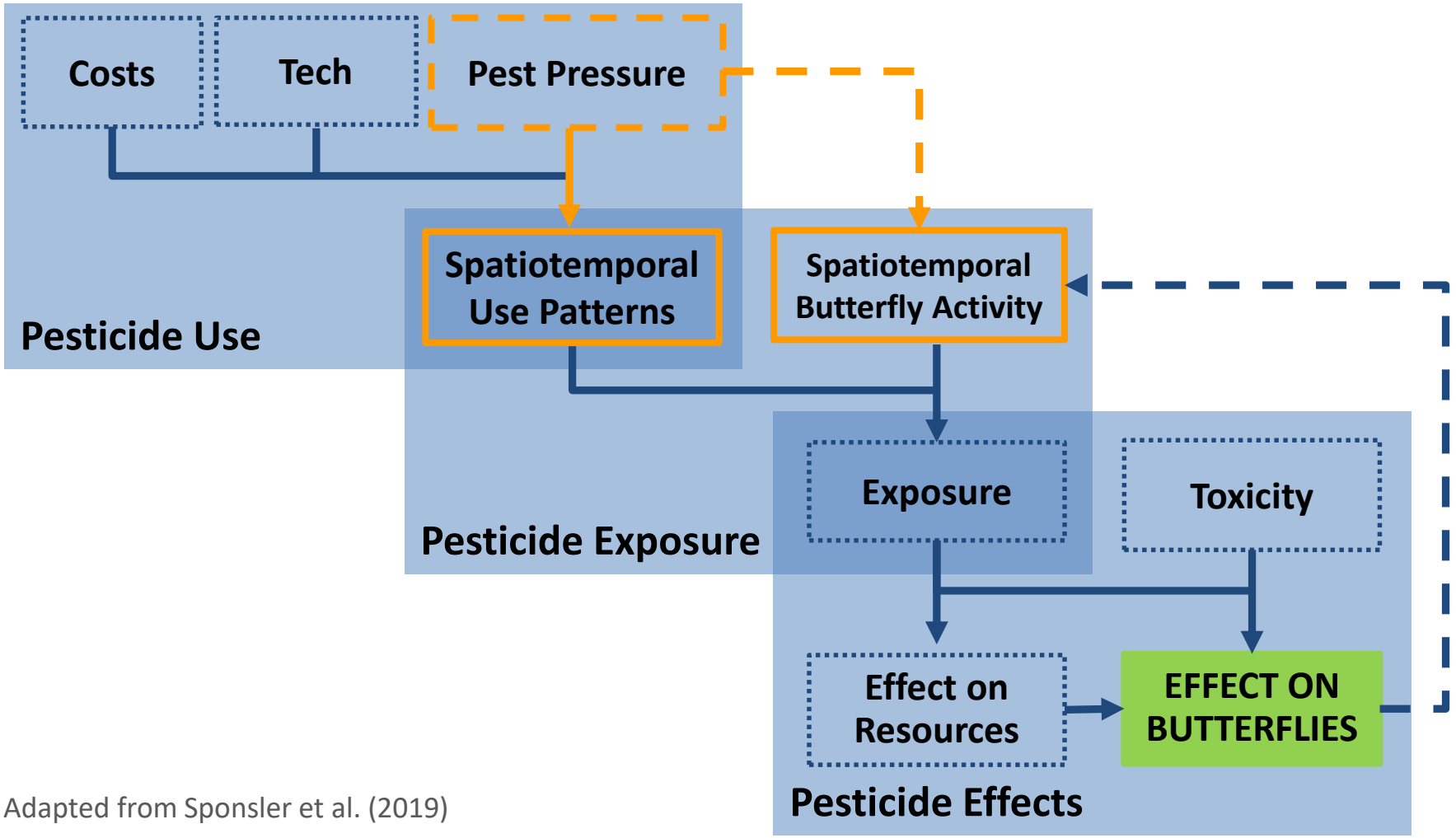
- Net effect is **negative**
- Similar argument for insecticides
- Consistent with upward bias of all pesticide estimates

Next Steps: Possible Source of Endogeneity?



