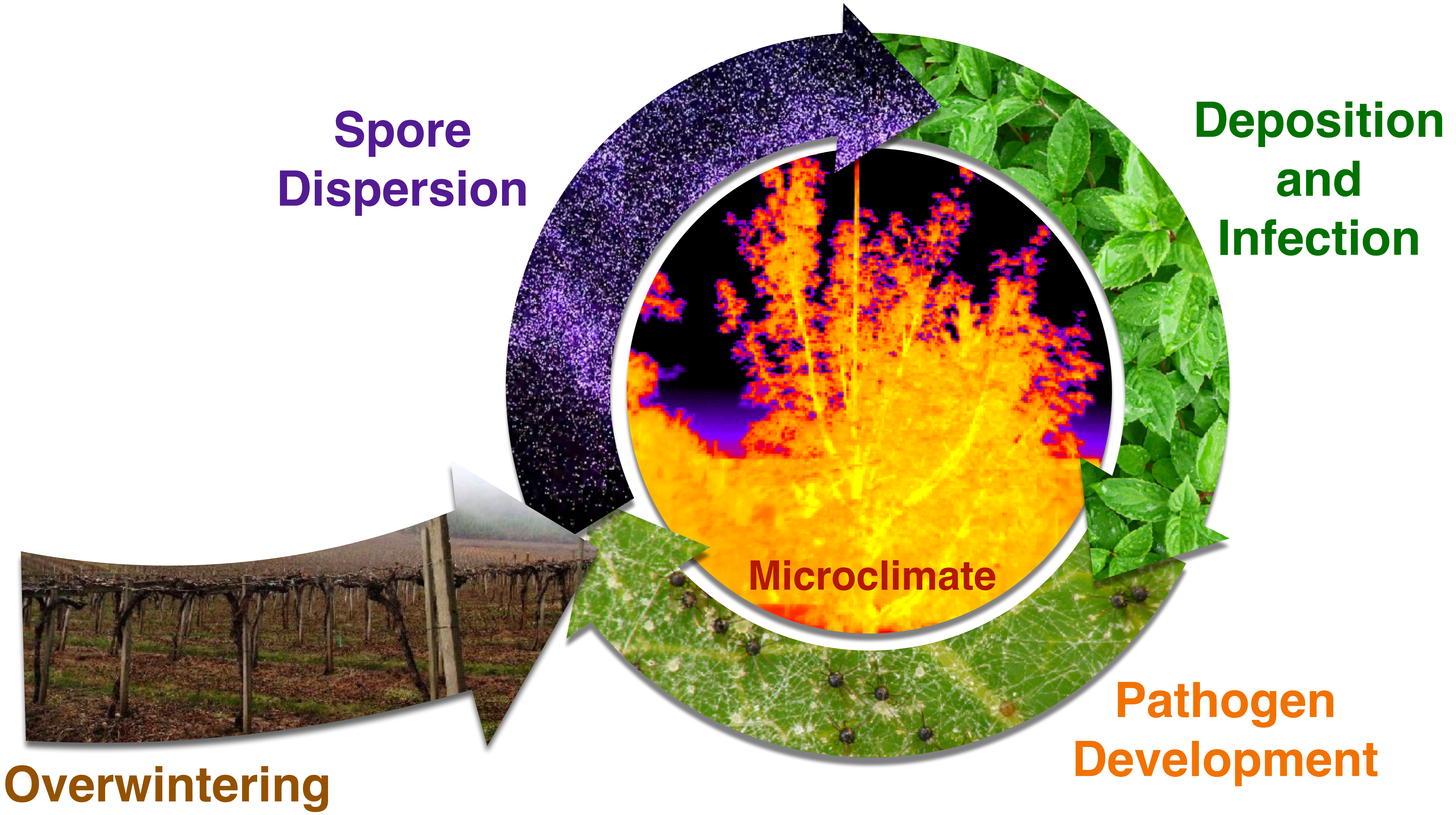
Innovation in data collection tools for surveillance and mitigation: crop and environment simulation tools

