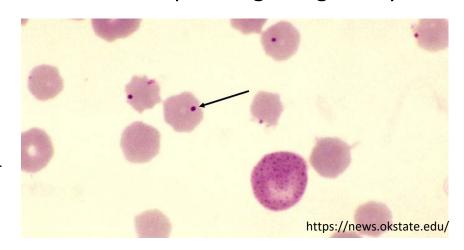
Diagnostic approaches for rapid detection of herd-level infections

Bovine anaplasmosis (BA) caused by the obligate intraerythrocytic, rickettsial organism Anaplasma marginale is endemic in tropical and sub-tropical regions globally

- Estimated economic impact of \$660 per clinically affected head in the United States
- BA induces production losses through several means.
 Infections of adult naïve cattle result in anemia,
 abortion, and acute death
- Infection of young calves establishes an inapparent carrier state where the animal may serve as a reservoir for infection



David R. Smith, DVM, PhD, Dipl. ACVPM, Dipl. Epidemiology

W. Isaac Jumper, DVM, PhD, Dipl. ACVPM

Kimberly A. Woodruff, DVM, MS, Dipl. ACVPM, Dipl. Epidemiology

Bindu Nanduri, PhD



Use of arthropod vectors to classify cattle herds by anaplasmosis infection status

Anaplasma marginale is endemic to the southeastern and northwestern United States





Tabanid flies as mechanical vectors



Dermacenter ticks as biological vectors

Anaplasma marginale organisms
replicate in the tick.

https://bugguide.net/node/view/560099

Blood feeding transmits

Anaplasma marginale directly from host to host



The goal is to determine whether a non-invasive method of sampling to detect *A. marginale* in free-living vector species, may be used to estimate the seroprevalence of anaplasmosis in cattle on the same pastures.

Objectives

- Determine the optimal sampling strategy for *Dermacentor variabilis*
 - Estimate the proportion of *D. variabilis* among ticks captured by dragging
- Determine the optimal sampling strategy for **female tabanids**
 - Estimate the proportion of female tabanids among insects captured by H-trap
- Relate to seroprevalence of anaplasmosis in adjacent cattle herds

Cross-sectional study: estimate prevalence and identify risk factors associated with diseases of beef cattle in Mississippi

- W. Isaac Jumper, DVM, PhD, Dipl. ACVPM
- Carla L. Huston, DVM, PhD, Dipl. ACVPM, Dipl. Epidemiology
- Brandi B. Karisch, PhD, Animal and Dairy Sciences
- David R. Smith, DVM, PhD, Dipl. ACVPM, Dipl. Epidemiology
- In 2023, 860,000 beef cattle on 15,980 farms in Mississippi.
 5th largest agriculture commodity in MS
- Prevalence and risk factors for some production-limiting diseases are not well known
 - Bovine anaplasmosis
 - Bluetongue virus
 - Bovine leukemia virus
 - Neospora caninum
 - Leptospirosis
 - Bovine Viral Diarrhea Virus



 Describe within and between herd prevalence, geographical distribution, as well as management and biosecurity risk factors for various productionlimiting diseases of beef cattle in Mississippi

Status of sample collection

- Blood samples collected from cattle in 40 herds in 23 counties across the state
 - 2,112 total serum samples collected
- Initial sample size calculations have been met (n=40)
 - Sample collection will continue as herds are available
- Serum testing currently underway





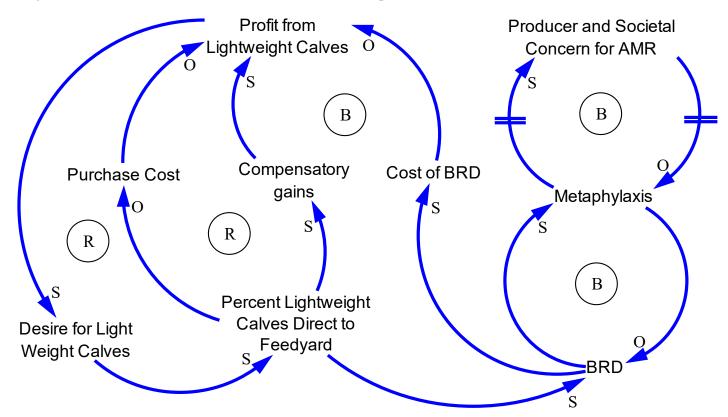
Preliminary results

- 17/20 herds had at least 1 animal test positive
 - 3 herds had 0 animals test positive
- Antimicrobials may be used to treat disease or mitigate risk
 - In-feed antimicrobial use raises stewardship concerns

