

*SHAPING LIVESTOCK FARMING FOR 2030*

Dr Andrew Byrne

AFBI



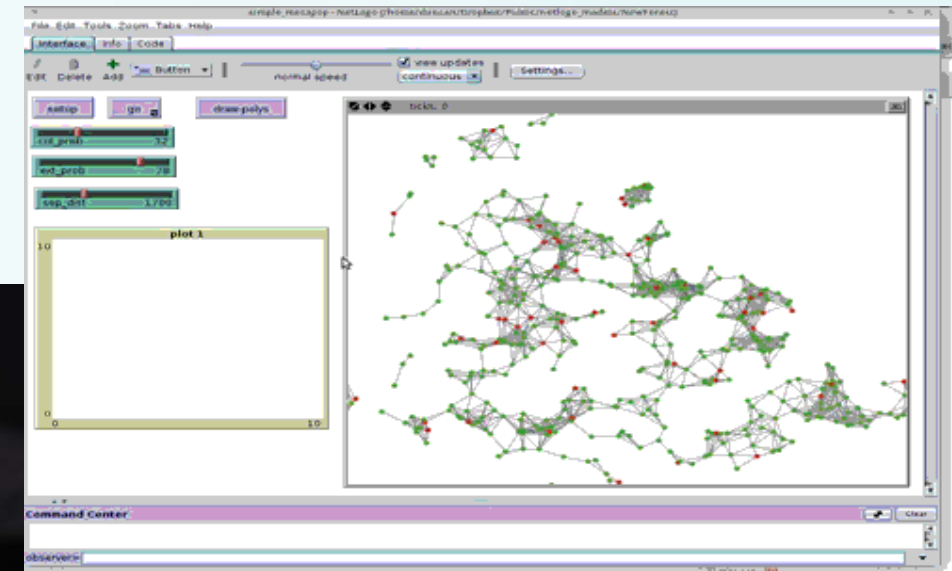
# What has veterinary epidemiology ever done for us?

The impact of epidemiological science in helping to  
understand the patterns of the present to plan for the future

Dr. Andrew Byrne  
Agri-Food and Biosciences Institute

# Veterinary Epidemiology – What is it?

- Veterinary epidemiology is concerned with the patterns and processes driving infection across animal populations.

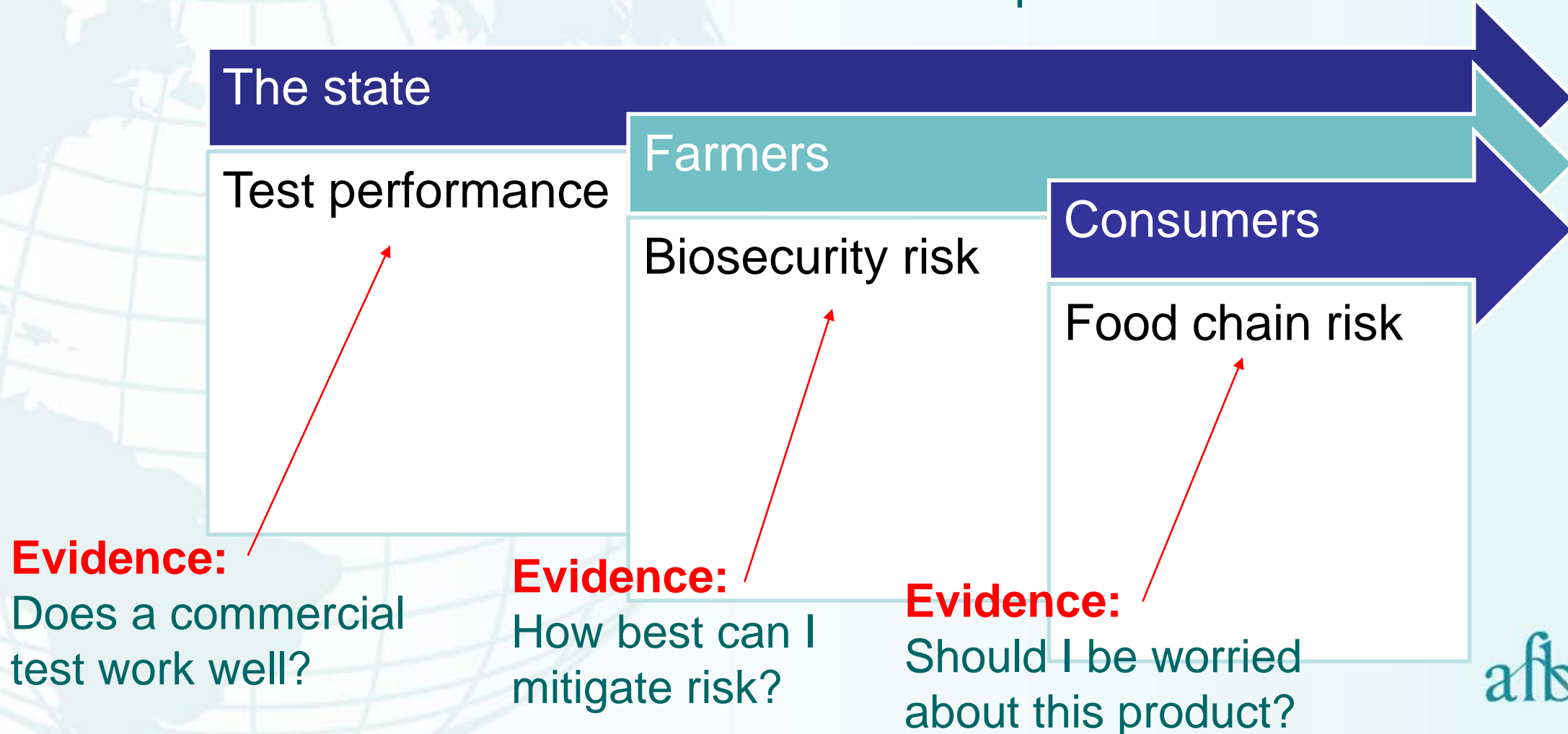


*“Concerned with quantifying risk, and forms an evidence base for understanding and controlling disease effectively.”*

# Veterinary Epidemiology

## — how does it impact disease control?

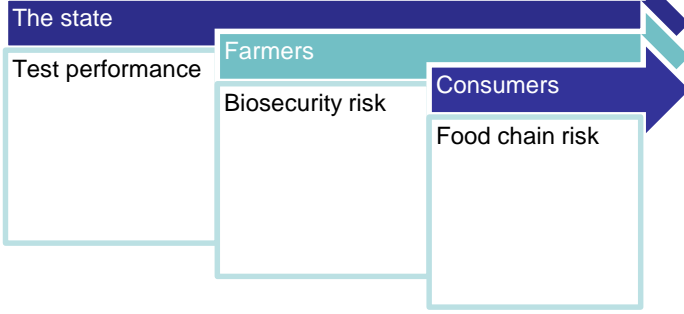
- Works with different stakeholders to provide evidence base





# Veterinary Epidemiology

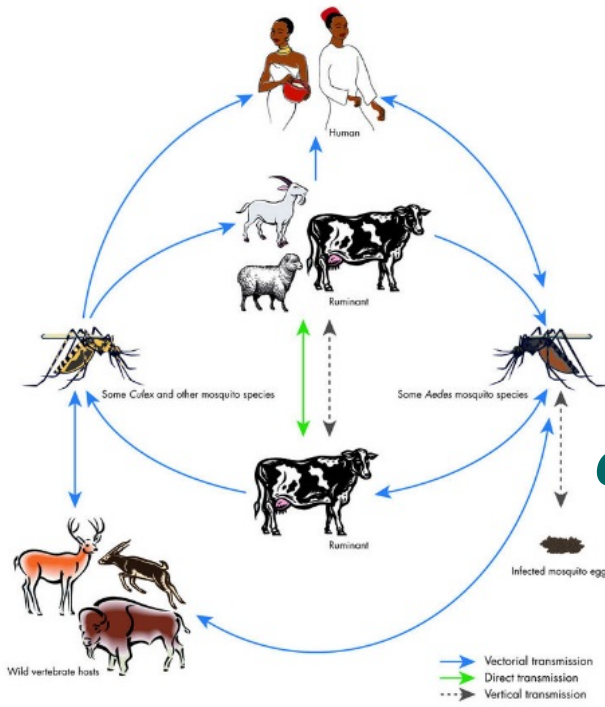
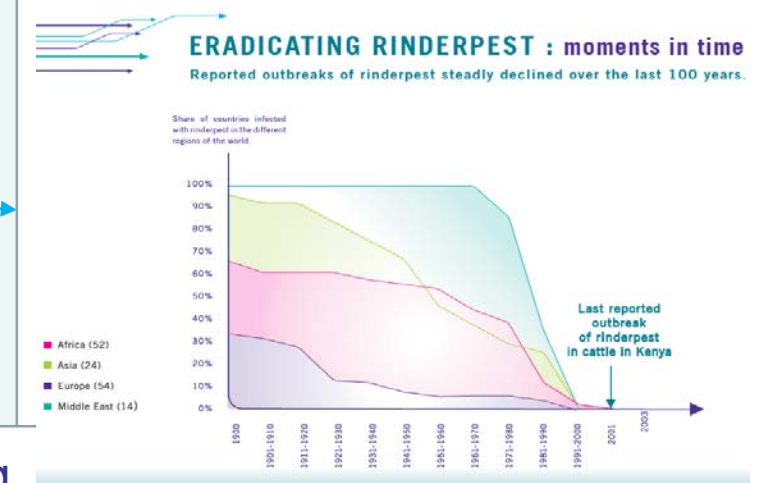
## — how does it impact disease control?



*National responses*

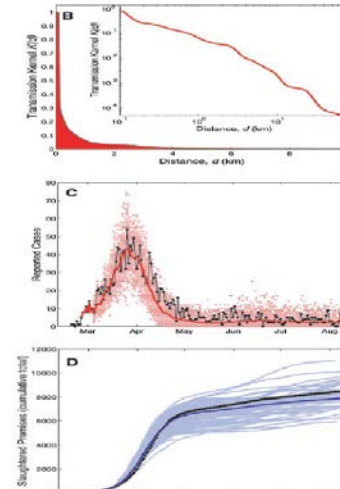
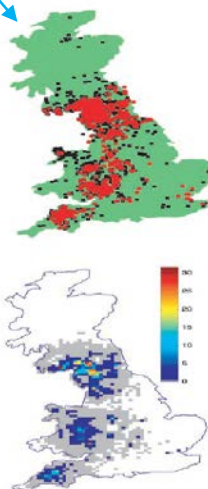
*Global efforts*

### Global success Rinderpest (OIE)

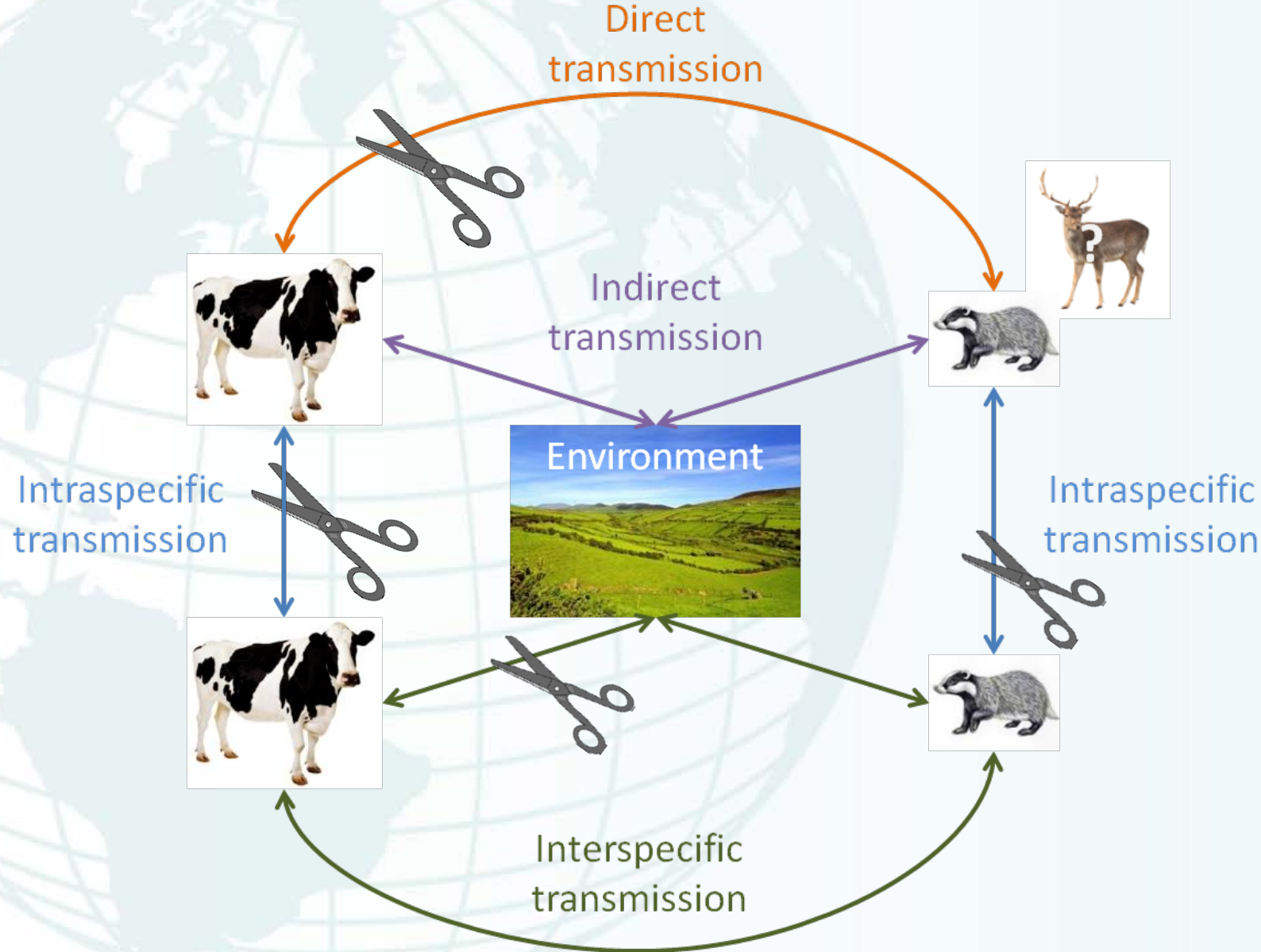


*Local coordination*

Designing interventions, tracking transmissions (Keeling et al. 2001)