Brian Bailey
Associate Professor
Department of Plant Sciences
U.C. Davis

Typical Fungal Pathogen Life Cycle



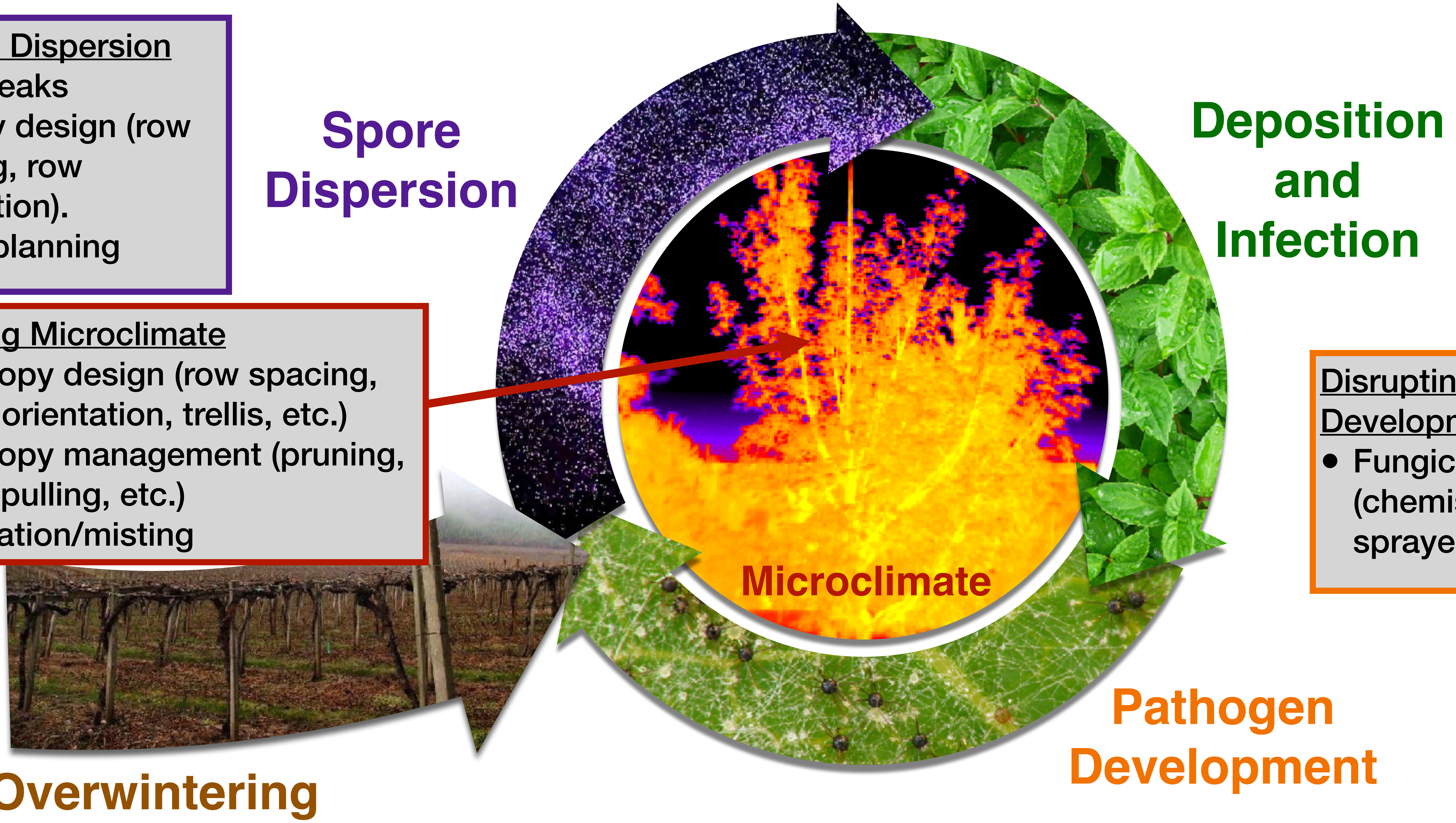
Typical Fungal Pathogen Life Cycle

<u>Reducing Dispersion</u>

- Windbreaks
- Canopy design (row spacing, row orientation).
- Urban planning

<u>Altering Microclimate</u>

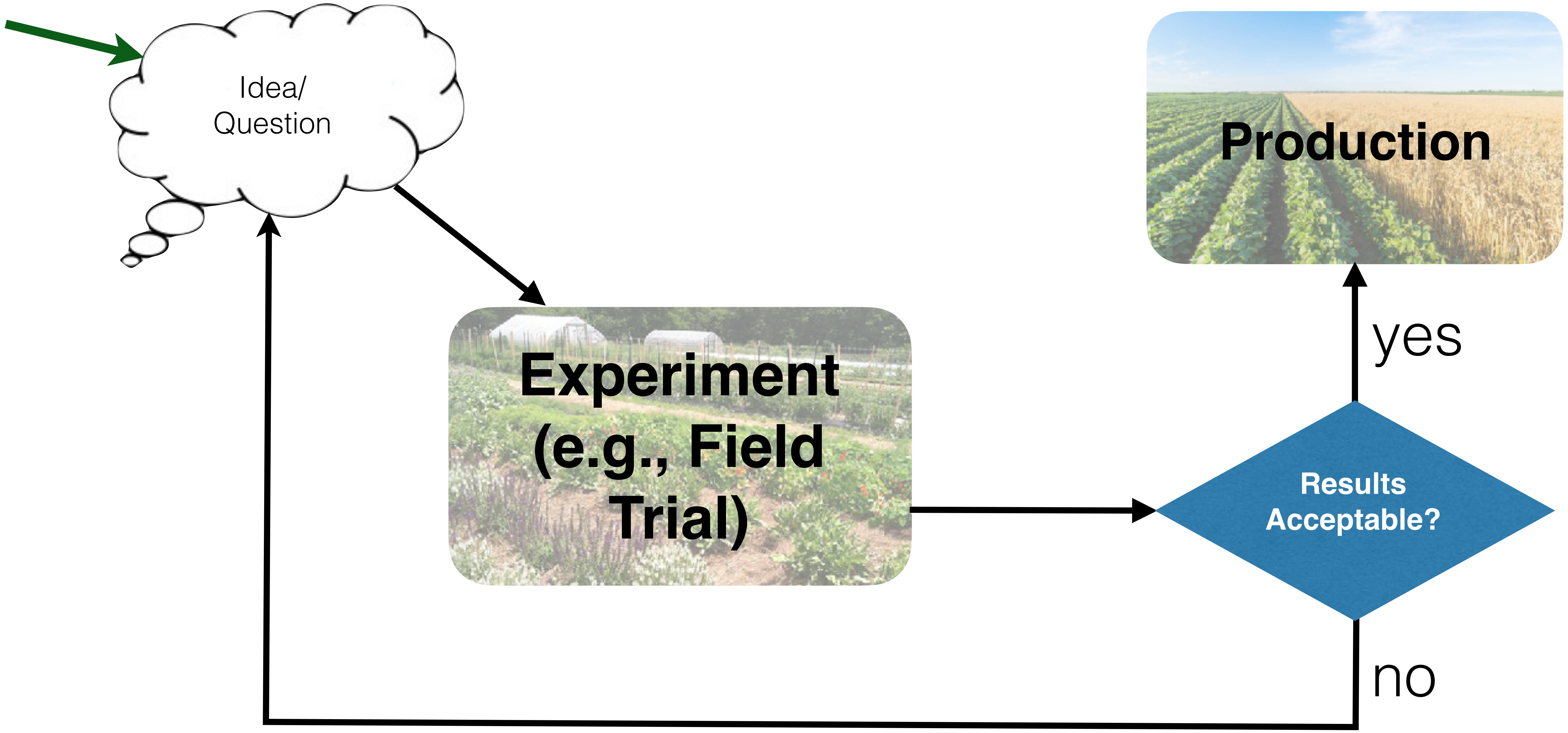
- Canopy design (row spacing, row orientation, trellis, etc.)
- Canopy management (pruning, leaf pulling, etc.)
- Irrigation/misting