Impact of feeding chlortetracycline (CTC) on BA seroprevalence

Univariable Model	Variable	Responses	Estimate	Standard	Odds	95% CI		P-Value
	Level		Value	Error	Ratio			
Intercept			-1.0296	0.4505				
CTC Free-Choice Mineral Usage								
	Yes	9	1.2088	0.5114	3.349	1.229	9.126	0.0221
	No	11	Ref.	Ref.				

What is the effect of policies against the use of antimicrobials in beef production on profit and animal well-being?



System dynamics model of beef production antimicrobial stewardship

Some cattle feeders desire lightweight calves despite increased risk for pneumonia. The problem is currently mitigated with mass antimicrobial therapy





Test performance of normal saline as a transport medium for detection of *Tritrichomonas foetus* in cattle herds by qRT-PCR

David R. Smith, DVM, PhD, Dipl. ACVPM, Dipl. Epidemiology

Obligate extracellular protozoan

Venereal transmission

Clinical signs → reproductive losses

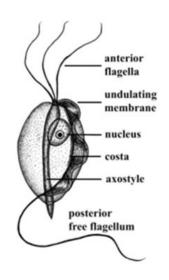
Bull = asymptomatic carrier

Economic impact

\$650 million annually (Speer CA, 1991)

\$44,000/ year for cow-calf producer (Anderson, 2014)

No FDA approved treatment







Machine Learning/Deep Learning/Graph Neural Networks

Mahalingam Ramkumar, PhD
Zhiqian Chen, PhD
Nisha Pillai, PhD

Dept. Of Computer Science and Engineering

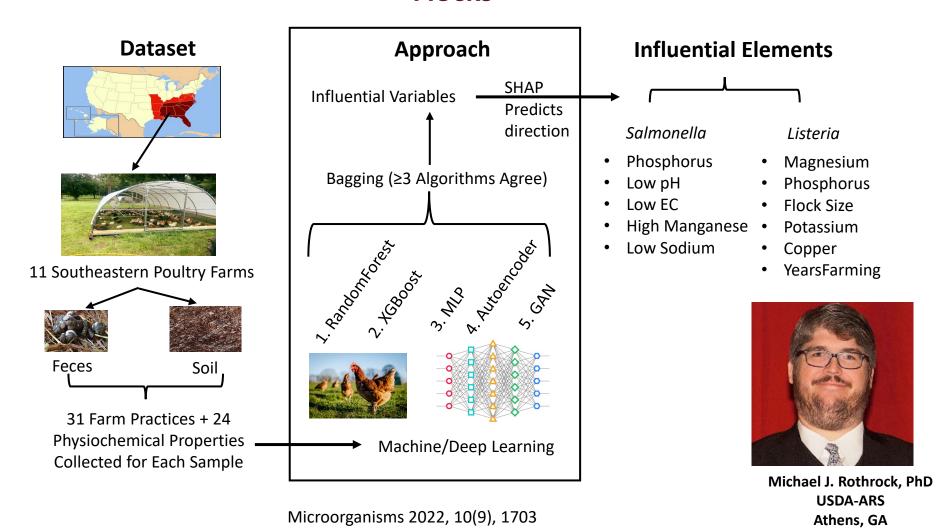
Bindu Nanduri, PhD

College of Veterinary Medicine

Moses B Ayoola PhD, Santhanakrishnan Boopalan PhD, Athish R Das MS, Ganga Gireesan MS



Preharvest Environmental and Management Drivers of Multi-Drug Resistance in Major Bacterial Zoonotic Pathogens in Pastured Poultry Flocks



Dataset

- Pastured Poultry
 - Management Practices, Soil physicochemical properties
 - Food safety: zoonotic bacterial pathogens
 - Antibiotic Resistance, MDR
 - Microbiome