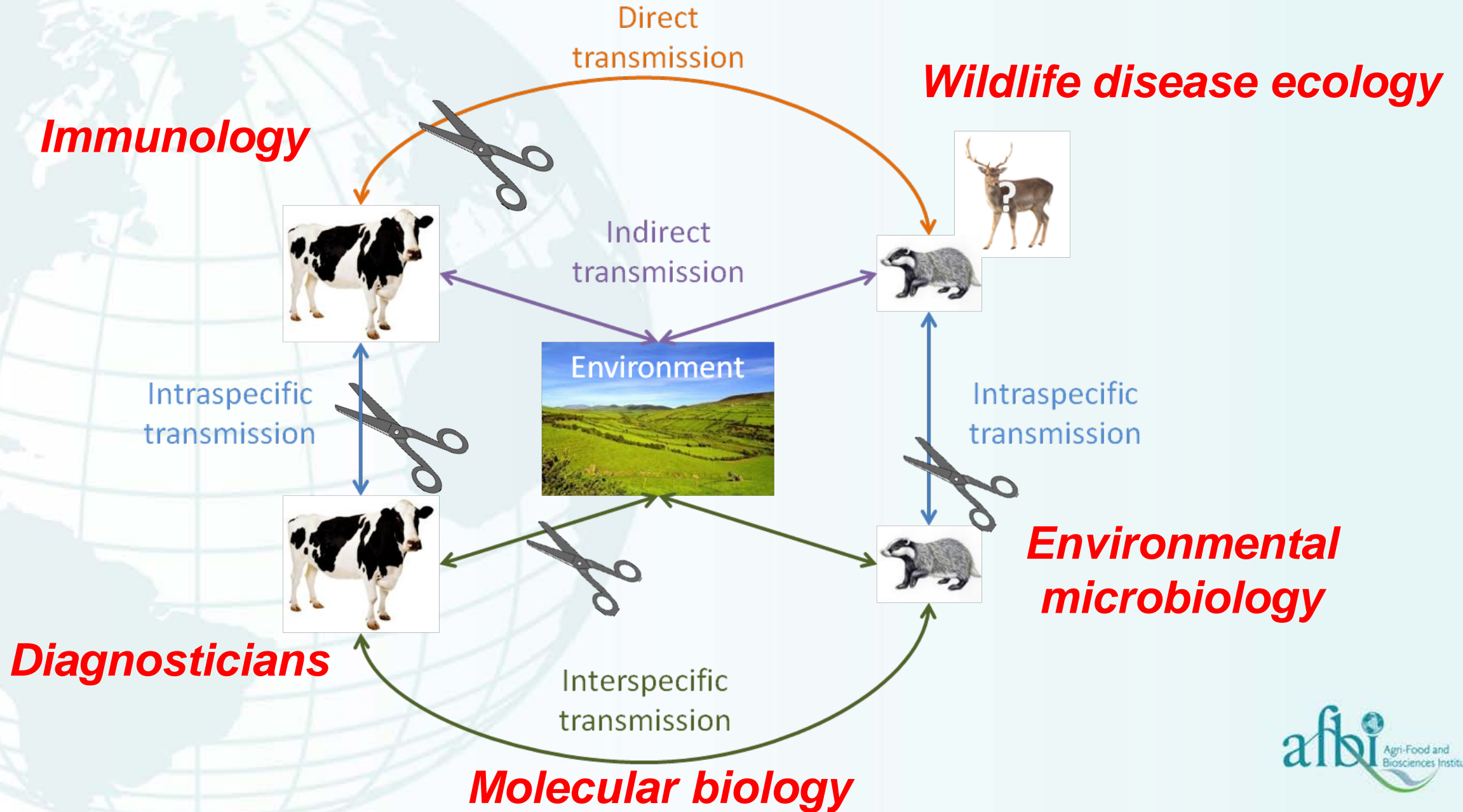


# Veterinary Epidemiology – Bovine TB



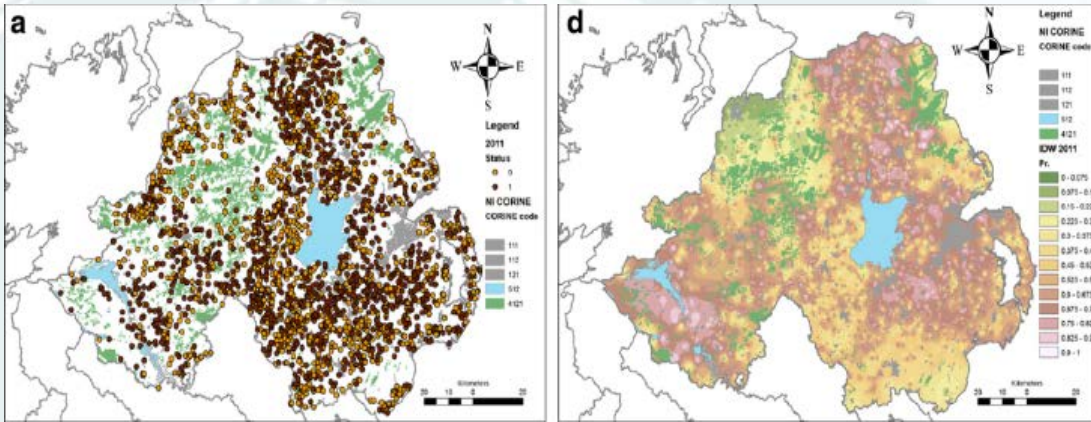
***Cut transmission chains  
– requires evidence and tools***

# Veterinary Epidemiology – Bovine TB

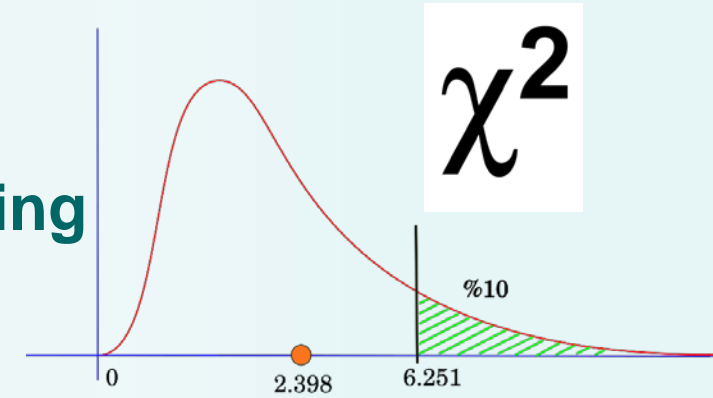




# Veterinary Epidemiology – Research base NI, the tools

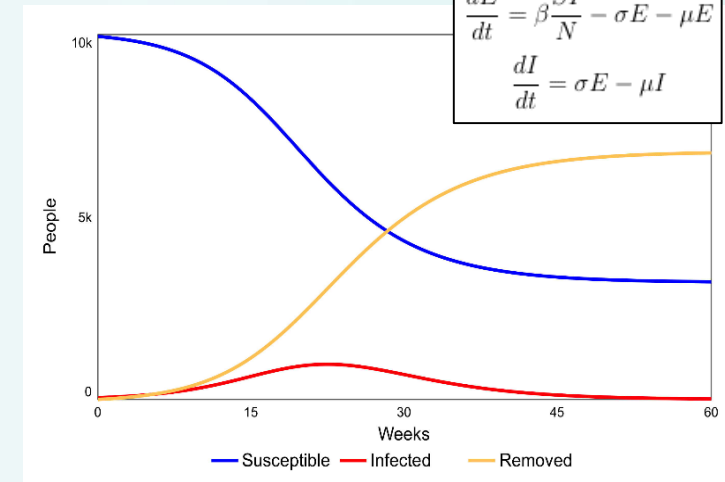


Statistical modelling



Mathematical modelling

$$\begin{aligned} \frac{dS}{dt} &= v - \beta \frac{SI}{N} - \mu S \\ \frac{dE}{dt} &= \beta \frac{SI}{N} - \sigma E - \mu E \\ \frac{dI}{dt} &= \sigma E - \mu I \end{aligned}$$

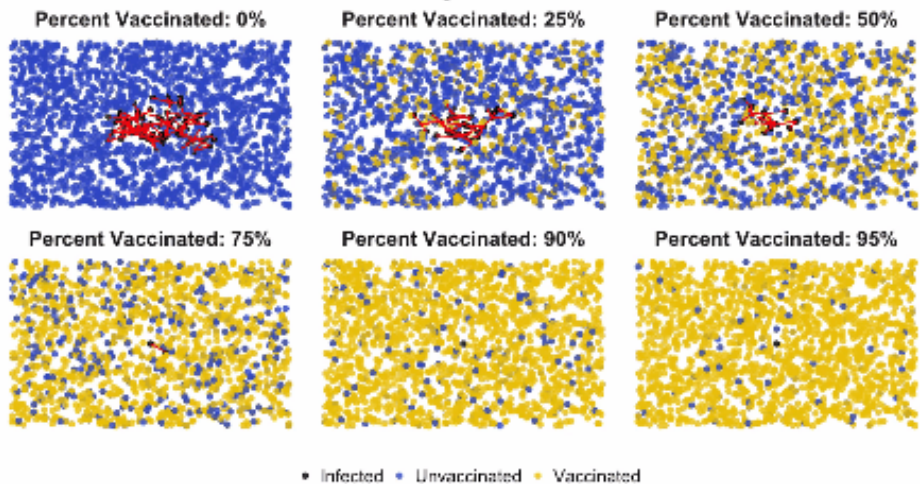


GeoSpatial modelling

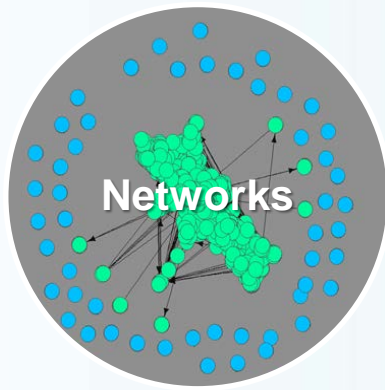
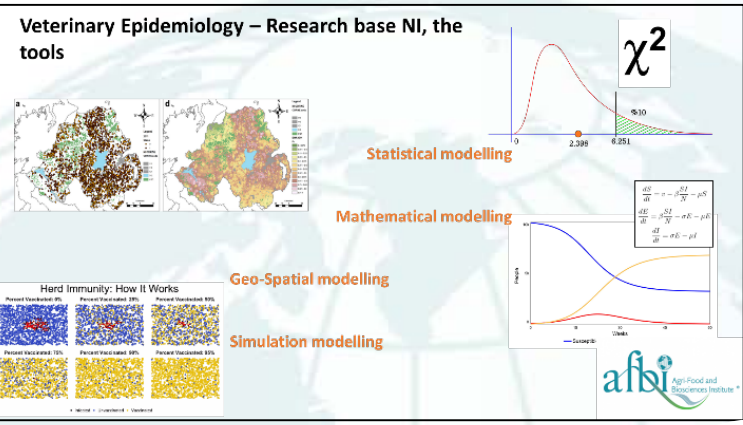
Simulation modelling