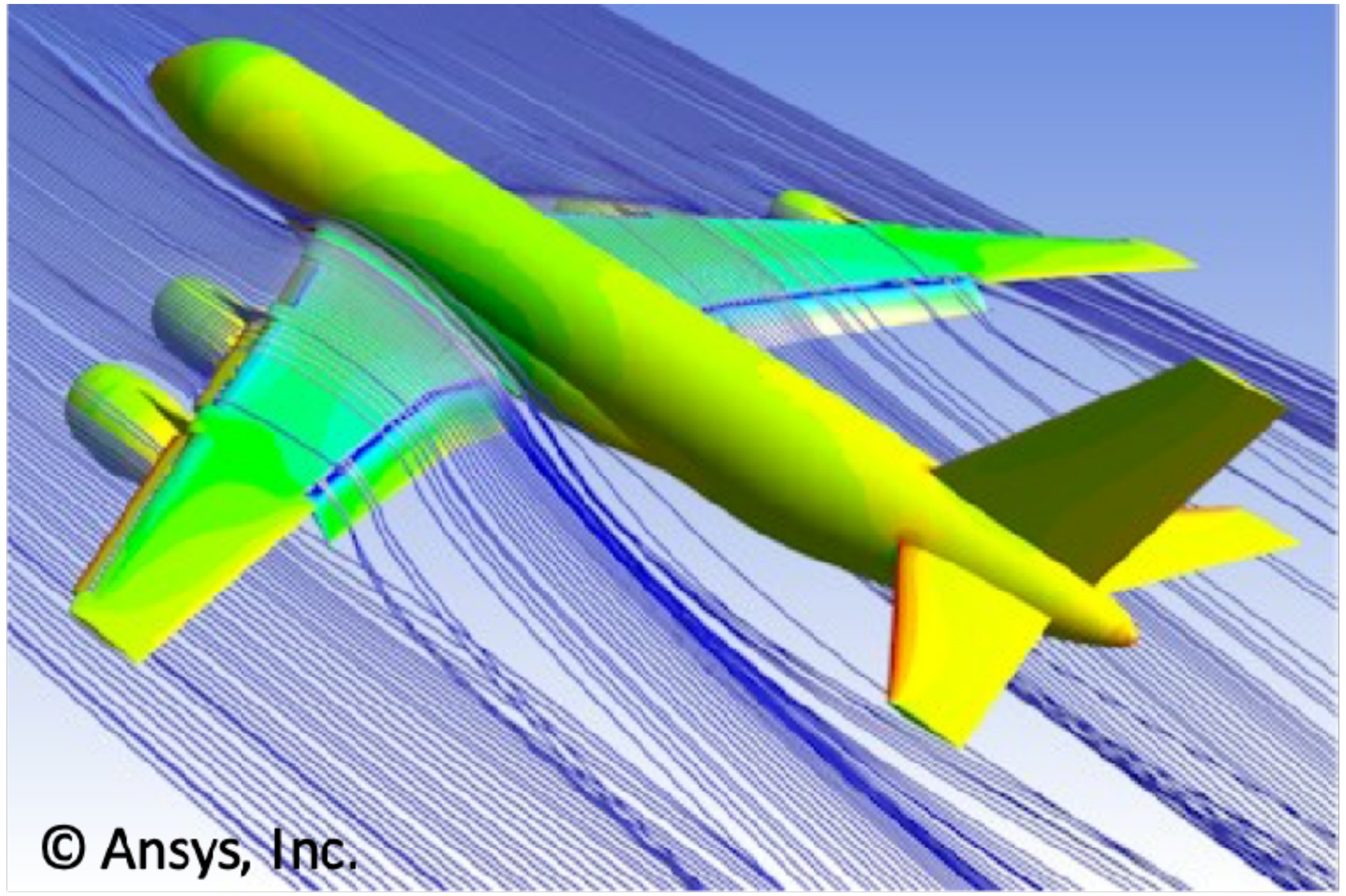
<u>Disrupting Pathogen Development</u>

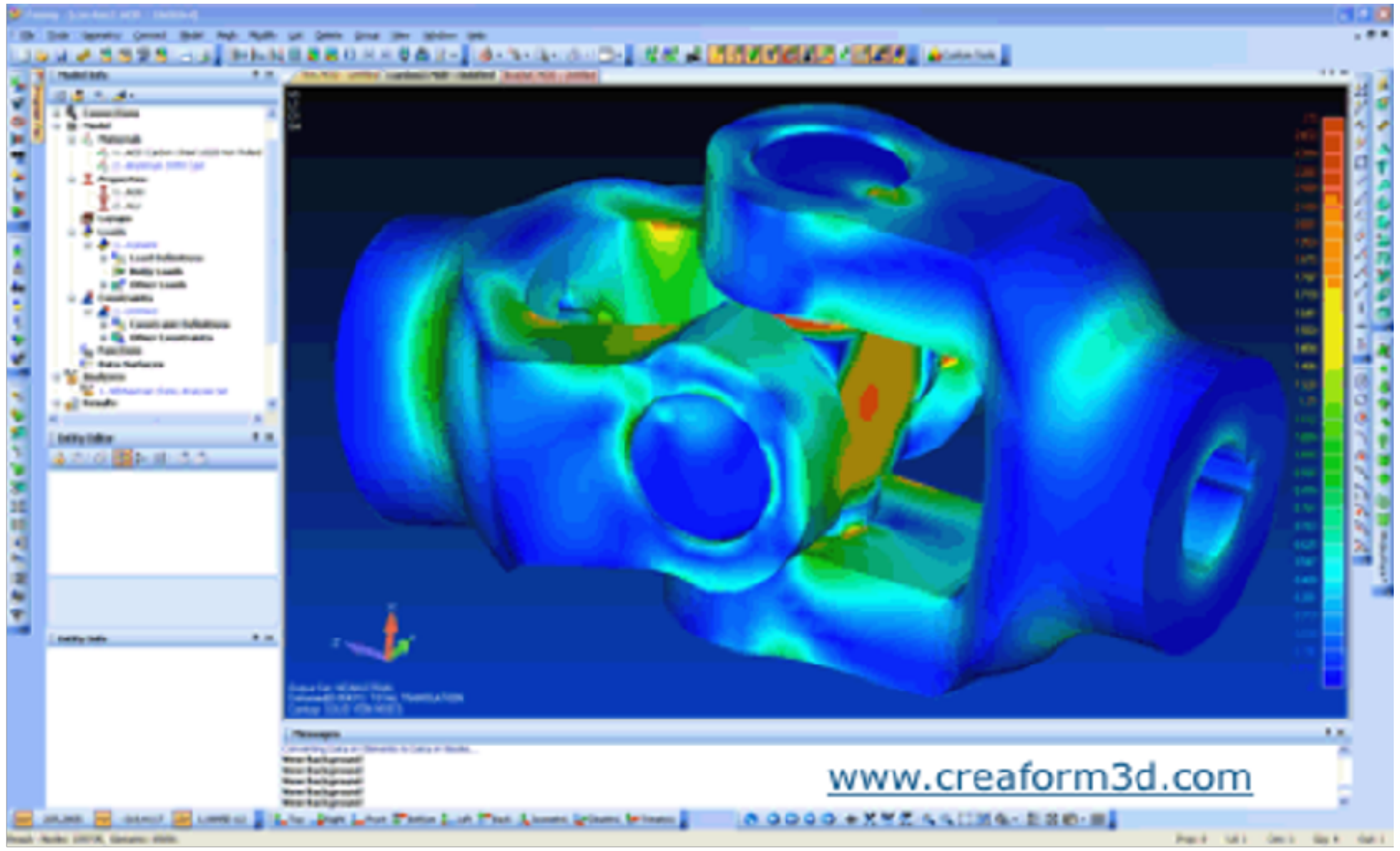
- Fungicides (chemistry, schedule, sprayer).

Agricultural Discovery and Innovation

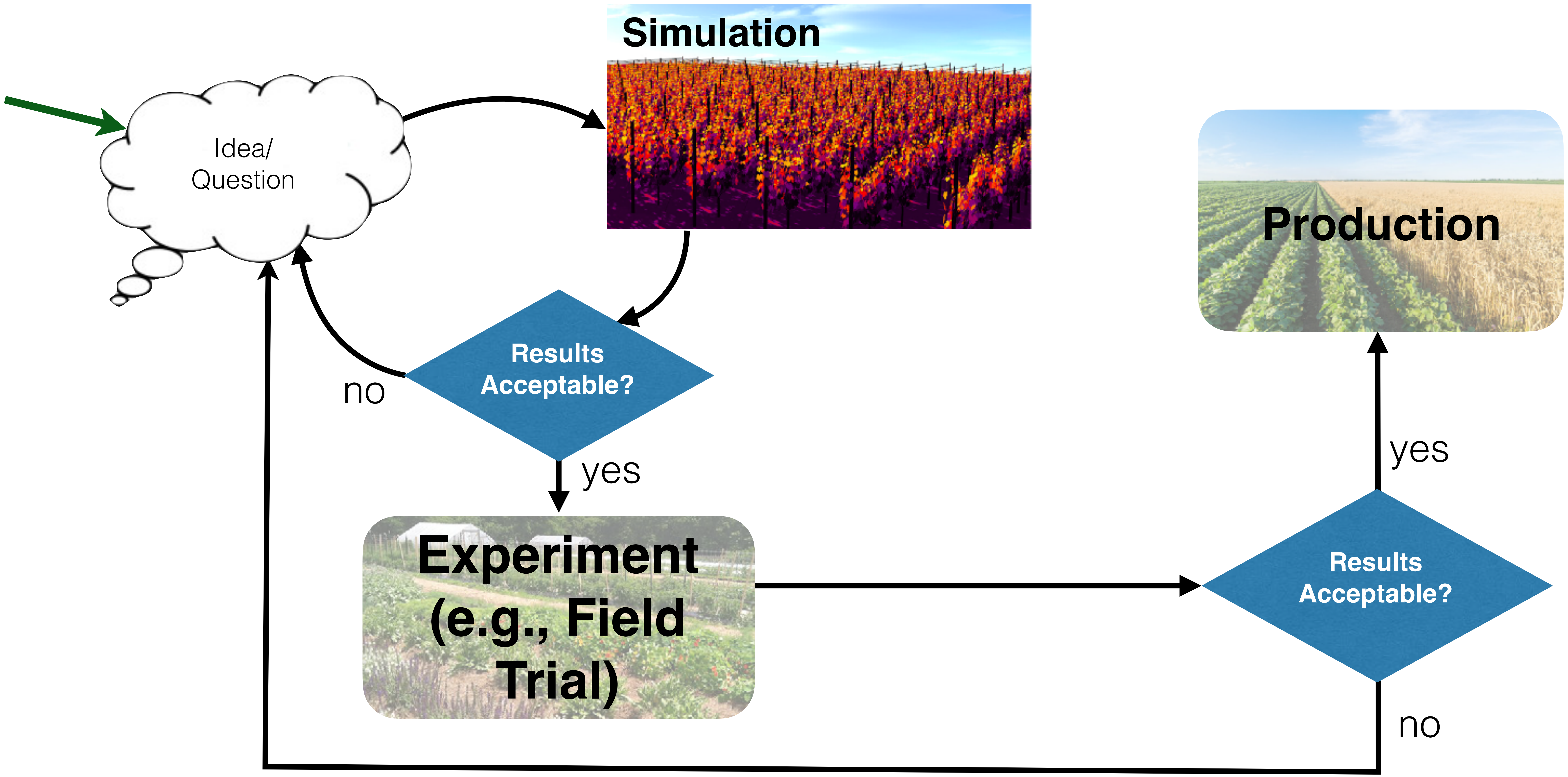


Discovery and Innovation in Other Industries





Agricultural Discovery and Innovation



Modeling Antimicrobial Resistance - Example

$$f \quad (\quad x \quad , \quad a \quad) = \quad y$$

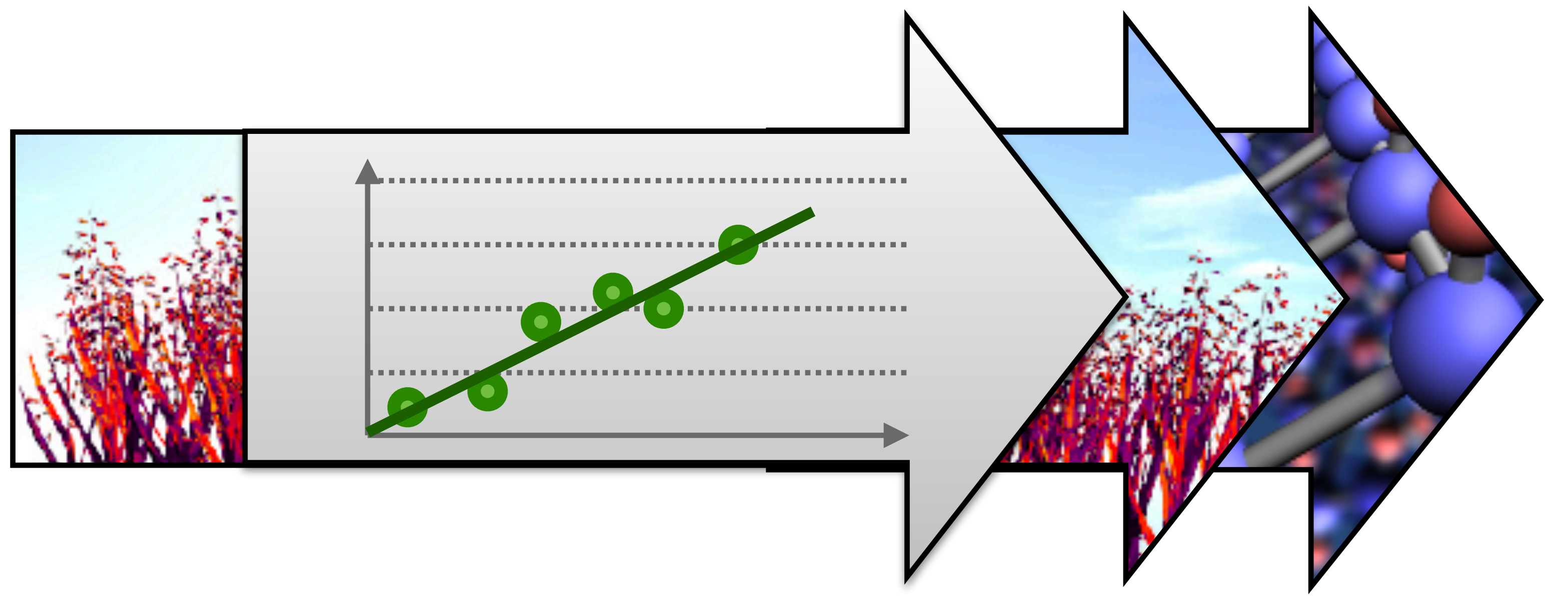
Important Processes
Turbulent Dispersion
Pathogen Infection, Colony Development
Plant Microclimate
Spray Coverage
Fungicide Mode of Action

Inputs
Climate/weather
Crop type, physiology
Pathogen biology
Geography
Management practices
Labor/Equipment Availability
Economics

Potential Mitigation Strategies
Fungicide Chemistry
Application Intervals
Sprayer Configuration
Crop Cultivar
Agronomic Practices
Canopy Design

Outputs
Fungicide Efficacy/ Resistance
Human pathogen exposure
Crop Yield
Profit

What Level of Model Detail is Needed?