Models

- Models for pathogens (Campylobacter, Listeria, Salmonella), MDR o Ensemble approach

 - Pair-Difference model
 - \blacksquare (N x M to N² x 2M)
- Explainable AI
 - Order of importance
 - Combinatorial optimization
 - Important feature pairs
 - Important triplets
- Deep sensitivity analysis for objective-oriented *combinatorial optimization*. International Conference on Computational Science & Computational Intelligence (CSCI'23)
- Towards Interpreting Multi-Objective Feature Associations, International Systems Conference (IEEE SysCon 2024)
 - Predicting foodborne pathogens and probiotics taxa within poultry-related *microbiomes* using a machine learning approach. Anim Microbiome. 2023
 - Towards optimal *microbiome* to inhibit multidrug resistance. IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB) 2023.
 - Bayesian-Guided Generation of Synthetic *Microbiomes* with Minimized Pathogenicity. International Conference of the IEEE Engineering in Medicine and Biology Society (IEEE EMBCm 2024)
- EndToEndML: An Open-Source End-to-End *Pipeline* for Machine Learning Applications. International Conference on Information and Computer Technologies (ICICT 2024, March 15-17).

NARMS

- Antibiotic Resistance (250000 samples)
- 4500 nontyphoidal Salmonella whole genome sequences
- MIC for 15 antibiotics

Antibiotic	Target	Resistance Genes Group		
Ampicillin	Cell Wall	β-lactam		
Amoxicillin-clavulanic acid	Cell Wall	β-lactam		
Ceftriaxone	Cell Wall	β-lactam		
Azithromycin	Protein	Macrolide		
Chloramphenicol	Protein	Phenicol		
Ciprofloxacin	DNA	Quinolone		
Trimethoprim-Sulfamethoxazole	DNA	Sulfonamide		
Sulfisoxazole	DNA	Sulfonamide		
Cefoxitin	Cell Wall	β-lactam		
Gentamicin	Protein	Aminoglycoside		
Kanamycin	Protein	Aminoglycoside		
Nalixidic acid	DNA	Quinolone		
Streptomycin	Protein	Aminoglycoside		
Tetracycline	Protein	Tetracycline		
Ceftiofur	Cell Wall	β-lactam		



The National Antimicrobial Resistance Monitoring System for Enteric Bacteria (NARMS) was established in 1996. NARMS is a collaboration among state and local public health departments, CDC, the <u>U.S. Food and Drug Administration</u> (FDA), and the <u>U.S. Department of Agriculture</u> (USDA).

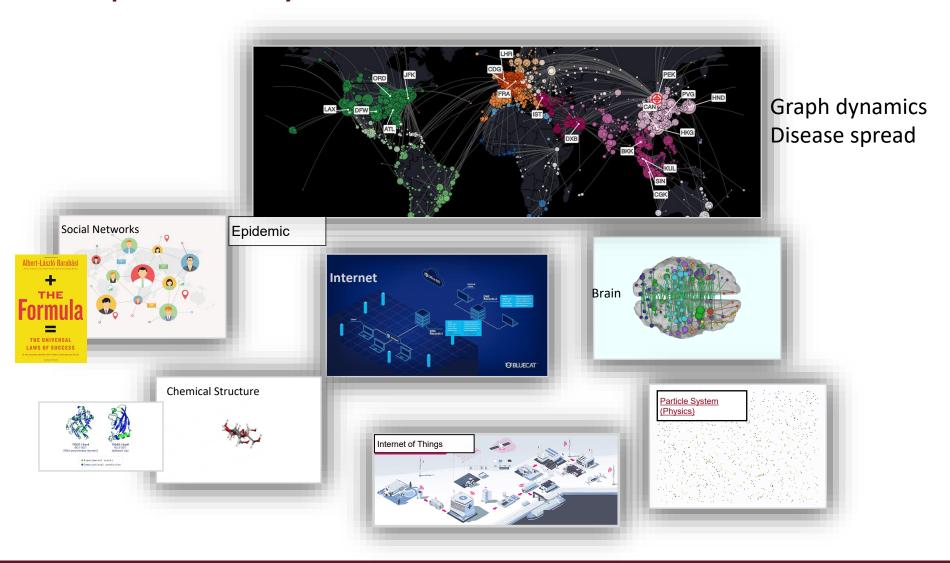
This national public health surveillance system tracks changes in the antimicrobial susceptibility of certain enteric (intestinal) bacteria found in ill people (CDC), retail meats (FDA), and food animals (USDA) in the United States. The NARMS program at CDC helps protect public health by providing information about emerging bacterial resistance, the ways in which resistance is spread, and how resistant infections differ from susceptible infections.