Qualitative epidemiology

## Herd Immunity: How It Works



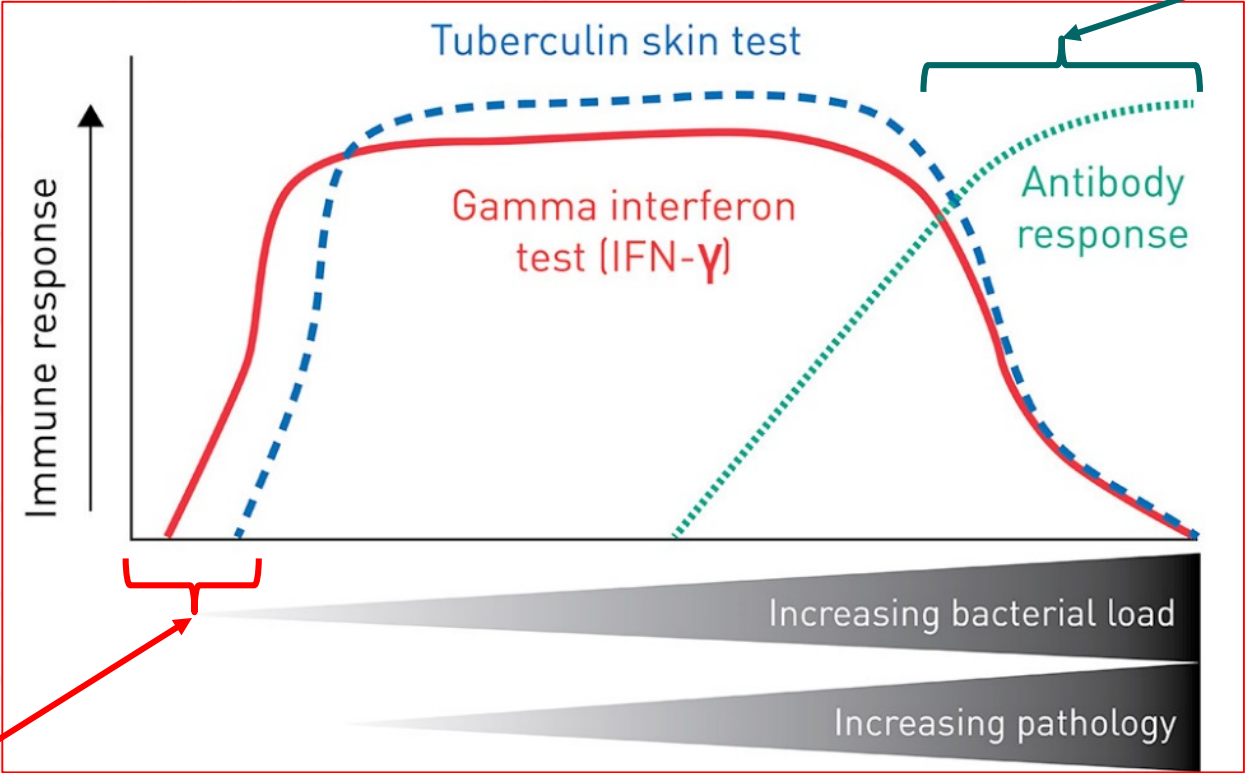






# Veterinary Epidemiology – diagnosis

**Anergic animals  
= serological  
(antibody) tests**

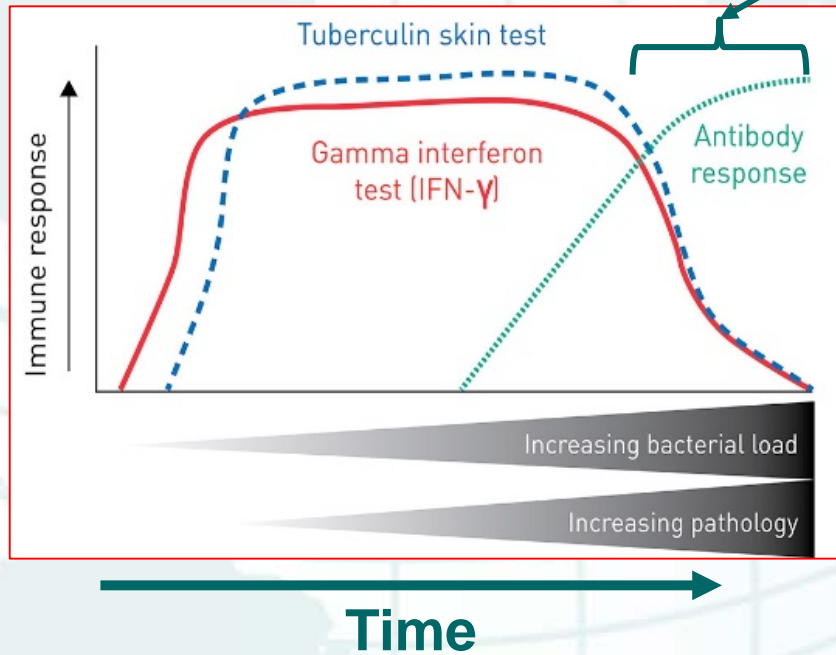


*McCallan et al. 2017a & 2017b*  
*Lahuerta-Marin et al. 2015, 2016, 2018 (in review)*

**Early responders**

*Pollock and Neill 2002*

# Veterinary Epidemiology – diagnosis



Anergic animals  
= serological  
(antibody) tests

- Two ‘flavours’ of **ENFER test** – undertaken blind in ENFER labs (ROI)
- Enfer2ag (positive to either MPB70, MPB83 antigens) or
- Enfer4ag (positive to two from four of the following antigens: MPB70, MPB83, Early secretory antigenic target-6 (ESAT-6), Culture filtrate protein-10 (CFP10))
- **IDEXX** – standalone kit, undertaken in-house: MPB70, MPB83 antigens

Assessment of “commercially available”  
**serological tests**

*McCallan et al. 2017a & 2017b*

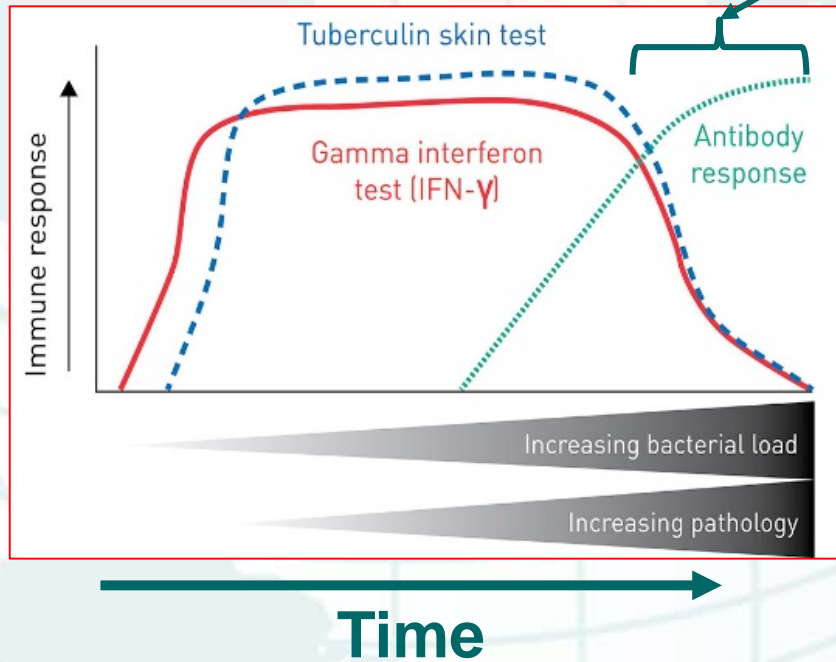


# Veterinary Epidemiology – diagnosis



Anergic animals  
= serological  
(antibody) tests

- *Results*
- High specificity, but **variable/low SE** – especially when blood samples taken prior to skin testing



*“When INF-g & skin test used together – serology testing was **not** disclosing additional infected animals”*

Assessment of “commercially available”  
**serological tests**

*McCallan et al. 2017a & 2017b*

Veterinary Record  
(2017) 181,  
cite as doi:  
10.1136/vr.104272

L. McCallan,  
C. Brooks,  
C. Couzens,  
F. Young,  
J. McNair,  
A. W. Byrne

## Assessment of serological tests for diagnosis of bovine tuberculosis

L. McCallan, C. Brooks, C. Couzens, F. Young, J. McNair, A. W. Byrne

### Context

Bovine tuberculosis (TB) remains a significant problem for the cattle industry. In this study, commercially available serological tests for the diagnosis of bovine TB were compared with antemortem and postmortem diagnostics of bovine TB from a cohort of high-risk animals from Northern Ireland.

positive- and negative predictive values were also calculated.

### Results

There was strong agreement from the Enfer test result interpretations ( $\kappa=0.85$ ), and the Enfer2ag and IDEXX ( $\kappa=0.64$ ), but weaker agreement between the Enfer4ag and IDEXX results ( $\kappa=0.51$ ). There was significant differ-



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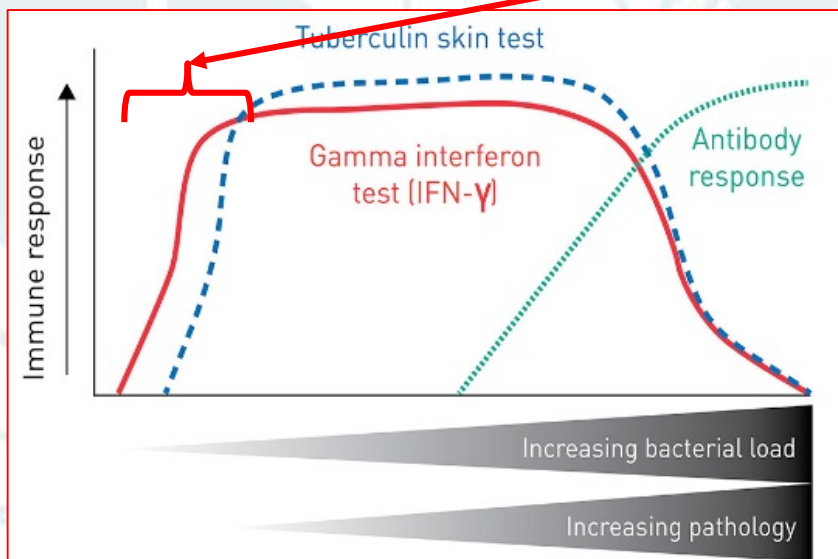
### New Results

**Performance of serological antibody tests for bovine tuberculosis in cattle from infected herds in Northern Ireland**

Lynne McCallan, Cathy Brooks, Catherine Couzens, Fiona Young, Andrew Byrne, Jim McNair  
doi: <https://doi.org/10.1101/235184>



# Veterinary Epidemiology – diagnosis

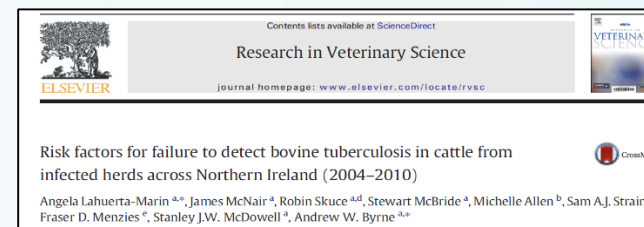
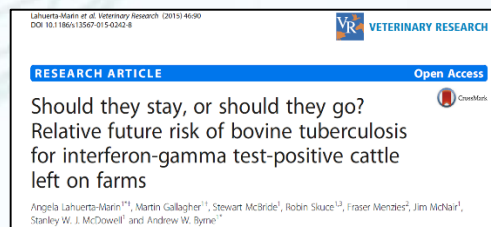


Early responders  
= gamma+, SCITT-

- Followed herds which retained animals that were INF-g positive, but SCITT negative
- Survival model
- 1107 IFN-g positive animals from 239 herds

Assessment of **INF-g** to find early infection

*Lahuerta-Marin et al.*  
2015, 2016,



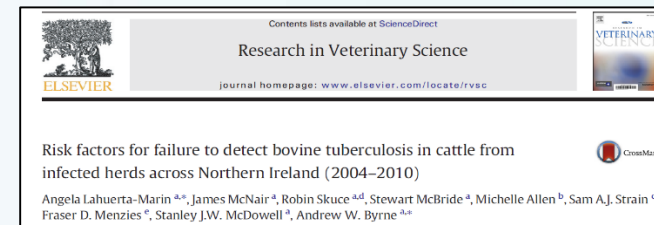
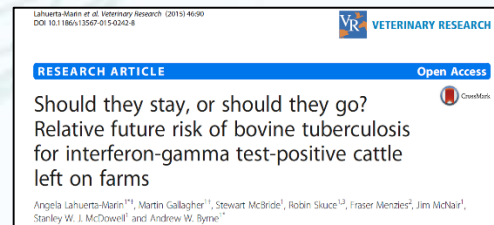
# Veterinary Epidemiology – diagnosis



INF-g+ animals were **2.3 times** more likely to fail a future TB test ( $p < 0.05$ ), than IFN-g negative herd-mates

- @ 18 months **22.6% for IFN-g positive animals versus 6.1% for IFN-g negative animals had failed the SICCT**
- **Parallel use of SCITT and IFN-g tests together resulted in the least missed infections**