Empirical **Mechanistic**

Empirical

Uses observed trends in data to quantify relationships between variables

Pros

Easier to develop; don't need to understand details of how things work

Cons

Need a lot of data that covers parameter space; extrapolation is risky

Mechanistic

Uses laws of nature to quantify relationships between variables

Pros

Generally requires less data; More robust when conditions change

Cons

Need theoretical understanding of how things work; can be computationally costly

What Level of Model Detail is Needed?

Field-level disease data is sparse!

Heuristic **Empirical** **Mechanistic**

Uses observed trends in data to quantify relationships between variables

Pros	Cons
Easier to develop; don't need to understand details of how things work	Need a lot of data that covers parameter space; extrapolation is risky

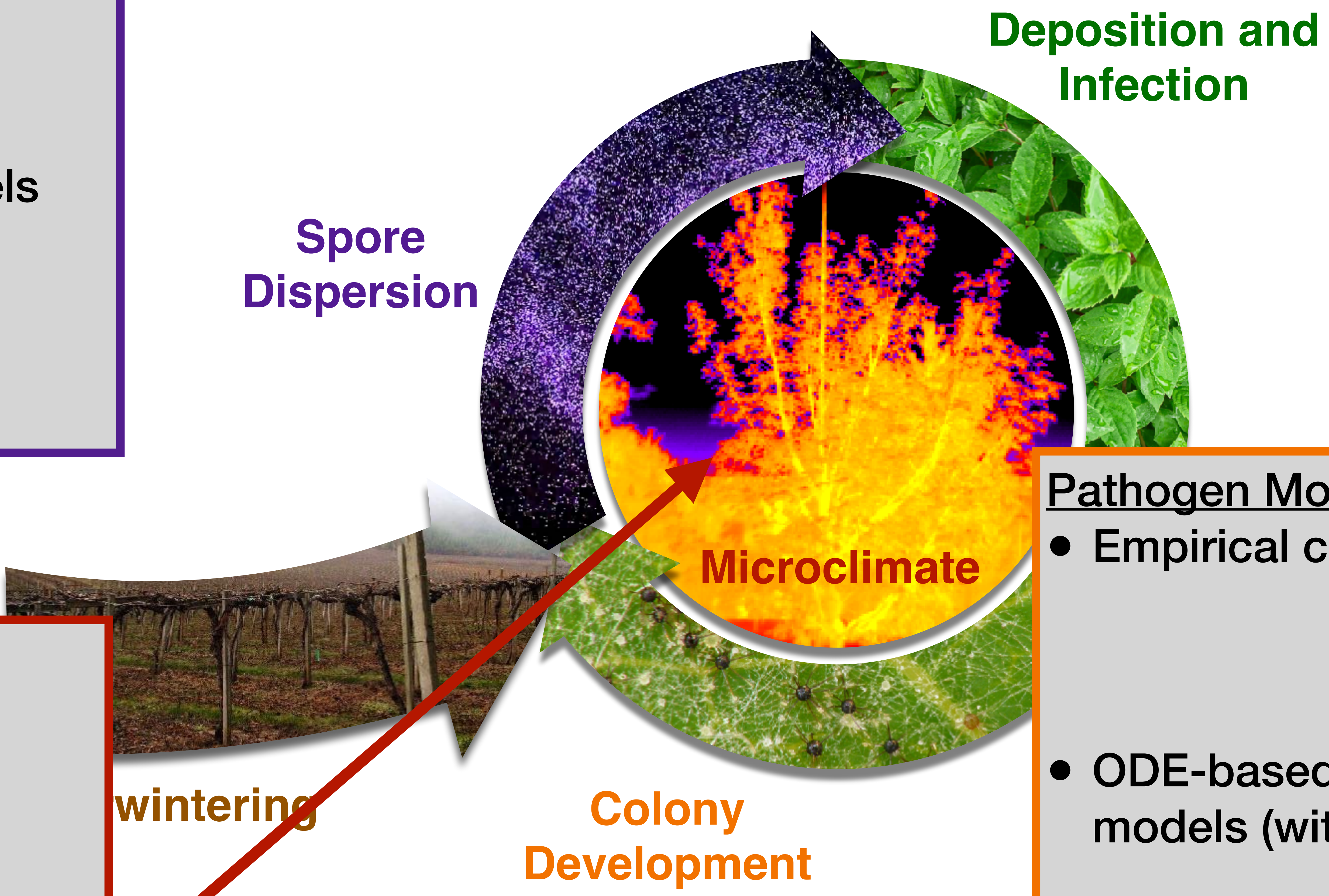
Uses laws of nature to quantify relationships between variables

Pros	Cons
Generally requires less data; More robust when conditions change	Need theoretical understanding of how things work; can be computationally costly

Model Components

Dispersion:
- Statistical models of field-scale dispersion
- Regional dispersion models

Host Models:
- Commonly assumed that susceptible host tissue is abundant
- Traditional crop models available for staple/annual crops



Microclimate:
- Usually driven by ambient measurements (neglects microclimate)

Pathogen Models:
- Empirical colony-scale models
- ODE-based population growth models (with resistance)

Helios 3D simulation framework

Collaborators: Walt Mahaffee, Rob Stoll

B. N. Bailey (2019). Helios: a scalable 3D plant and environmental biophysical modelling framework. Front. Plant Sci. **10:**1185

What About Artificial Intelligence Models?

Challenges:

- Machine learning models rely on trends extracted from massive datasets to describe relationships between all variables - where to get this volume and quality of data?