Traditional machine learning (random forest) with deep learning models (multilayer perceptron and DeepLift) for WGS-based MIC prediction using K-mers.

• Predicting *Salmonella* MIC and deciphering genomic determinants of antibiotic resistance and susceptibility. Microorganisms. 2024; Jan 10; 12(1): 134

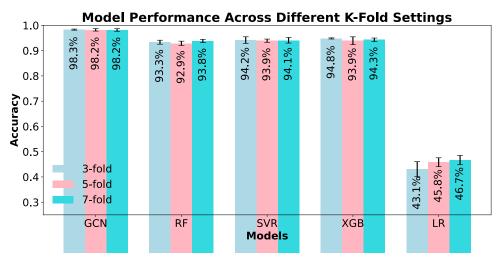


Graph is Everywhere



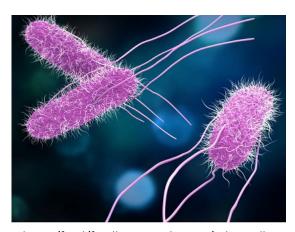
Graph Neural Networks (GNN) for MIC Prediction

- GNNs offer advantages over conventional ML methods by incorporating connectivity, topology, and non-Euclidean data into the learning process.
- K-mer GNN model
 - Nodes are k-mers, edges show sequence similarity
 - Encodes k-mer presence/absence as features
- Integrates graph structure and sequence data
 - Allows predicting MICs and understanding resistance
- Evaluated *Salmonella* MIC prediction model by conducting comparative analyses with including Linear Regression, Random Forest Regressor (RF), Support Vector Regressor(SVR), and XGBoost (XGB).



• Leveraging Graph Neural Networks for MIC Prediction in Antimicrobial Resistance Studies. International Conference of the IEEE Engineering in Medicine & Biology Society, 2024

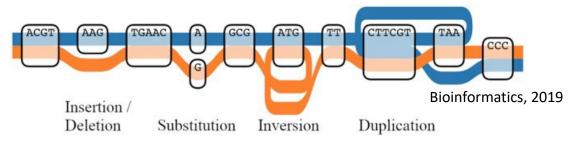
Ongoing / Planned Work



Fda.gov/food/foodborne-pathogens/salmonella

LLM for Salmonella

- Salmonella genomes (over 550,000)
 - Pan Genome Graph



- 80,000 with labelled MIC
 - 6000 in NARMS
- Purpose: a core model to allow fine tuning of smaller models
- Not trained to just predict next / missing token
 - Predict all available labels
 - API for going from genome subsequence (in a sample window)
 to trainable labels
- Pros and Cons of generative (GPT like) or predictive (Bert-like)
- GNN for serotype prediction

USDA-ARS: Adam Rivers, GBRU, GEERU, Gainesville, FL Jonathan Frye, Athens, GA.

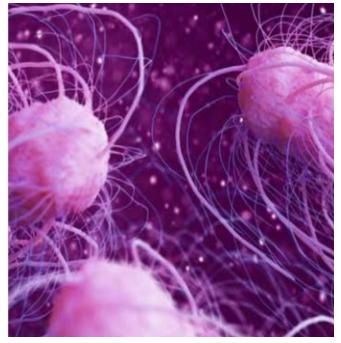


LLM for Microbiomes

Science of the Microbiome

The collective genomes of all the microbes (bacteria, fungi, viruses, et al.) in a human, plant, animal, or environmental community have tremendous potential. The microbiome for plants affects productivity as well as stress and disease resistance. A cow's microbiome can influence the amount of methane produced by the animal. A soil's microbiome can be enhanced for more nutritious crops, to sequester more carbon, to capture more water, or to prevent erosion. Microbiomes maintain the healthy function of these diverse ecosystems and influence human health, climate resiliency, food security, and other important and critical phenomena.