*Lahuerta-Marin et al.  
2015, 2016,*

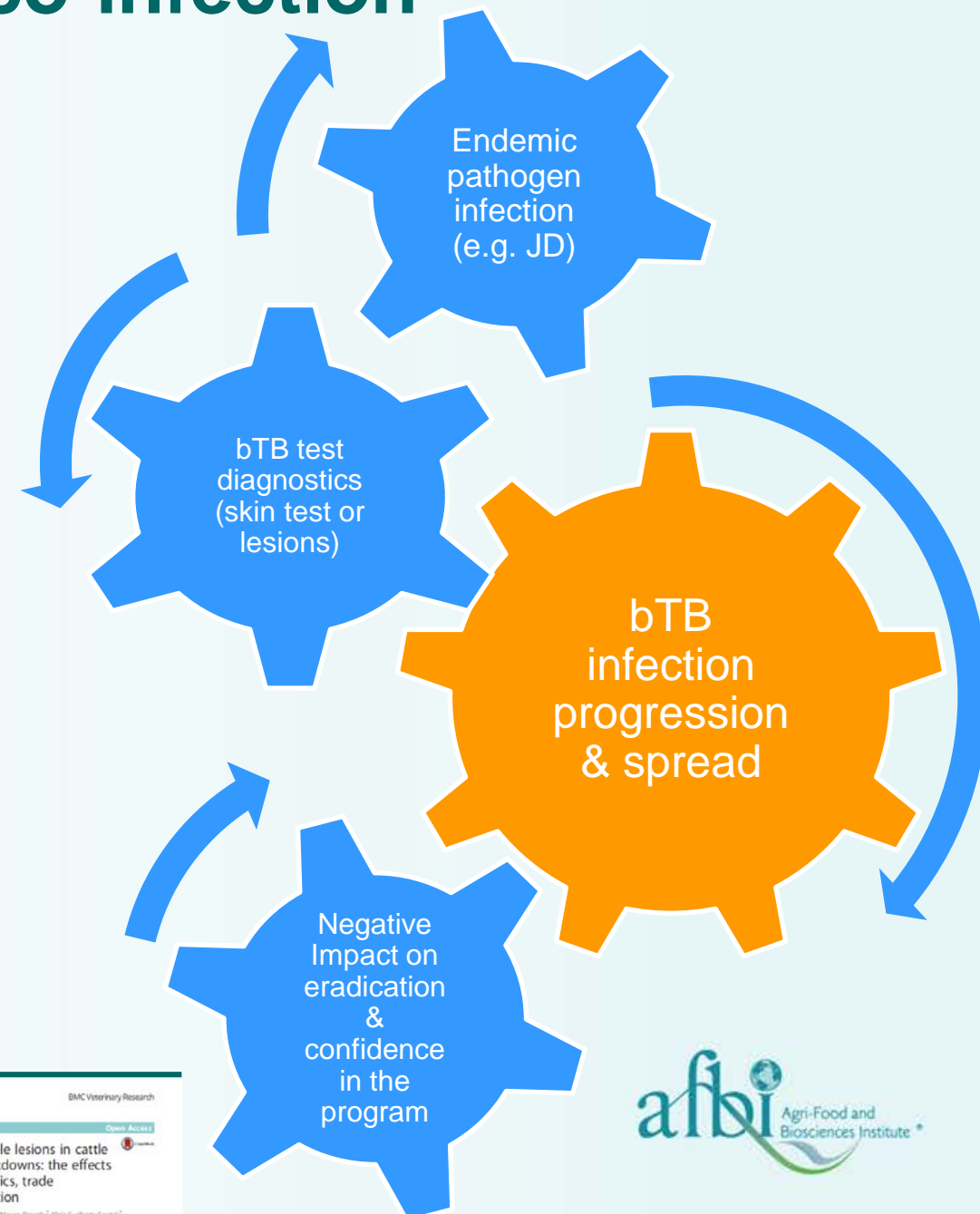


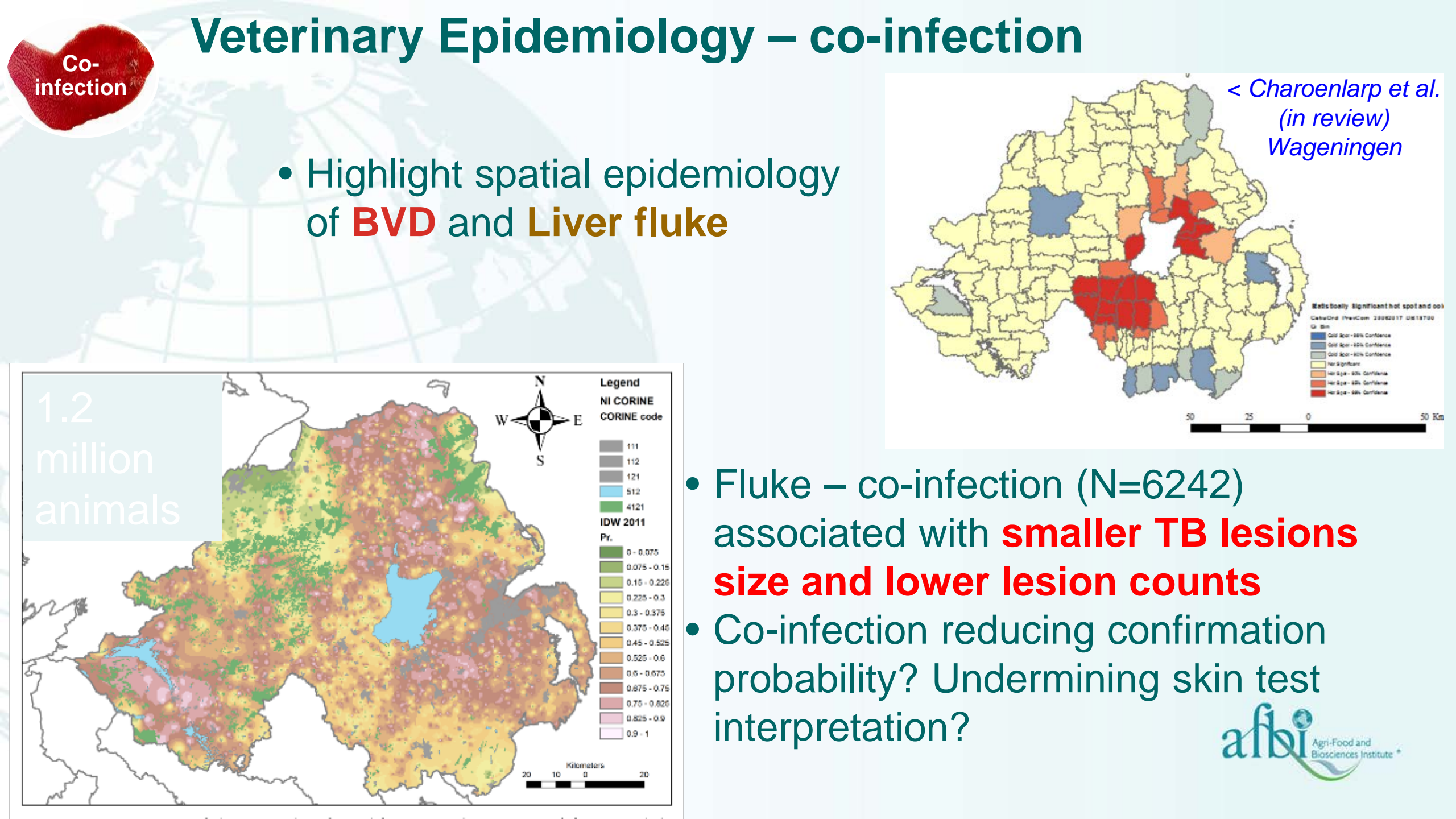


## Co-infection

# Veterinary Epidemiology – co-infection

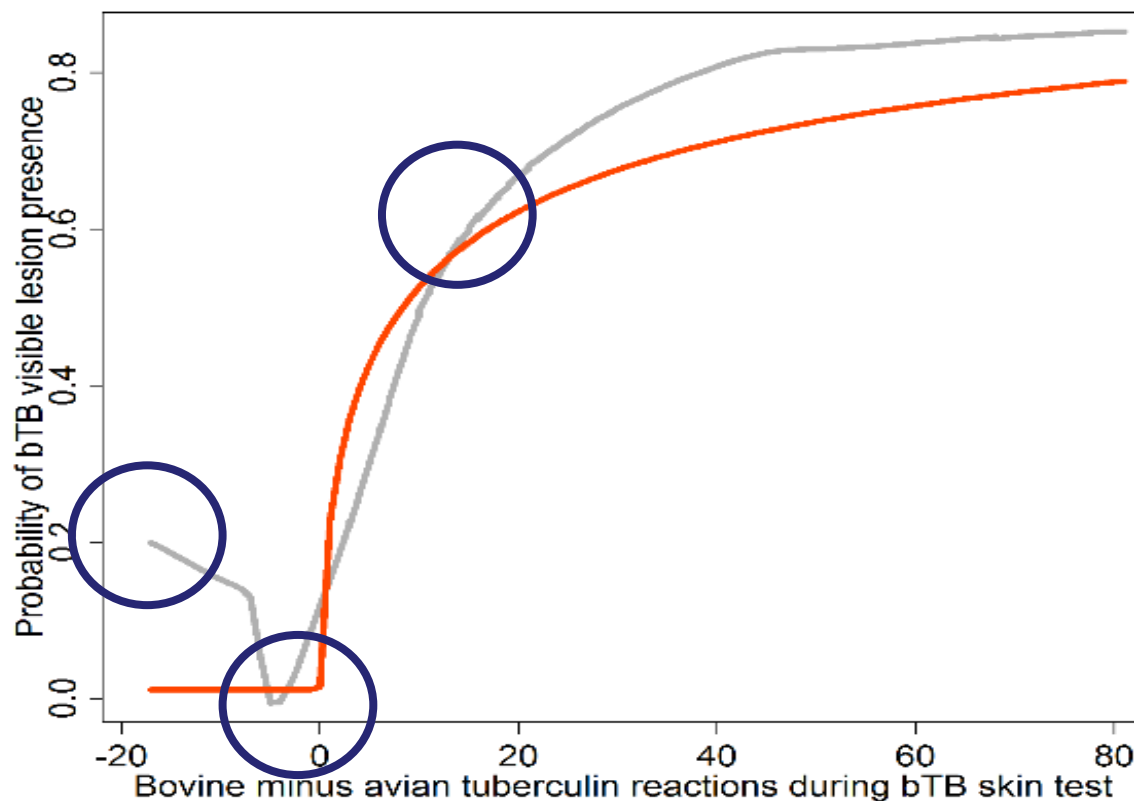
- Co-infection can modulate immunological responses
  - Impact on diagnostics
  - Exacerbate infection
- Some data on the potential impacts in bTB in all three pathogens of interest
  - BVDV
    - Liver fluke
    - Johne's Disease





# Veterinary Epidemiology – co-infection

- Retrospective animal-level assessment **Johne's disease** co-infection
  - “Avian reactors” – negative B-A tuberculin
  - Confirmation (VL) probability vs non-reactors ( $b-a=0$ )



- **Avian reactors higher risk of being missed** when infected  
( $n=6,242$ ) reactors/NICs

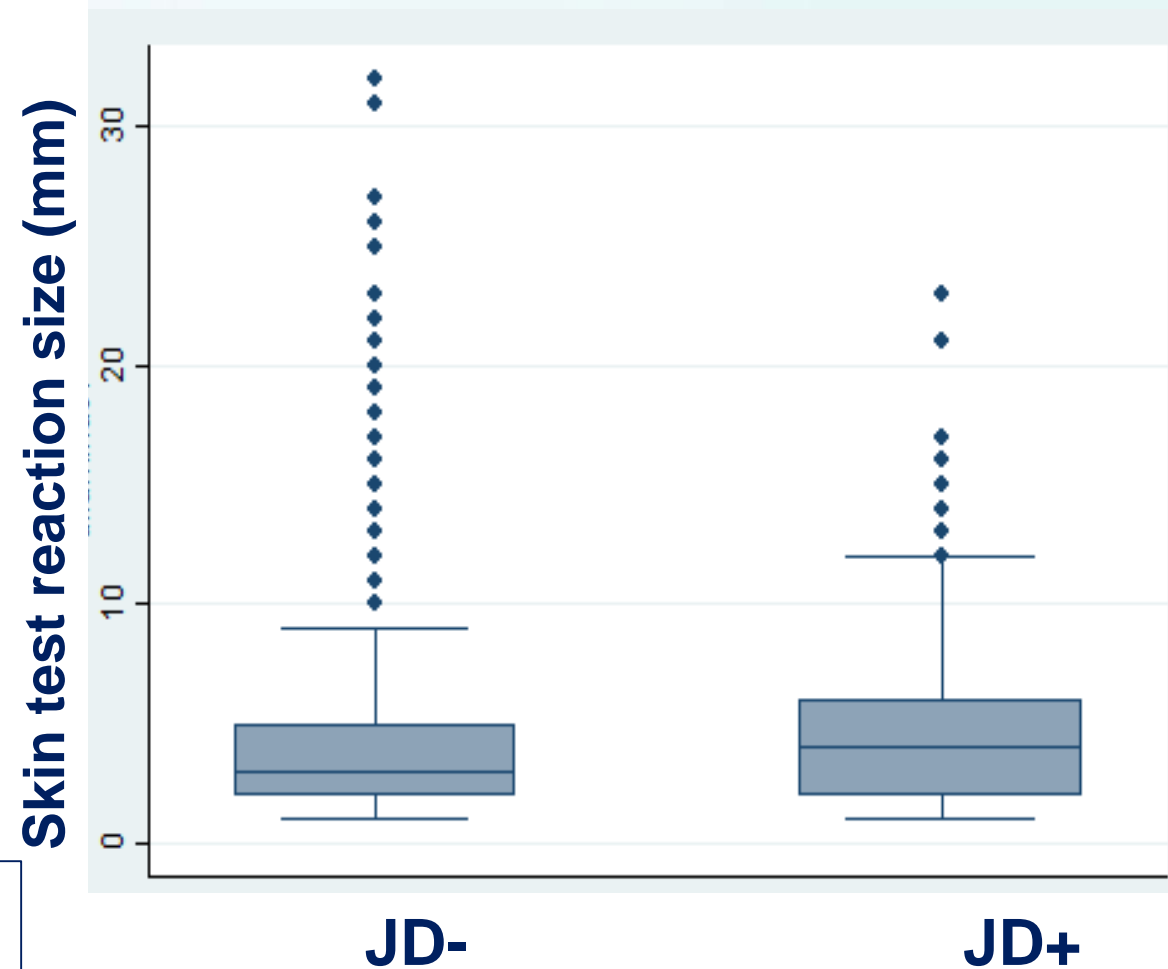




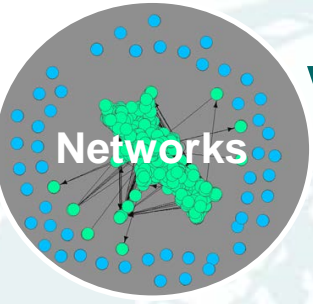
# Veterinary Epidemiology – co-infection