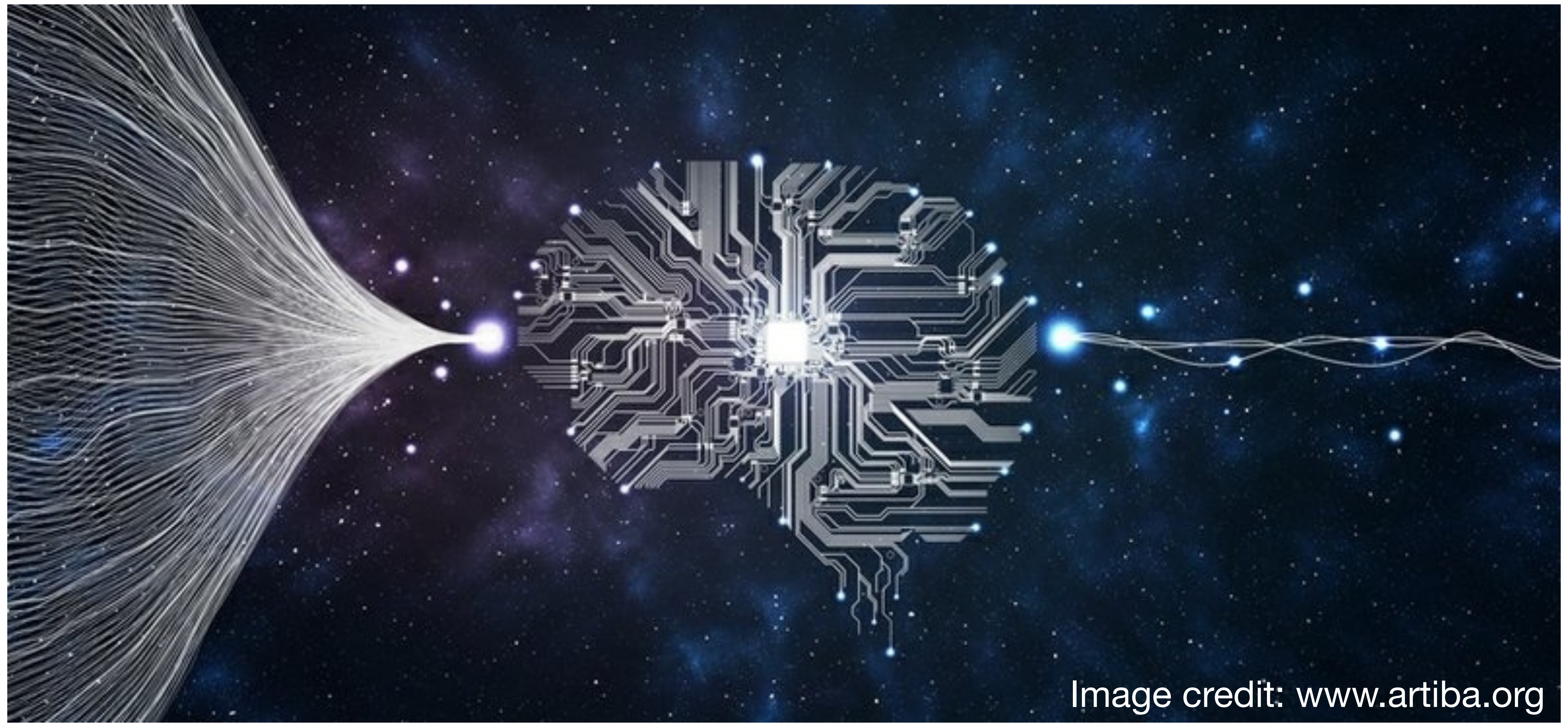
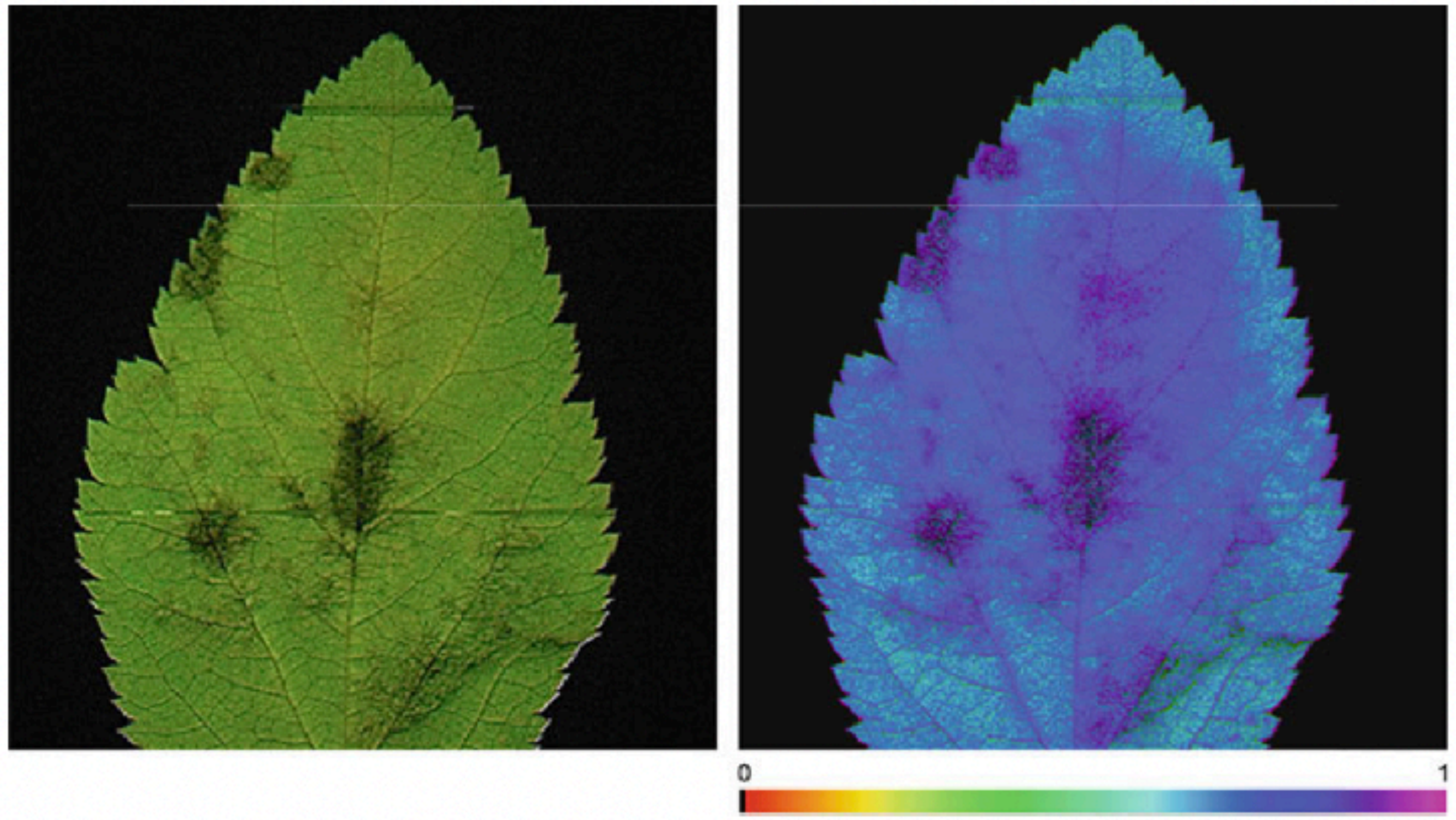


Image credit: www.artiba.org

What About Artificial Intelligence Models?

Challenges:

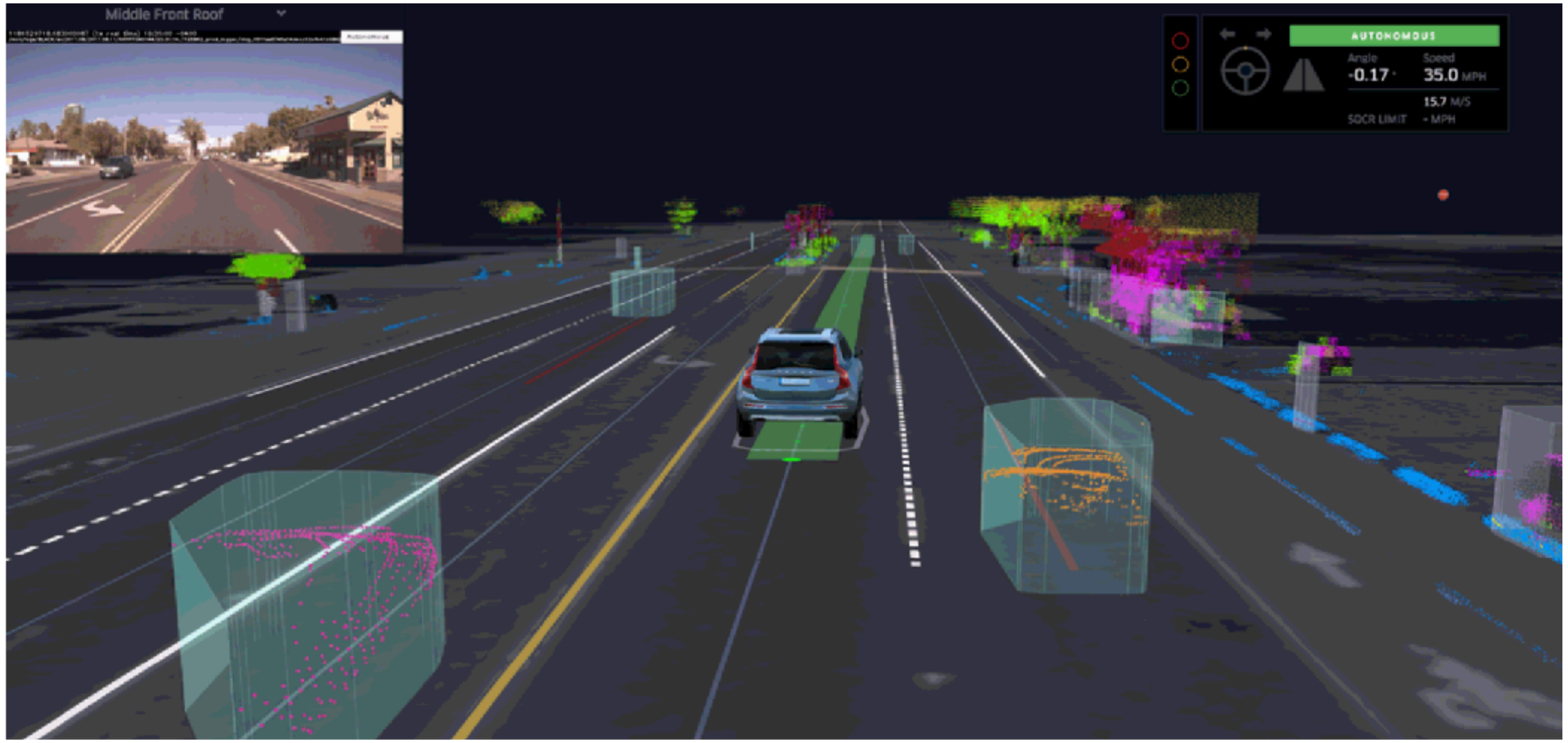
- Machine learning models rely on trends extracted from massive datasets to describe relationships between all variables - where to get this volume and quality of data?
- “High throughput” (proximal remote) sensing approaches struggle with multiple stressors.