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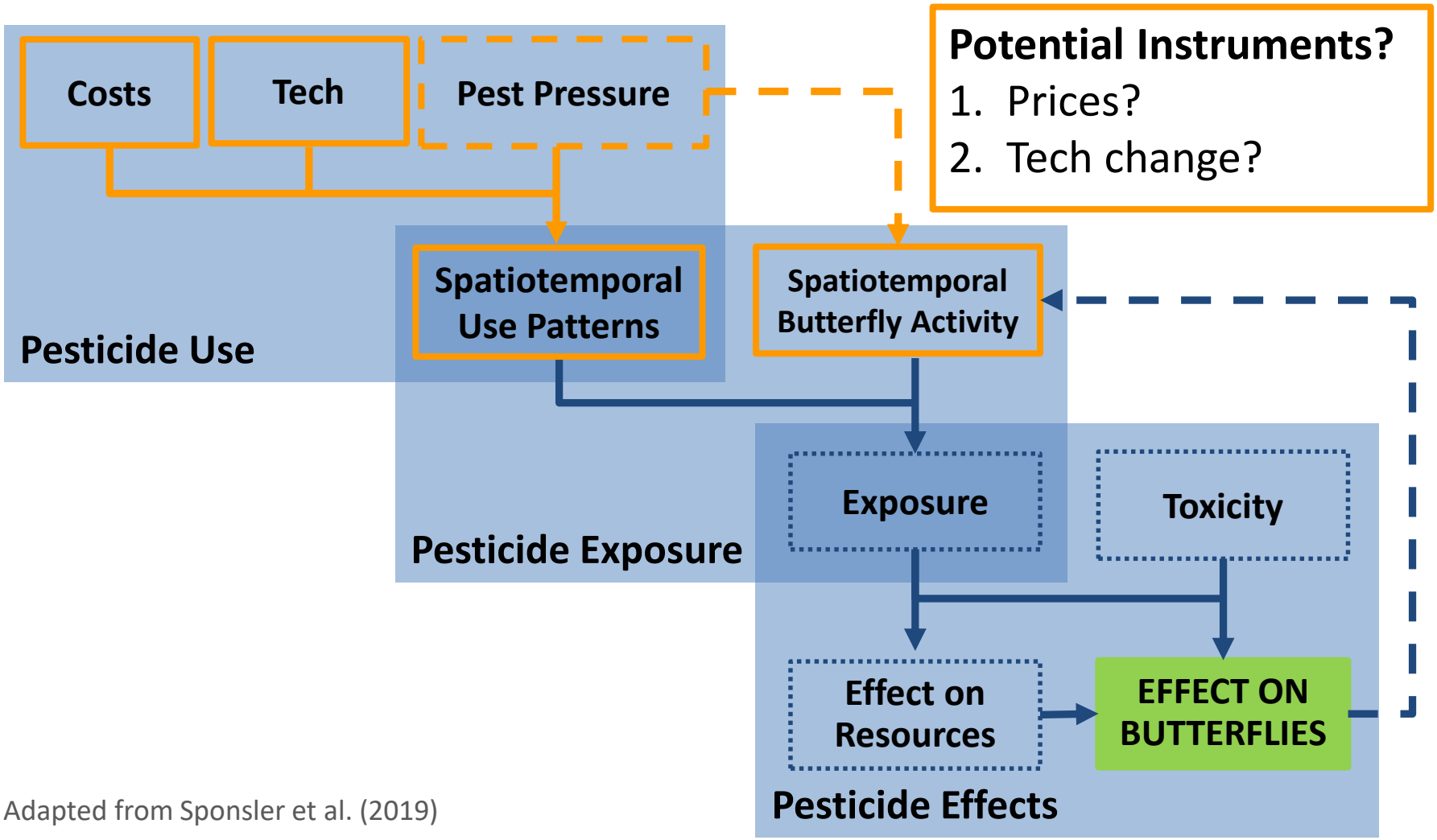

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Next Steps: Model Site-Level Data

- Avoid information loss from aggregation for more precise estimation
- Localized cropland measures possible for more accurate accounting for exposure

Ohio Transect Locations

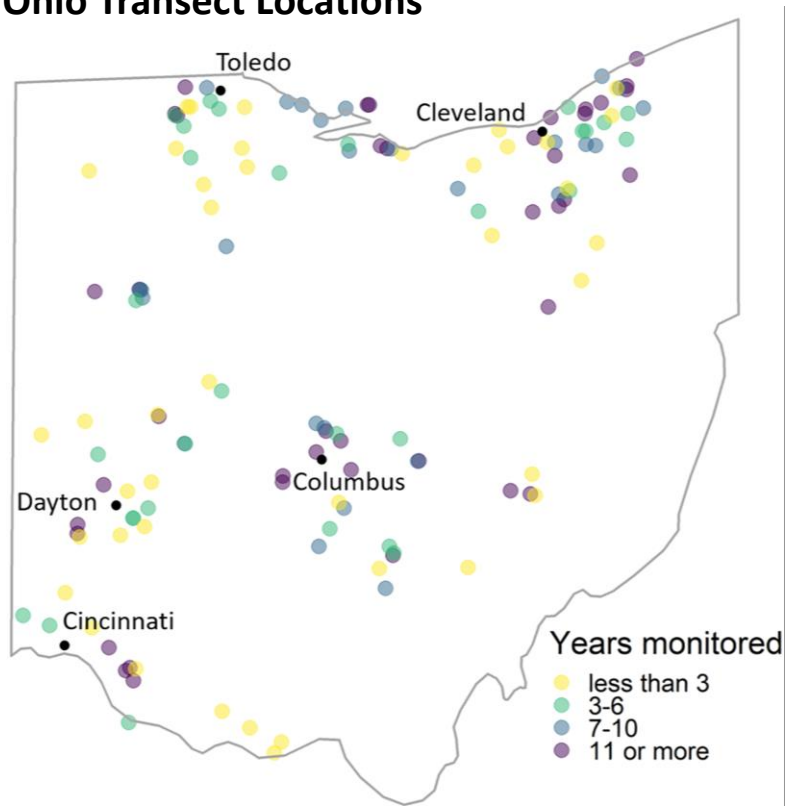

Figure from Wepprich et al. (2019)

Next Steps: And More…

- Adapt to models more robust to overdispersion
  - Negative binomial
  - Observation-level random effects
  - Quasi-poisson
- Model more species
  - Do effects differ by functional traits?
  - Migratory vs. non-migratory
  - Generalist vs. specialist
  - Number of generations per season

Comments? Suggestions? Questions?

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