- Avium reactions were also higher for Johnes Disease ELISA+ ( $p < 0.001$ )

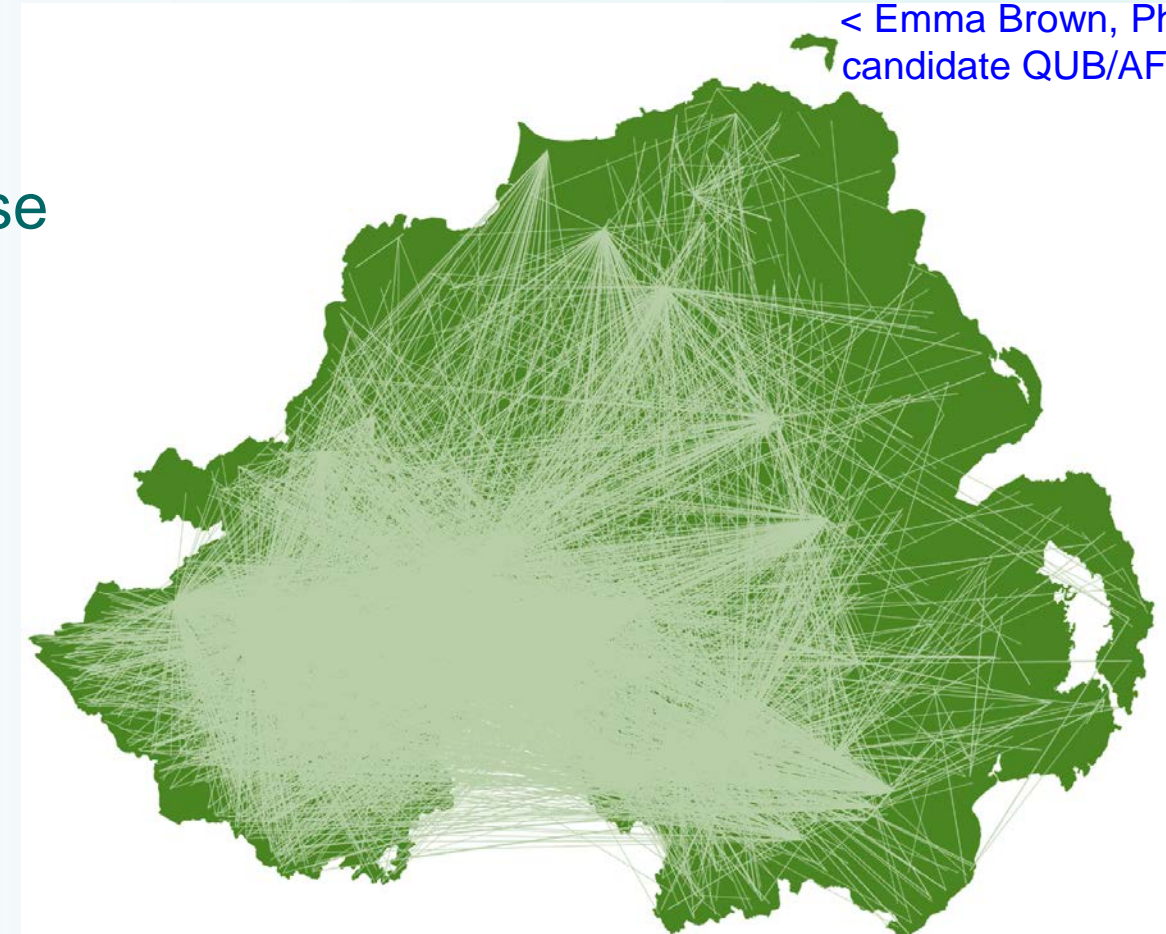
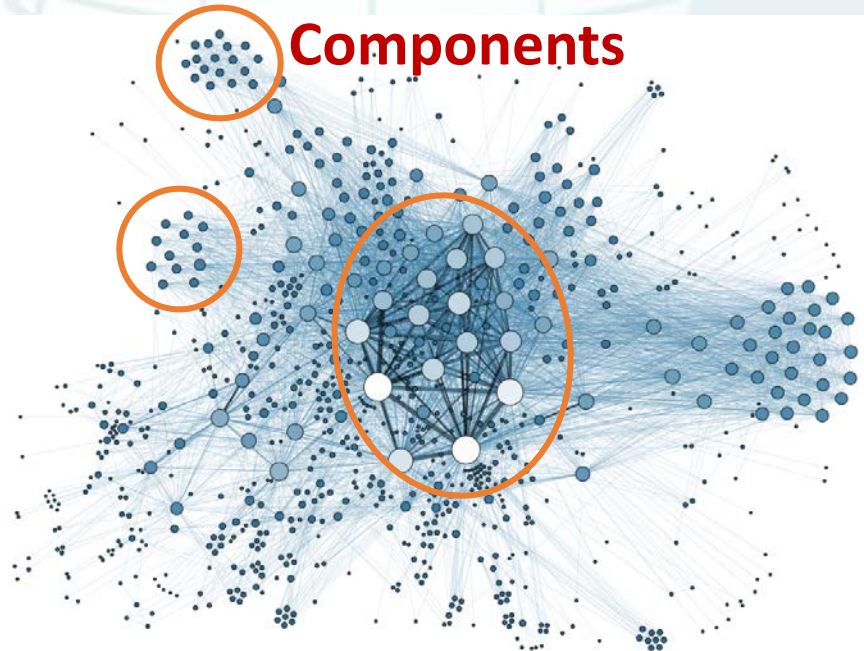
**MAP effects bTB diagnosis**



# Veterinary Epidemiology – Movement networks



- Movement of animals is important for disease spread
- Movement can be modelled using **social network analysis** – farms are “nodes”, trade/moves are “edges” connecting nodes



< Emma Brown, PhD  
candidate QUB/AFBI

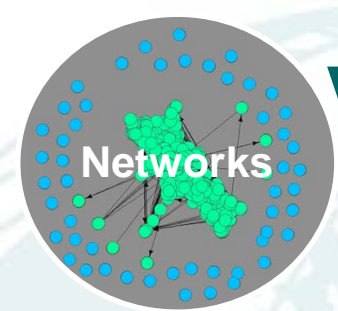
AFBI working on visualising network & mapping



QUEEN'S  
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BELFAST

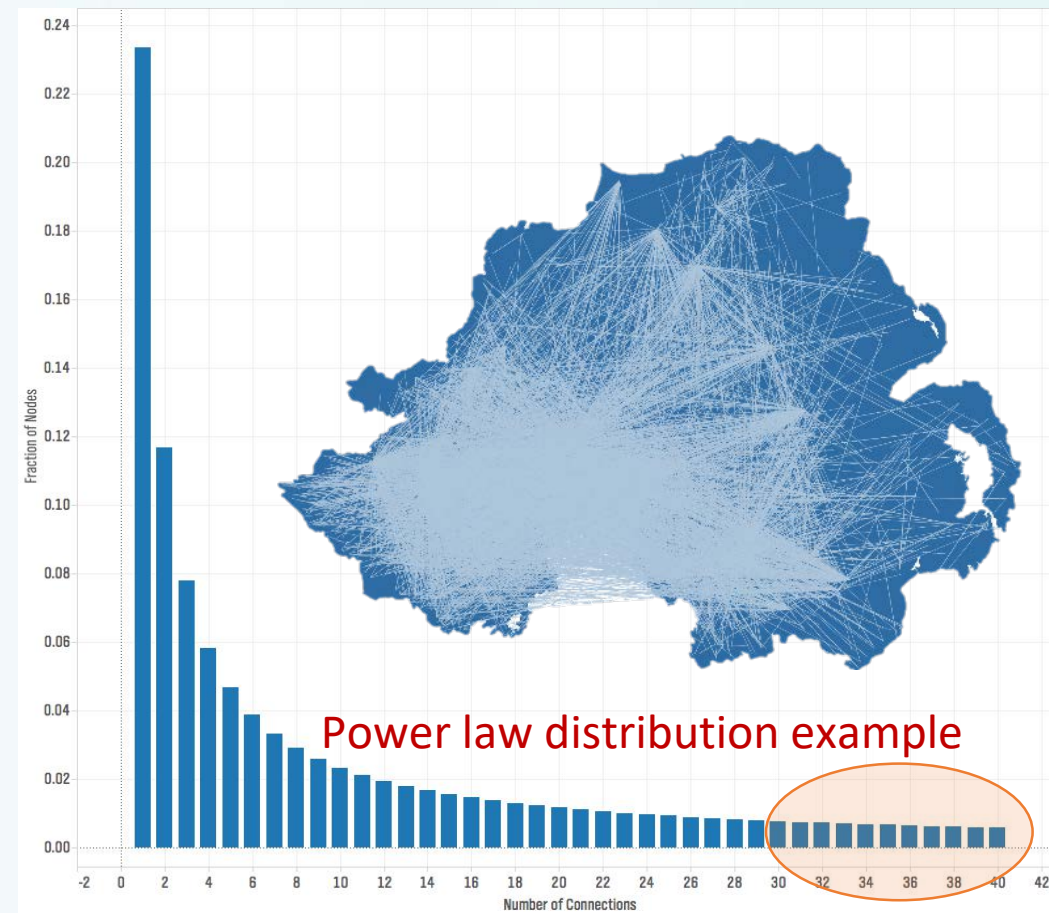






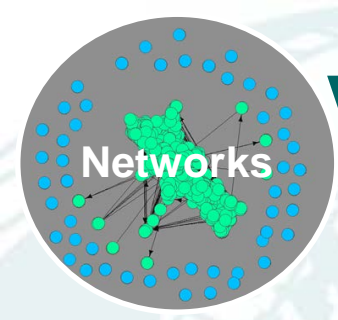
# Veterinary Epidemiology – Movement networks

- Network modelling constitute a **'big data'** challenge
- For example, **21,963,941 movements** in the database for **6,154,451 cattle** over the 10 year period



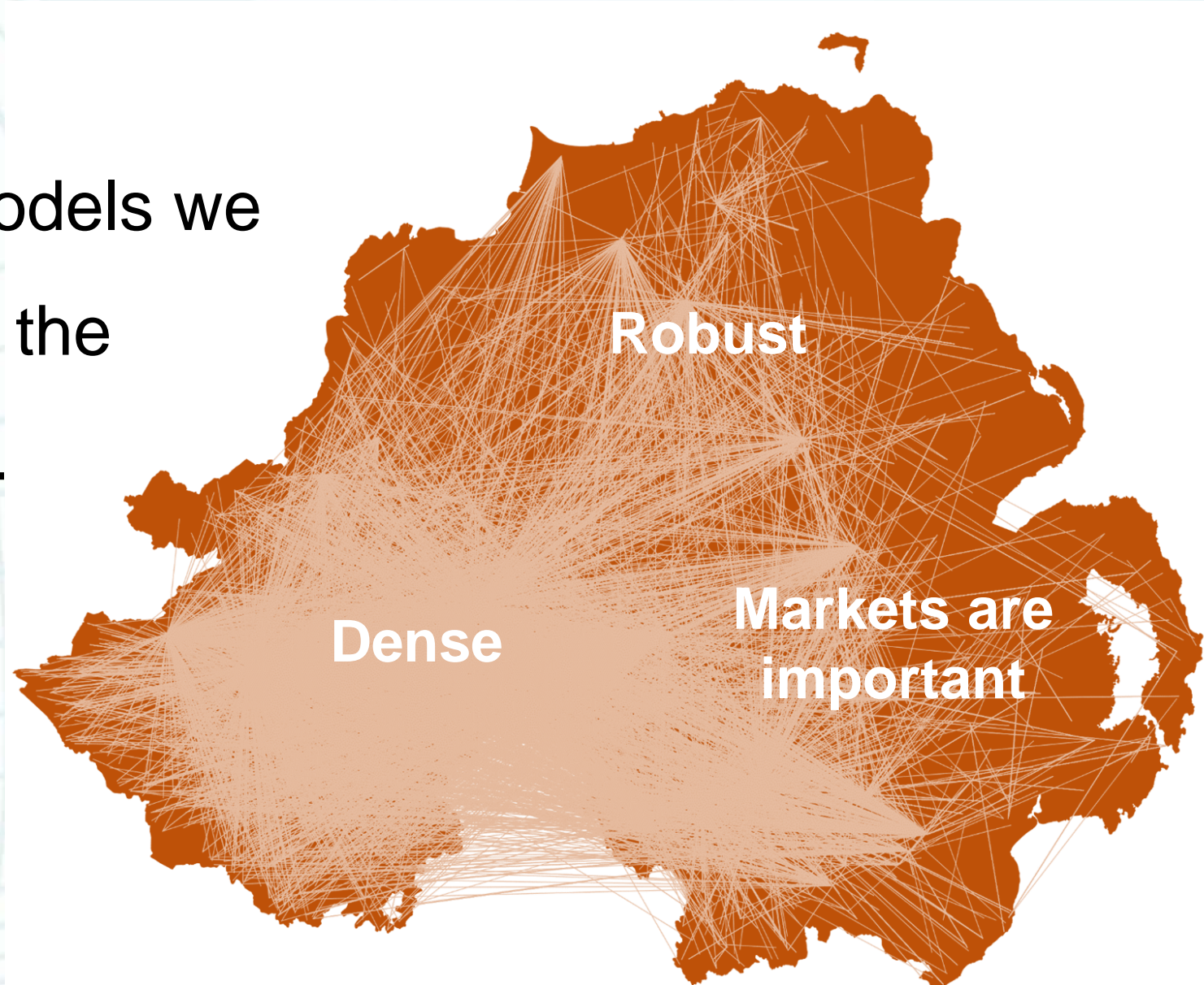
***“Not all nodes are equal!”***





# Veterinary Epidemiology – Movement networks

From our models we  
learned that the  
network is...