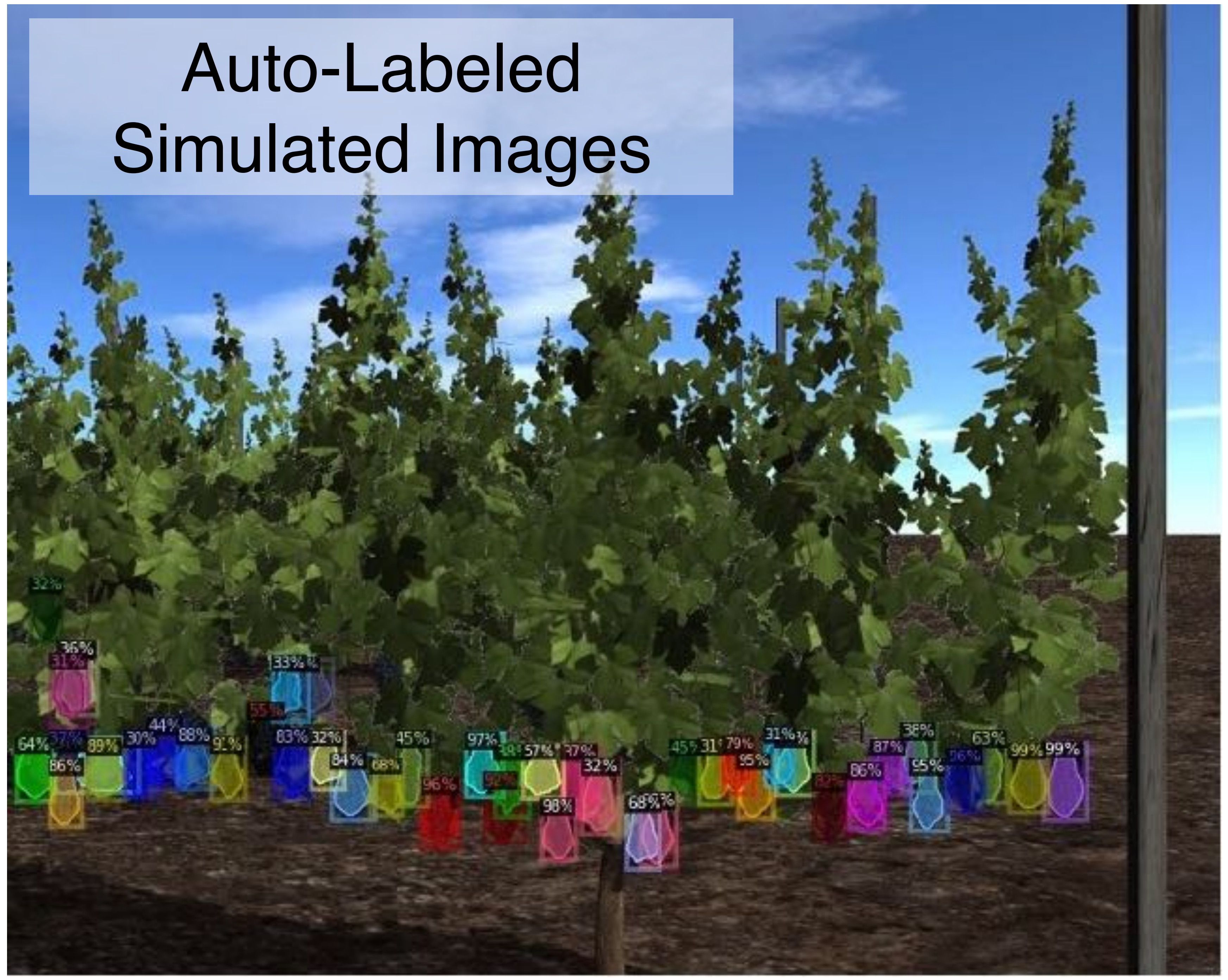
Oerke, E. C., Mahlein, A. K., & Steiner, U. (2014). Proximal sensing of plant diseases. In *Detection and diagnostics of plant pathogens* (pp. 55-68). Springer, Dordrecht.

What About Artificial Intelligence Models?

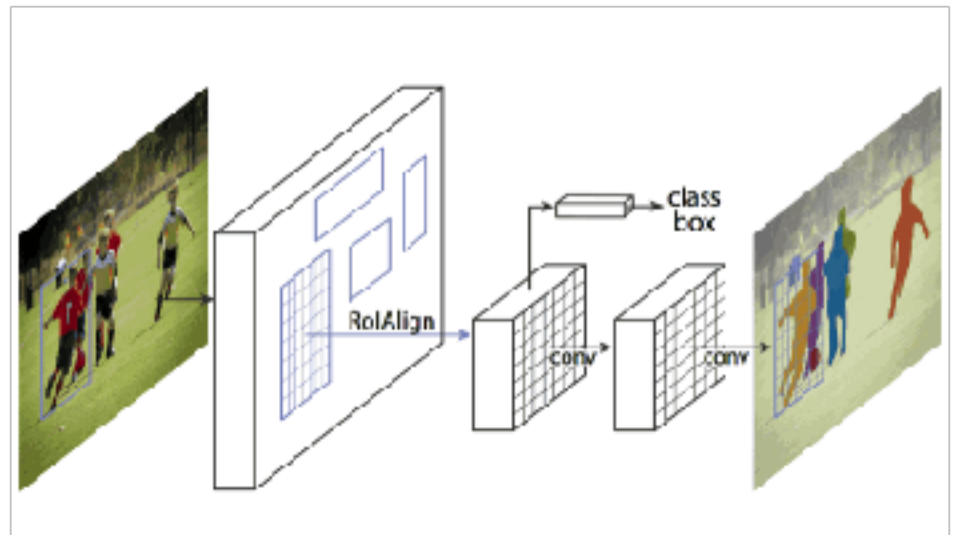
In other industries, simulated data is used to supplement real data in order to effectively train AI models



Simulated Data for Training AI-Based Models



Custom CNN
Architecture



Fei, Z., Olenskyj, A., Bailey, B.N., and Earles, M. (2021). Enlisting 3D Crop Models and GANs for More Data Efficient and Generalizable Fruit Detection. *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV) Workshops* pp. 1269-1277.