USDA Science Blueprint 2020-2025



- Variety of small microbiome abundance data available
 - From a wide range of unrelated experiments
 - Different types of samples
 - Different species, soil, feces

USDA-ARS: Michael J. Rothrock & Adelumola Oladeinde , Athens, GA, Laxmi Yeruva, Little Rock, AR

Transformers for Tabular Data

- ML models ignore the deeper meaning of "features"
 - o Input variables like temperature, salinity, *E. coli* CFUs, etc., are just $x_1, x_2, ... x_n$ for the model
 - Are reasonably good *embeddings* possible for various features?
 - Using data created for possibly unrelated and even unknown purposes...
- Better explainability
 - Attention matrix can be interpreted as an edge graph showing transition probabilities
 - A model for feature importance (calculable for every sample) using PageRank
 - Exploring Pathogen Presence Prediction in Pastured Poultry Farms through Transformer-Based Models and Attention Mechanism Explainability. (Ready for submission)
 Michael J. Rothrock, USDA-ARS, Athens, GA.

Realtime Animal Health Monitoring



Current Research: Real-time pasture surveillance tool using drones and remotely sensed data

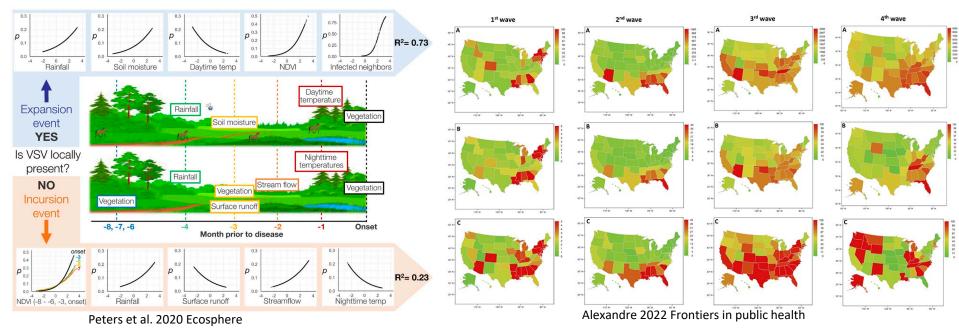
- → Animal counts, weight, and body temperature
- → Mass and nutritional value
- → Thermal, hyper, 3-D, and multispectral data
- → Convolutional Neural Networks, Vision Transformers

Objective: Develop Artificial Intelligence based Smart Tools for Farmers for detecting animal disease and responding to animal welfare challenges

Amanda Ashworth, USDA-ARS, Fayetteville, AR.

Spatial Modeling the Spread of Vesicular Stomatitis (VS)

- **Research**: When will VS enter the US? Once VS does spread into the US, where will it go next?
 - Microcosmic: temperature, soil moisture, vegetation, etc
 - Macroscopic: geospatial propagation patterns



Microcosmic: ecological factor

+ Macroscopic: Geospatial patterns

Amy R Hudson, USDA-ARS, Manhattan, KS.



Research Plan

To integrate Macroscopic and Microcosmic factors

 Epidemic Modeling with Spatial Constraints: Integrate traditional epidemiological models, such as the SIR with spatial graph structures.

To reduce the data demand

Bayesian Inference for spatial graph: Employ Bayesian inference techniques to quantify the
uncertainty in disease spreading predictions and model parameters. This could involve
developing hierarchical Bayesian models or using Markov Chain Monte Carlo (MCMC) methods
to estimate posterior distributions over the model parameters, accounting for spatial and
temporal uncertainties.

To unify and utilize different data granularities

 Multi-Scale Modeling: Develop multi-scale models that capture disease spreading at different spatial resolutions, from individual-level interactions to regional or global-scale dynamics. This could maximize the utilization of data collected from every level.

To provide scientific conclusion

Causal Inference and Intervention Modeling: Explore causal inference techniques to identify
the causal factors and interventions that can effectively mitigate disease spreading in spatial
networks. This could involve methods like causal graphical models, counterfactual reasoning, or
structural equation modeling, enabling the development of targeted interventions and policy
recommendations.