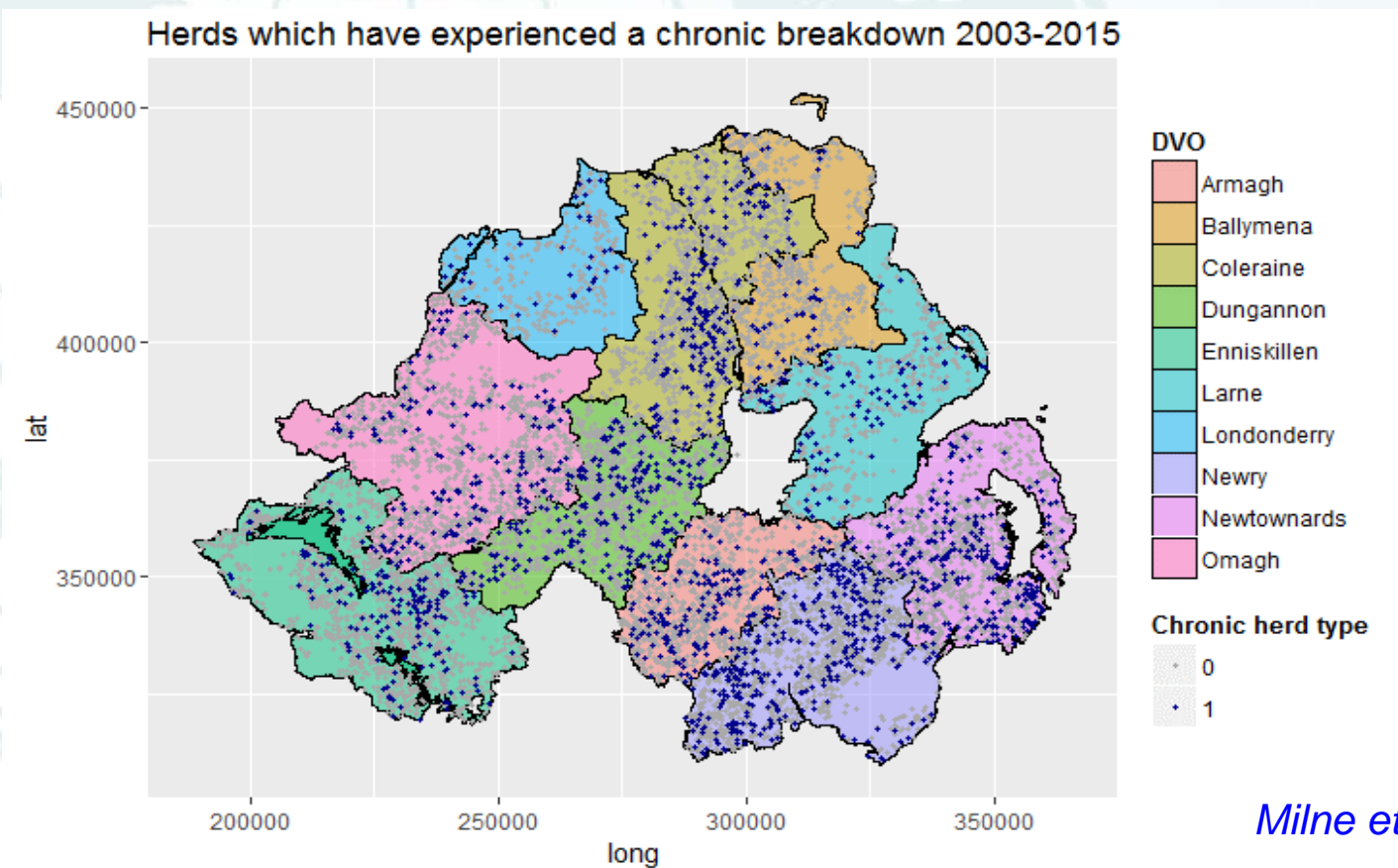




# Veterinary Epidemiology – Chronic herds

*“The majority of reactors in Northern Ireland come from a small amount of herd”*

These herds are characterised as having long or recurrent breakdowns - **chronic herds**



We addressed two questions?  
What risk factors are associated with  
“chronicity”?  
Are there spatial clusters in space  
and time?

*Milne et al. 2018a & 2018b (in review)*





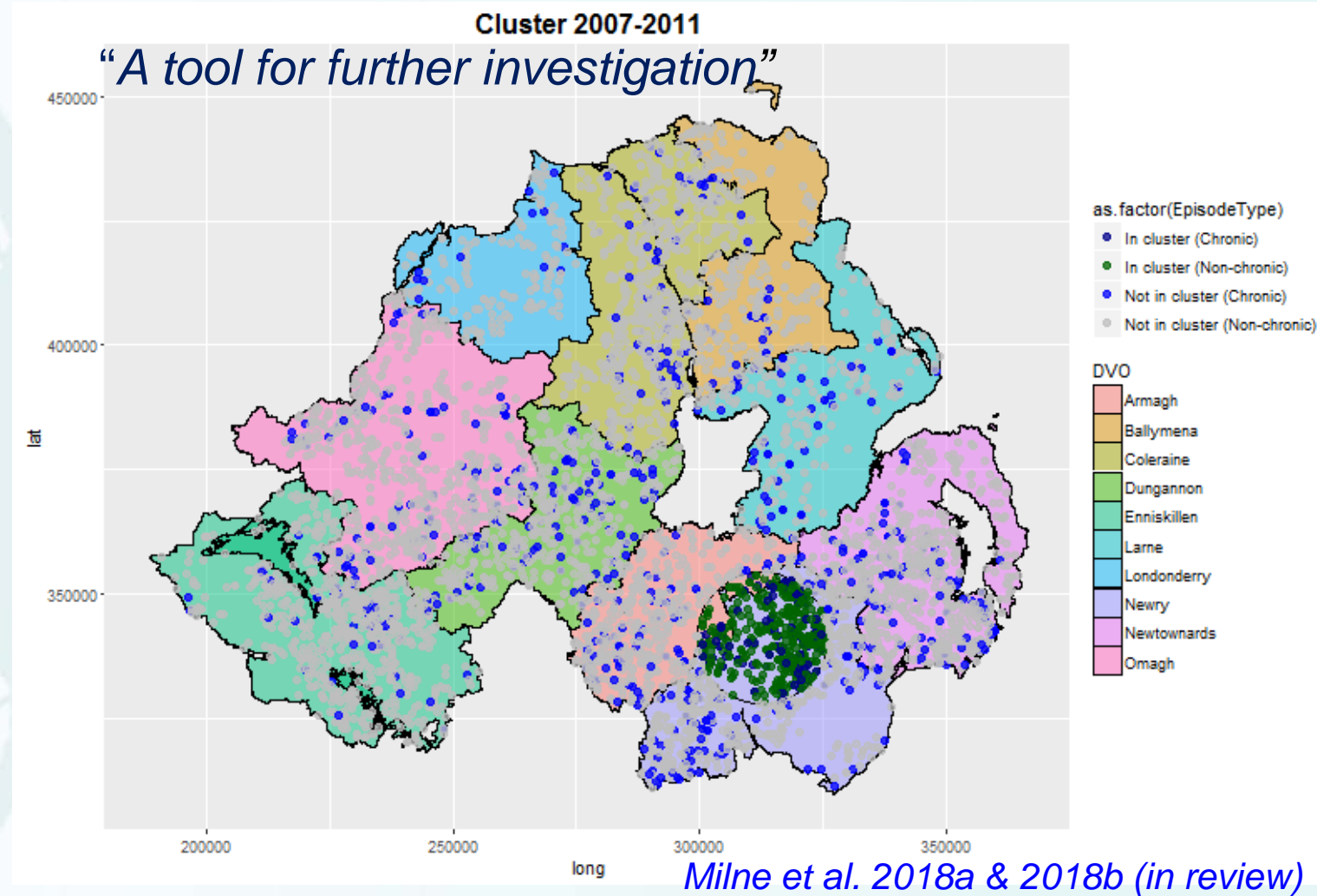
# Veterinary Epidemiology – Chronic herds

We addressed two questions?

1. Are there spatial clusters in space and time?

**Answer: Yes!**

Mapping of genotypic strains of *M. bovis* suggested movement from outside “home range” may be important



Purchasing strategy is important for managing risk





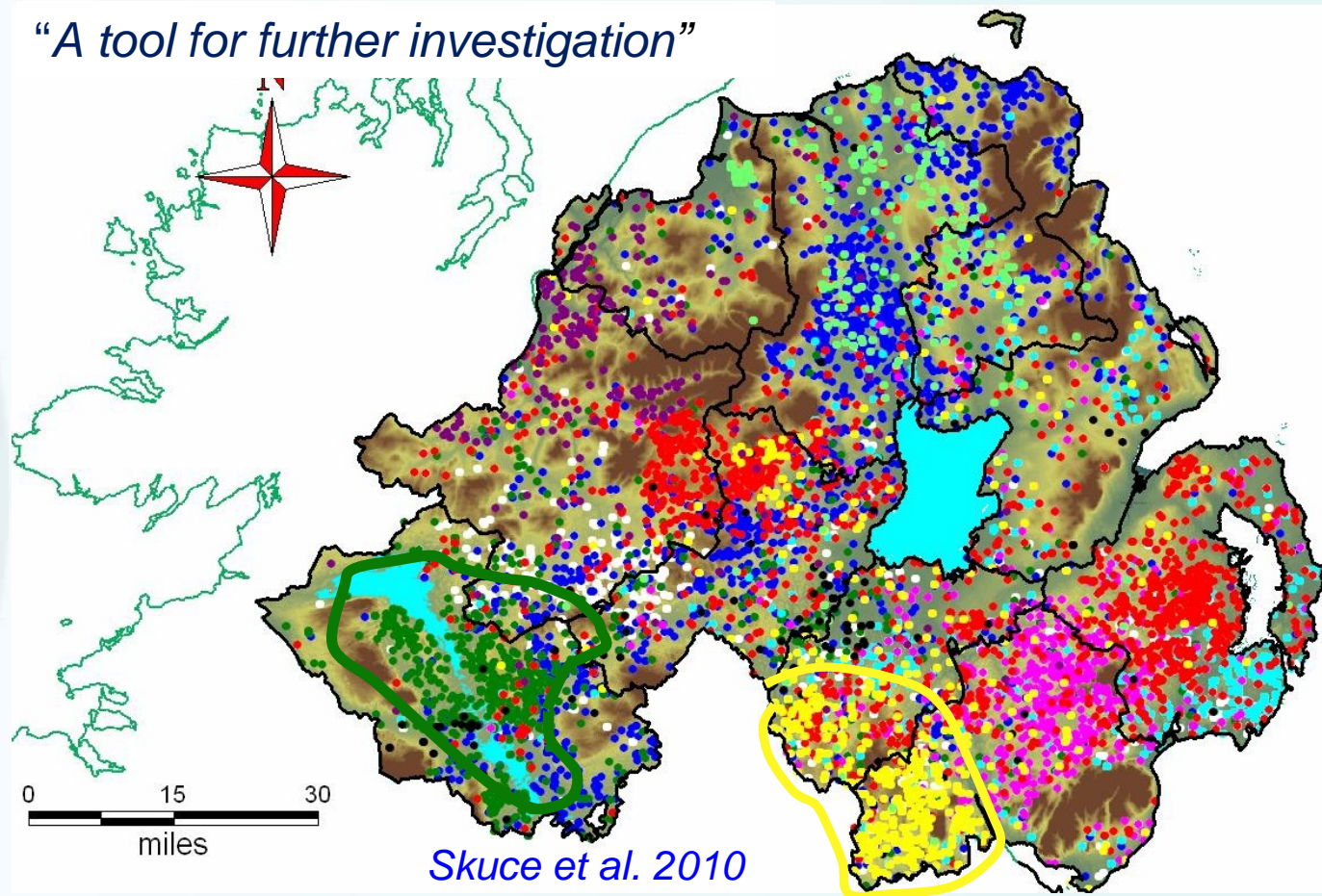
# Veterinary Epidemiology – Chronic herds