Simulated Data for Training AI-Based Models

Collaborators: Mason Earles, Christine Diepenbrock

Helios 3D Biophysical Models

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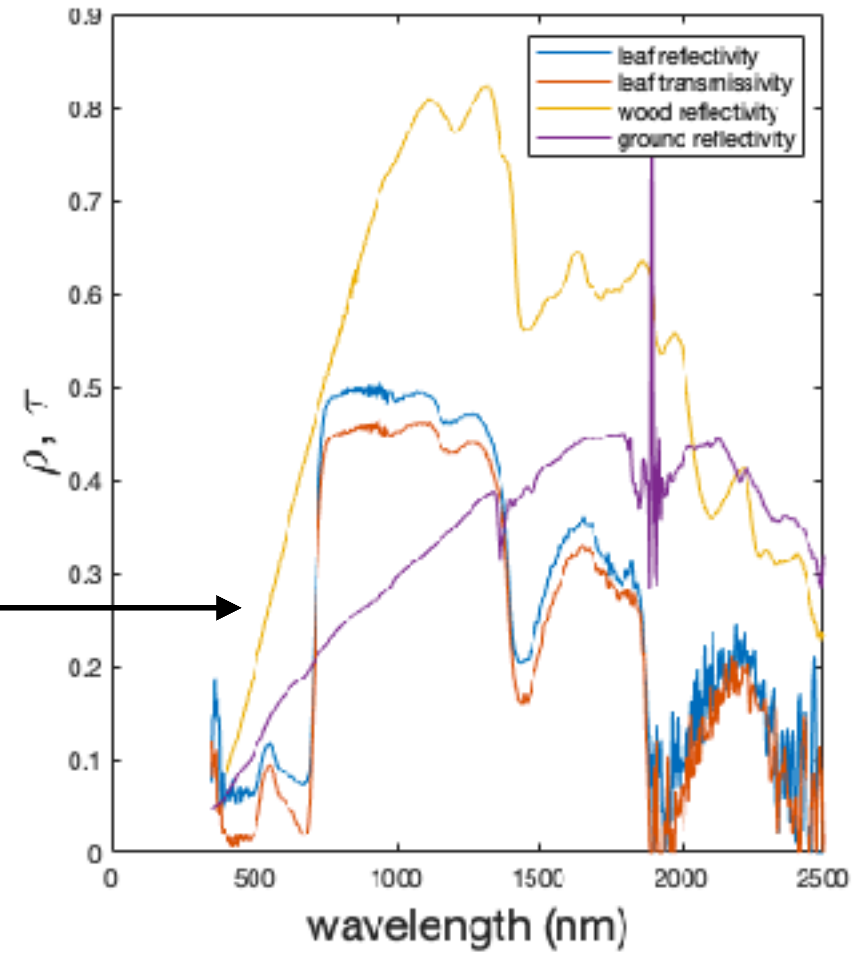
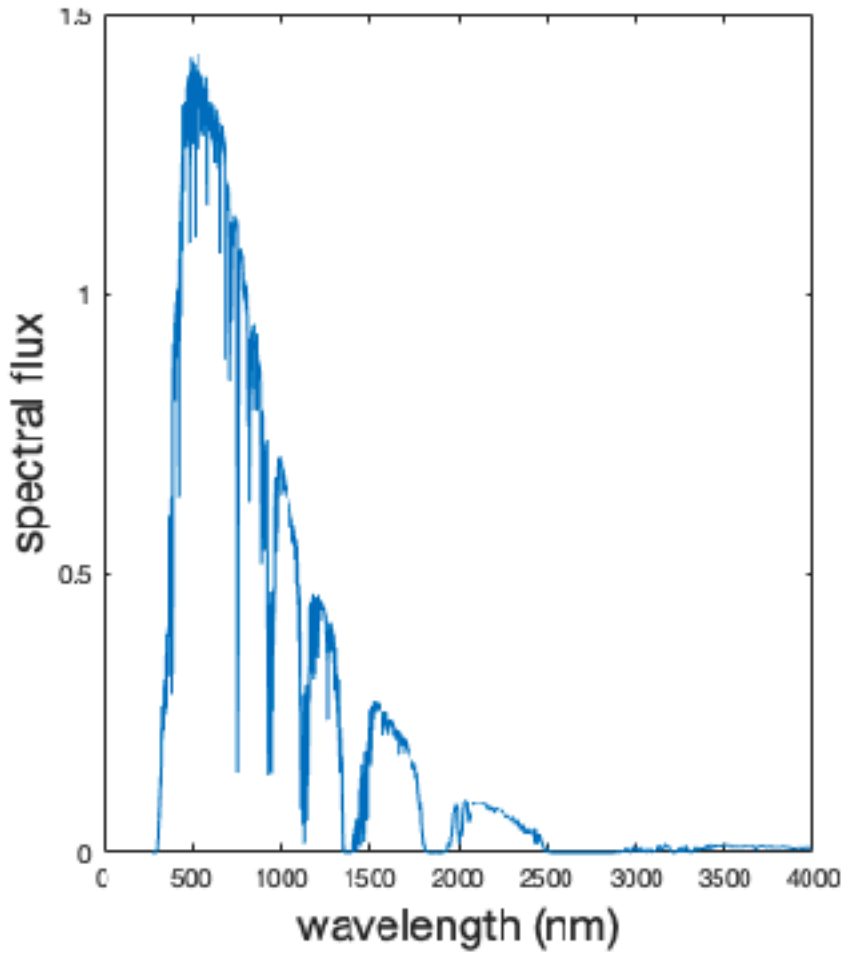
Leaf Optical Model (PROSPECT)