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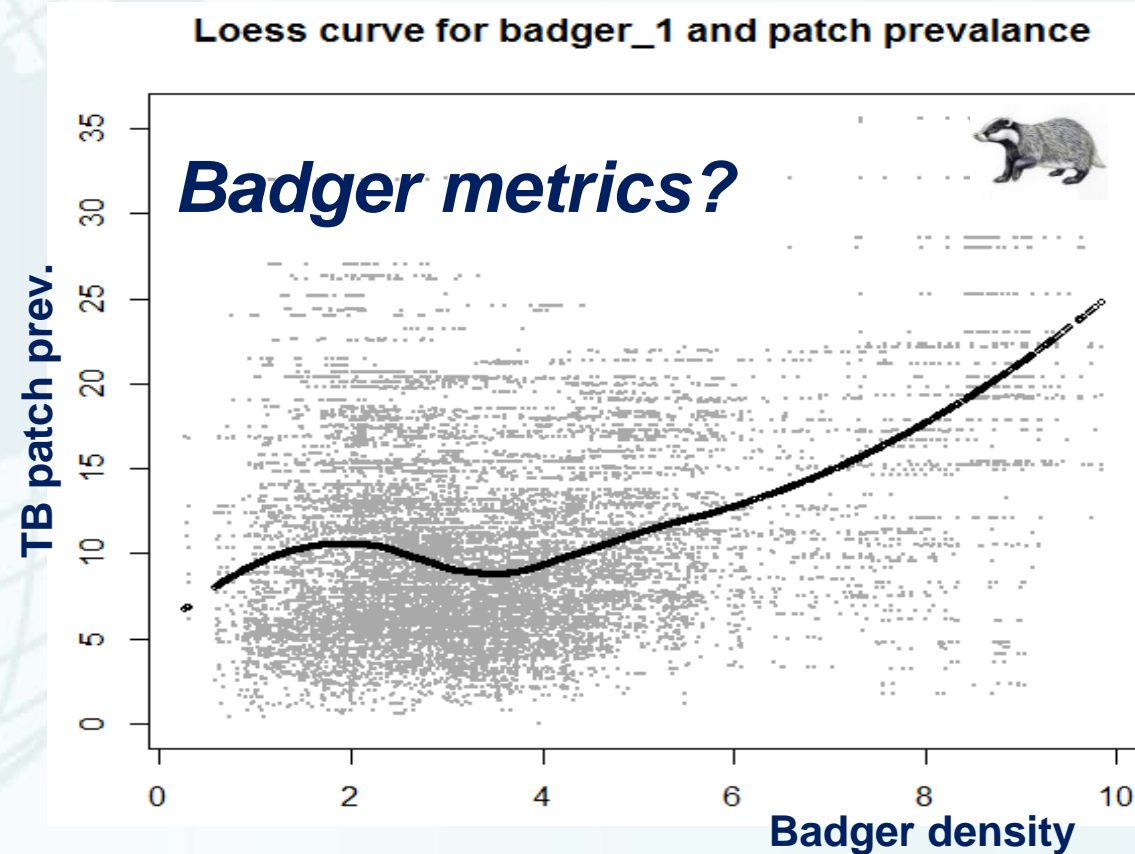
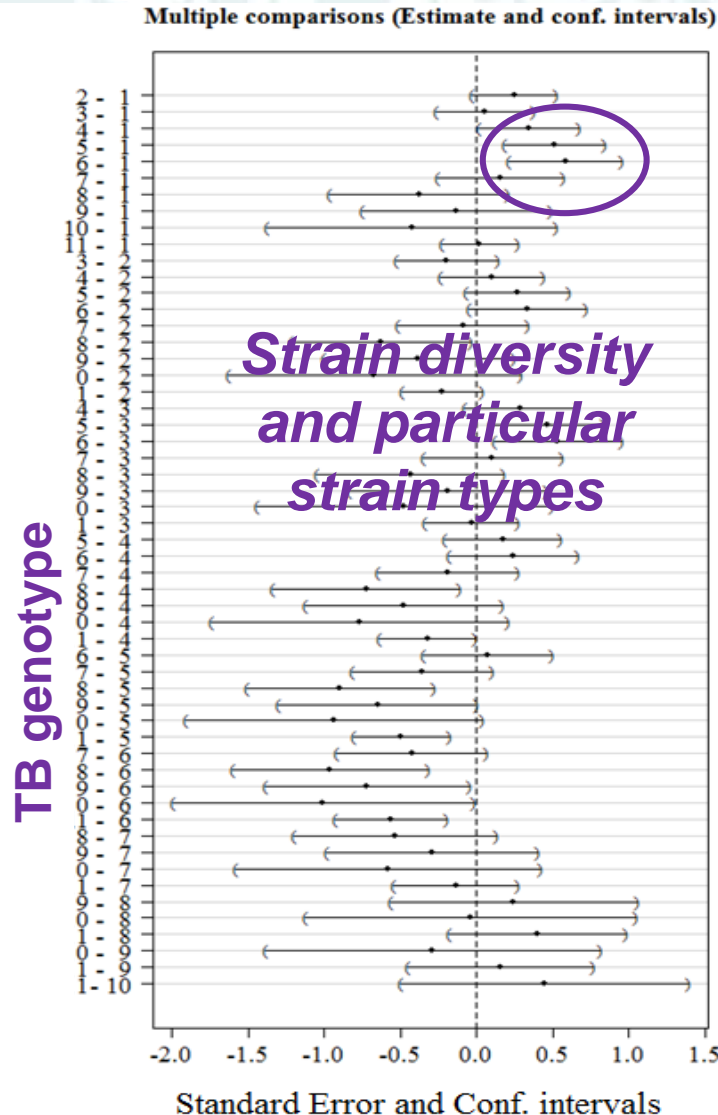
**Purchasing strategy is important for managing risk**



# Veterinary Epidemiology – Chronic herds

2. What risk factors are associated with “chronicity”?

Herd-size, buying-in, local prevalence, associated herds



*Milne et al. 2018a & 2018b (in review)*

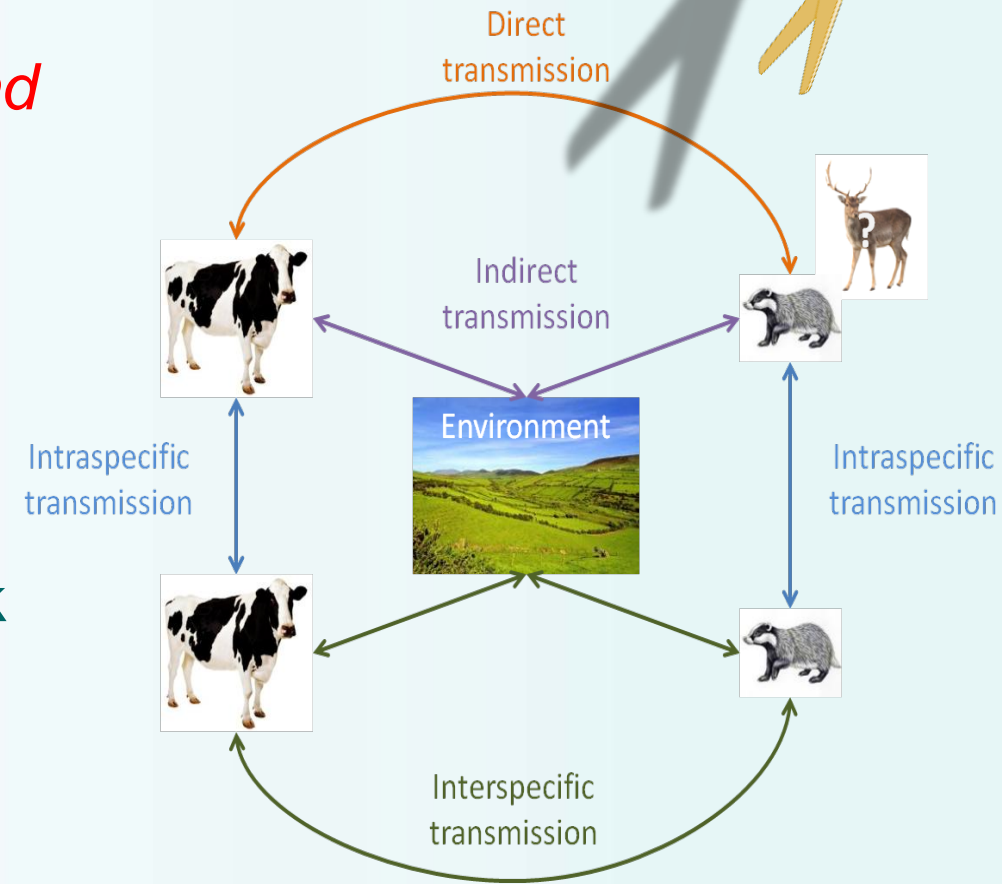




# Veterinary Epidemiology – Wildlife

*A research basis is fundamental to understanding and potentially mitigating the wildlife risk*

1. Establish effects of historic badger interventions
  2. Spatial and temporal variation in badger TB prevalence
  3. Fundamental ecological studies to understand risk – density and movement
- Ultimately, research can feed into mathematical and simulation models to test “what if” scenarios?

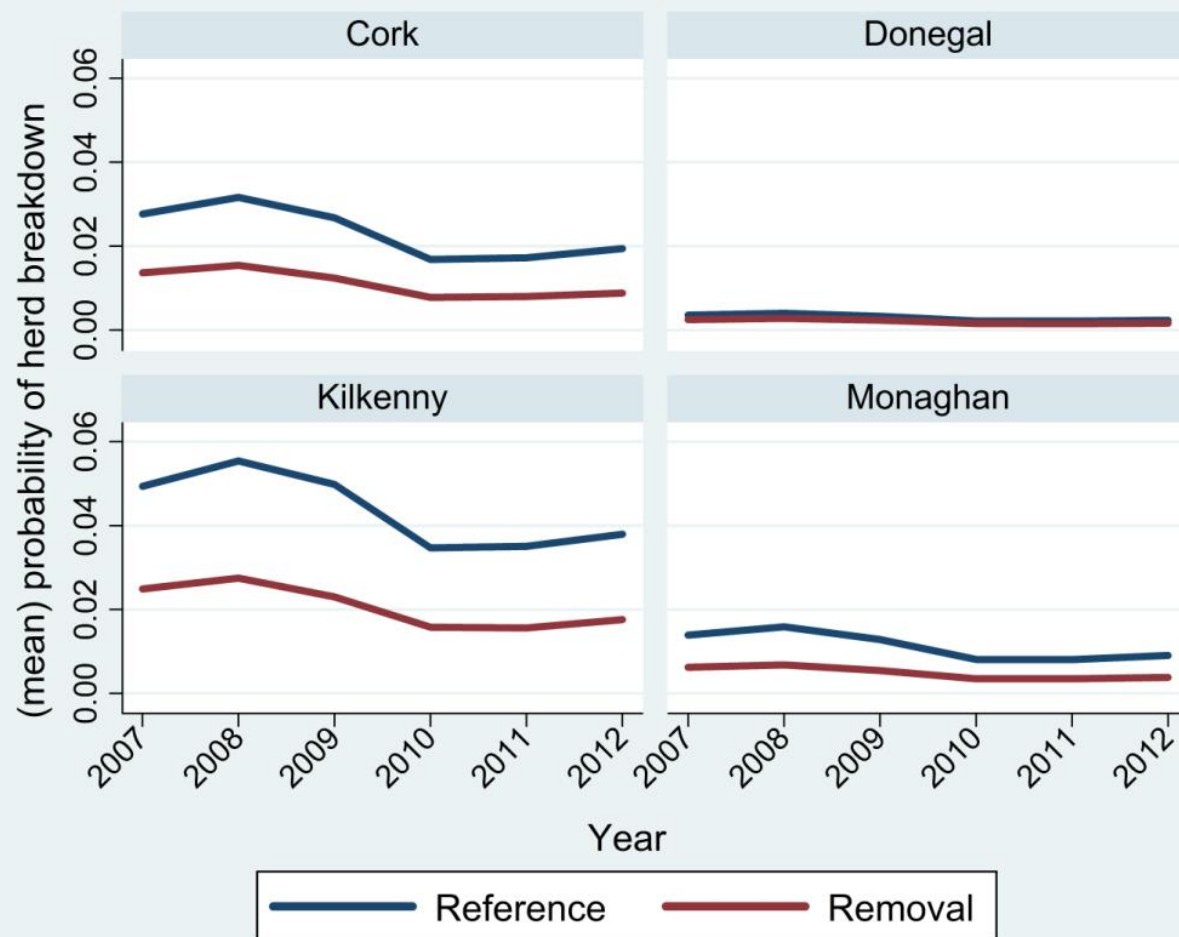






# Veterinary Epidemiology – Wildlife

## 1. Establish effects of historic badger interventions



- Large-scale intensive interventions can have measurable effects 10 years on



Byrne et al. Veterinary Research 2014, 45:109  
http://www.veterinaryresearch.org/content/45/1/109



RESEARCH Open Access

Risk of tuberculosis cattle herd breakdowns in Ireland: effects of badger culling effort, density and historic large-scale interventions

Andrew W Byrne<sup>1,2\*</sup>, Paul W White<sup>1,3</sup>, Guy McGrath<sup>1</sup>, James O'Keeffe<sup>1,3</sup> and S Wayne Martin<sup>4</sup>