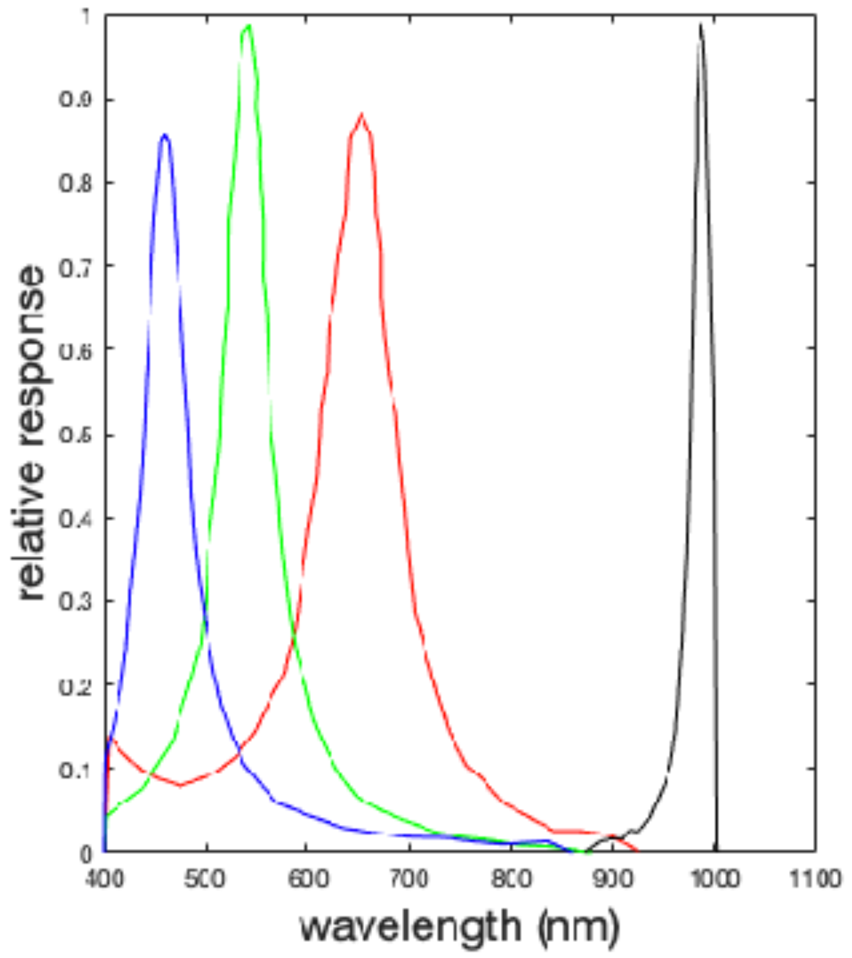
Surface Properties



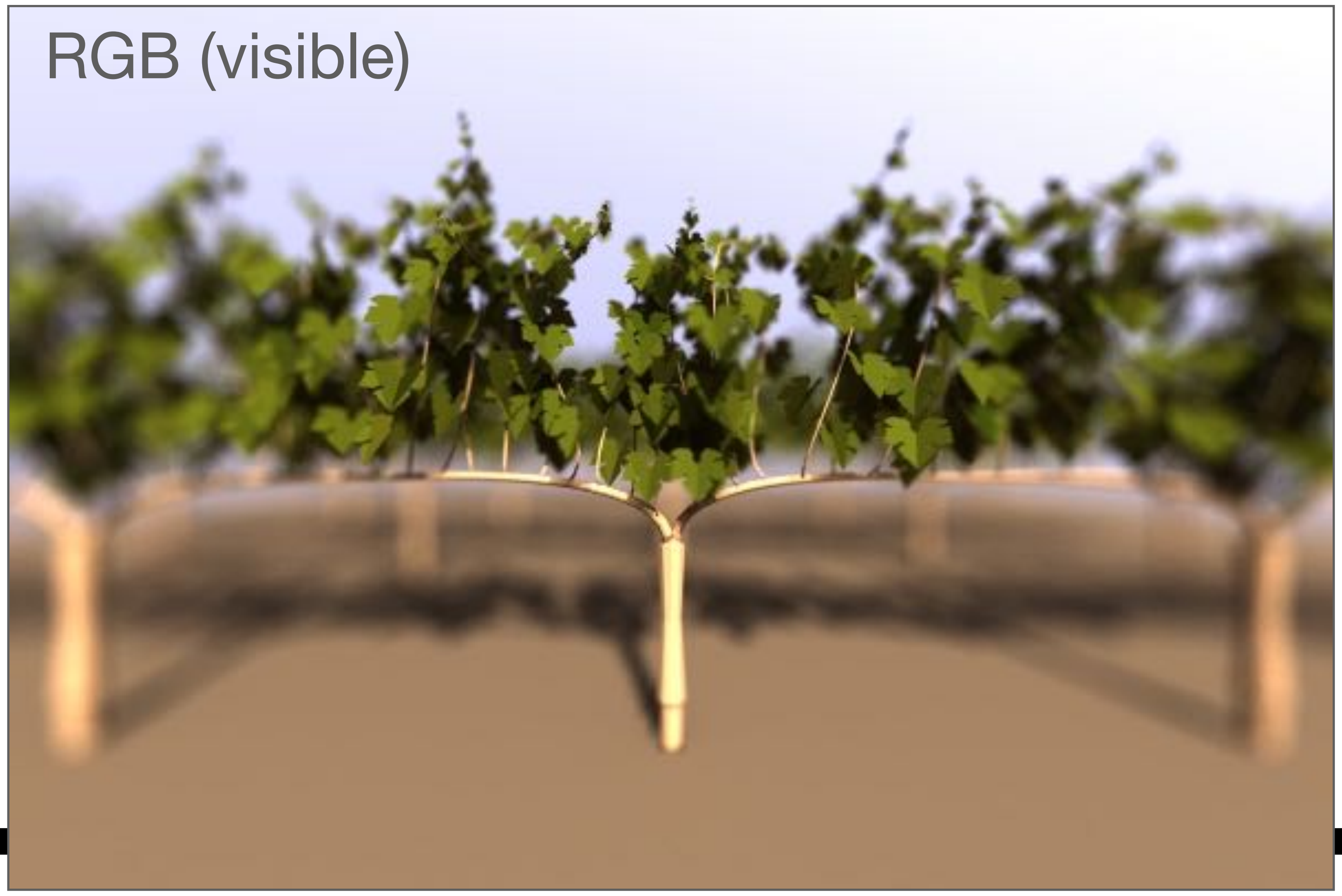
Solar Spectrum

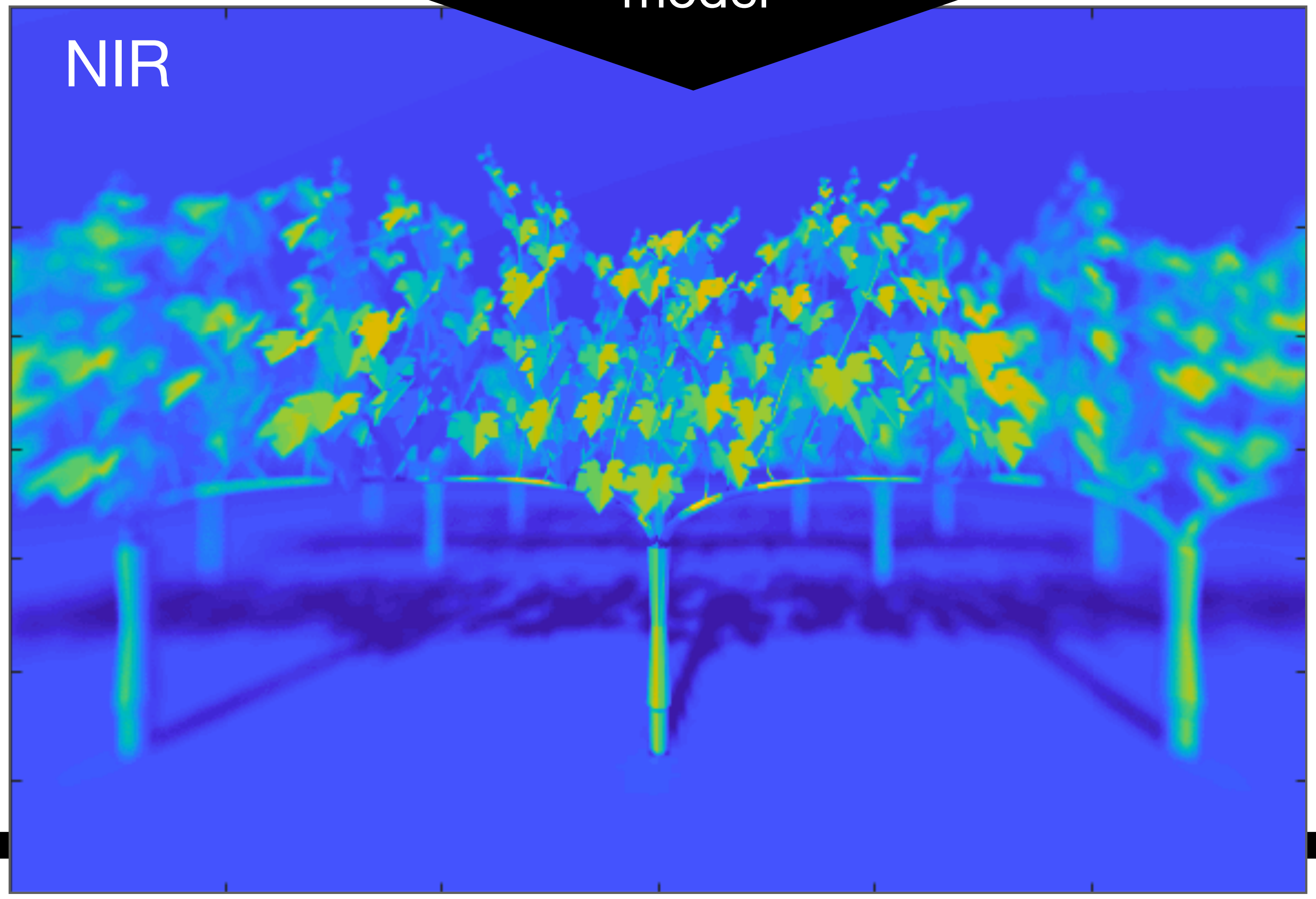


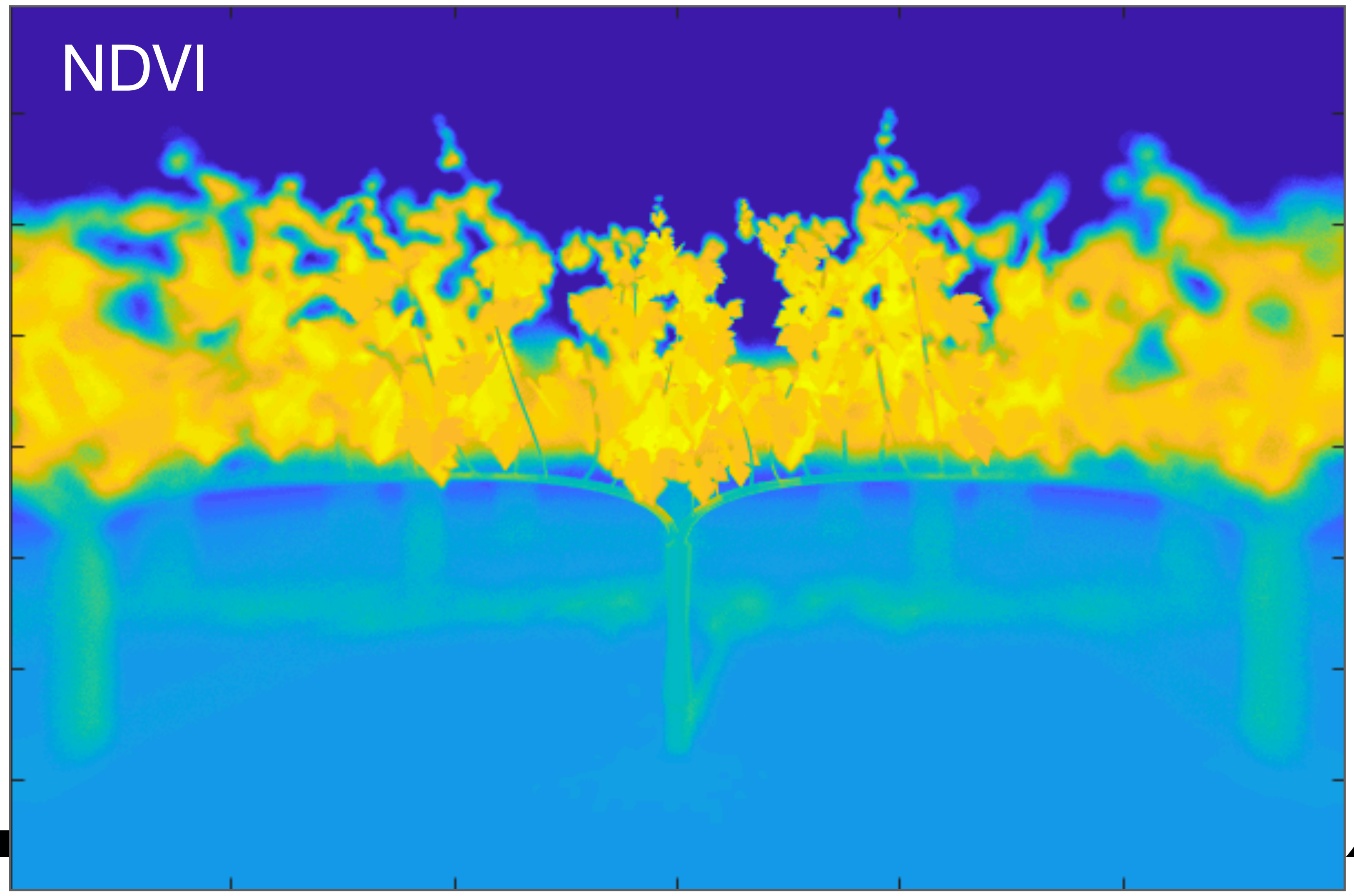
Camera Response



3D radiation model







Take-Home Messages

1. Field-level disease data is sparse (relatively speaking), which complicates monitoring and rapid development of effective disease/resistance mitigation strategies and empirical models.

2. Models provide a means of *in silico* development of practices that may reduce fungicide application, reduce the probability of resistance, and minimize human exposure.

3. Currently, generalized system-level models of AMR do not exist, and will likely need a mechanistic basis to be feasible.

Thank You

Contact:

- bnbailey@ucdavis.edu
- baileylab.ucdavis.edu

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www.github.com/PlantSimulationLab/Helios

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