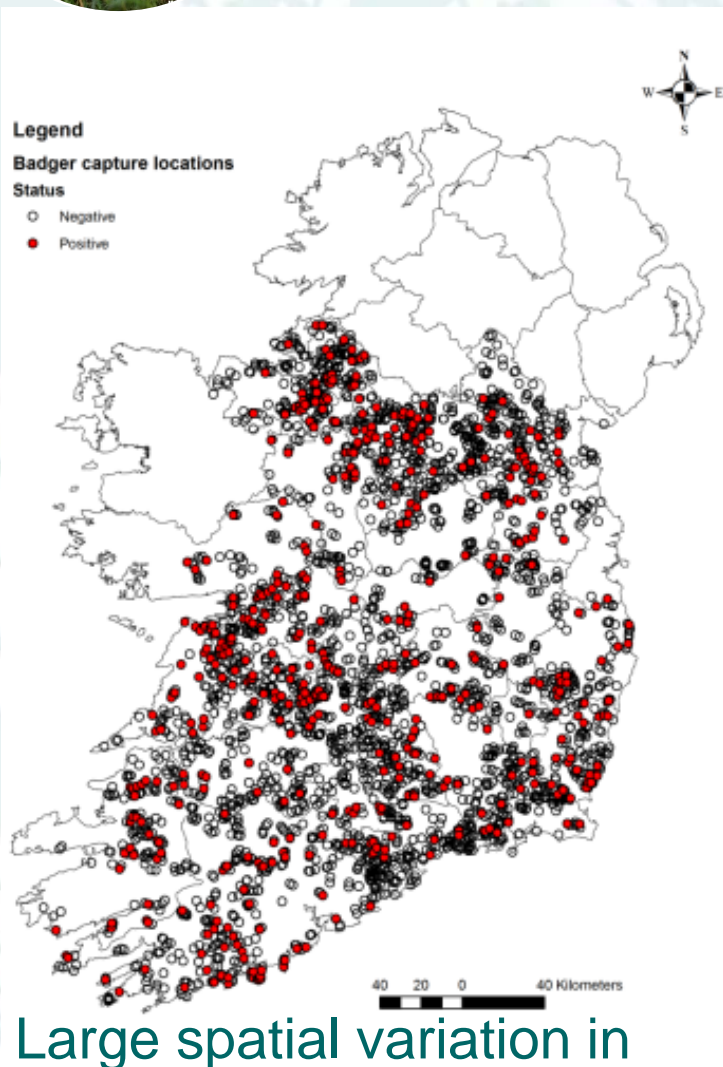
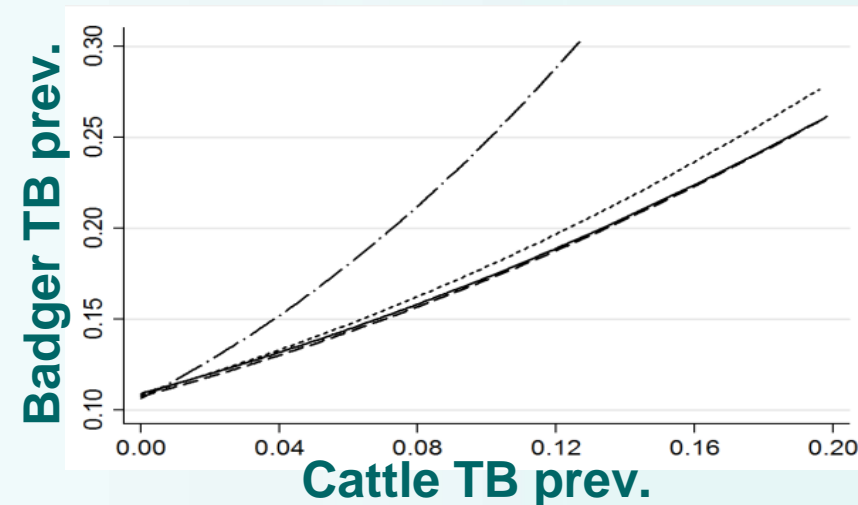
Graphs by County



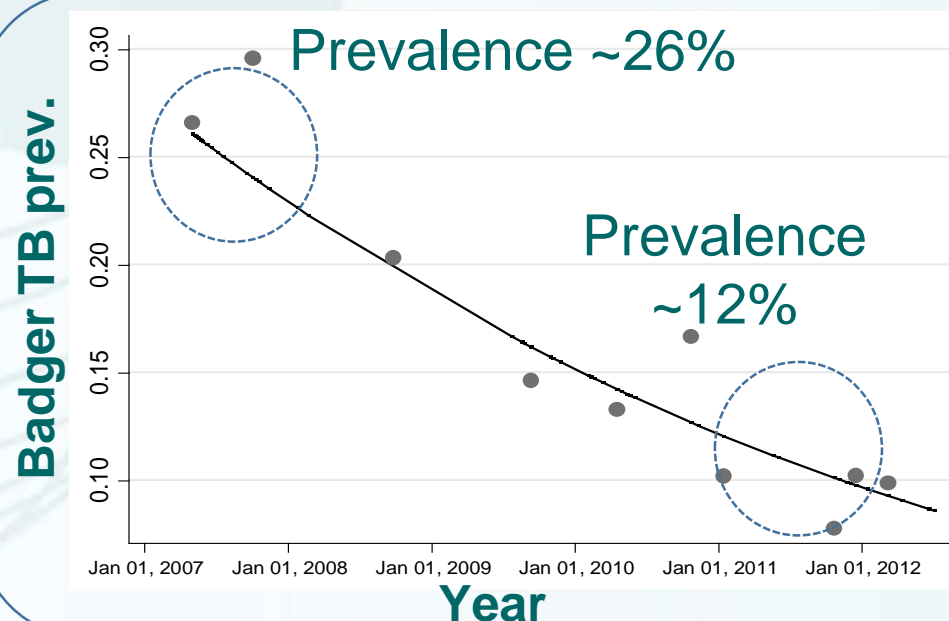
# Veterinary Epidemiology – Wildlife

## 2. Spatial and temporal variation in badger TB prevalence

- Significant correlation between cattle and badger risk



Large spatial variation in local badger prevalence



- Tracked the changing dynamics of the epidemic

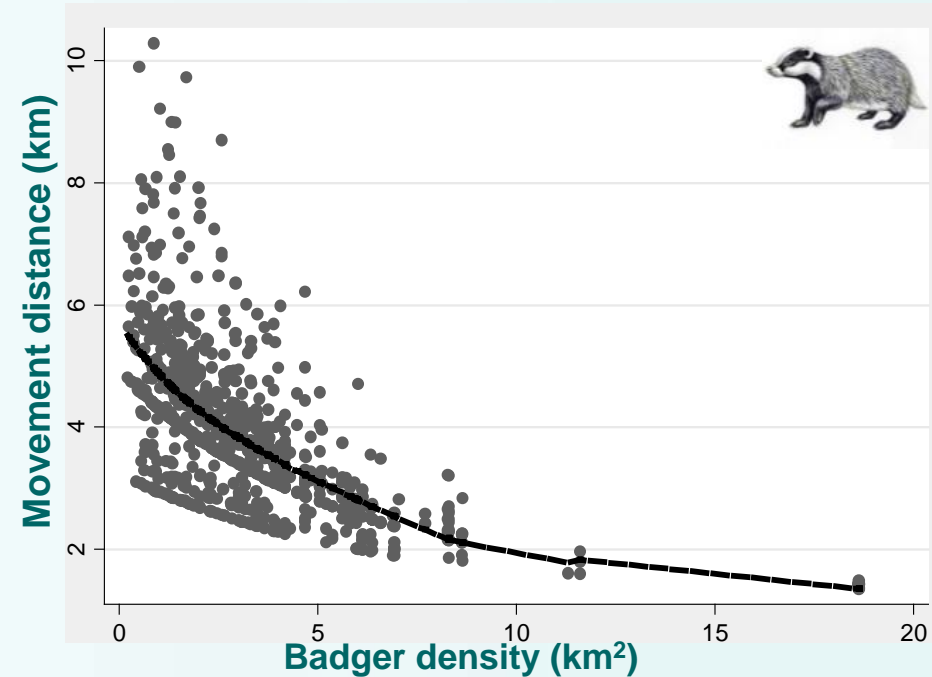
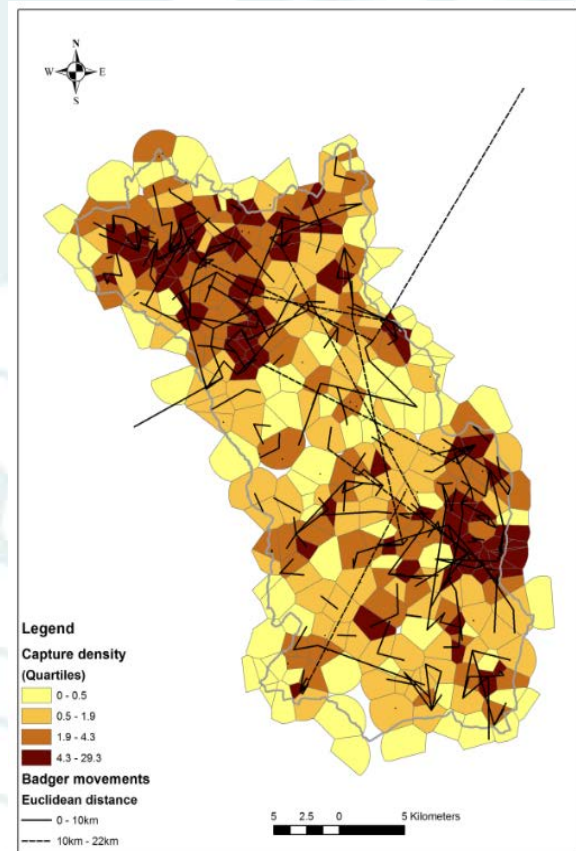




# Veterinary Epidemiology – Wildlife

## 3. Fundamental ecological studies to understand risk – density and movement

- Badgers move over longer distances than previously thought
- Movements were significantly affected by density
- Future NI work essential – TVR & TBSPG



**Journal of Animal Ecology**  
*Journal of Animal Ecology* 2014, 83, 991–1001  
 doi: 10.1111/1365-2656.12197

**Large-scale movements in European badgers: has the tail of the movement kernel been underestimated?**

Andrew W. Byrne<sup>1,2,3\*</sup>, John L. Quinn<sup>2</sup>, James J. O’Keeffe<sup>3,4</sup>, Stuart Green<sup>5</sup>, D. Paddy Sleeman<sup>2</sup>, S. Wayne Martin<sup>6</sup> and John Davenport<sup>2</sup>

**nature**  
 Badgers roam many miles  
 Andrew W. Byrne, John L. Quinn, James J. O’Keeffe, Stuart Green, D. Paddy Sleeman, S. Wayne Martin and John Davenport  
 Published online: 10 March 2014

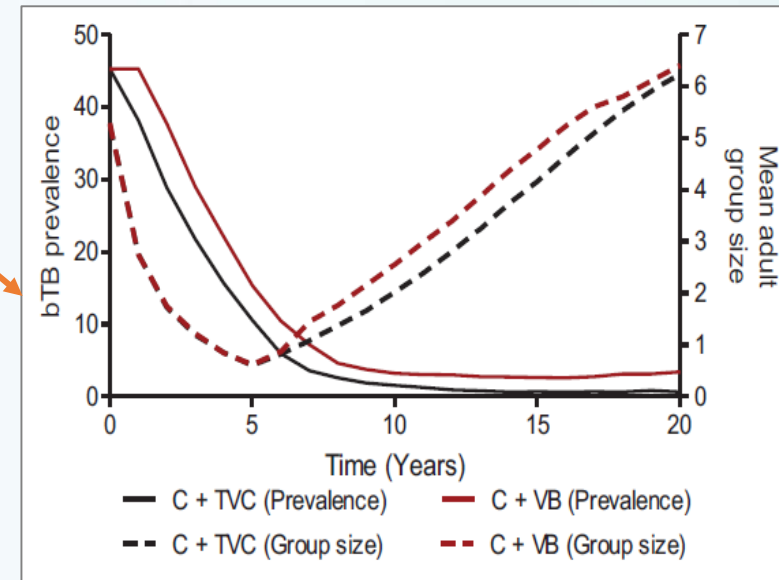
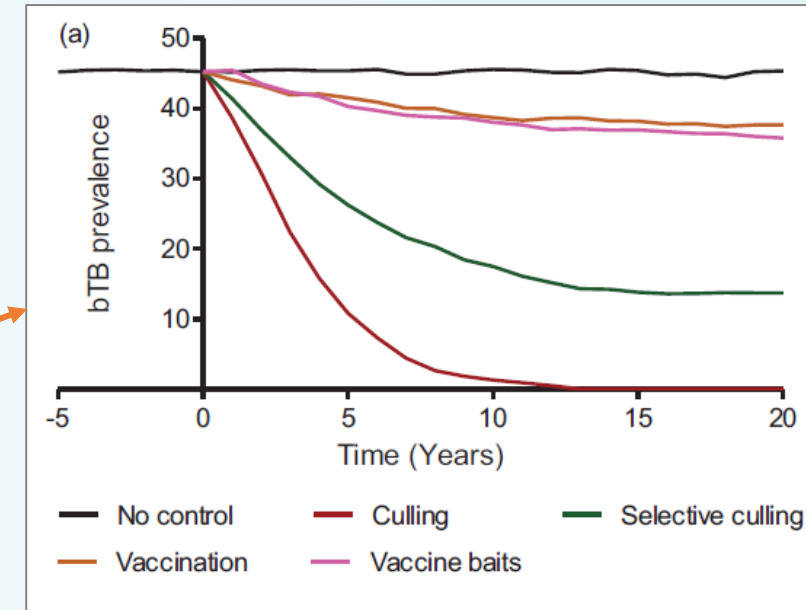
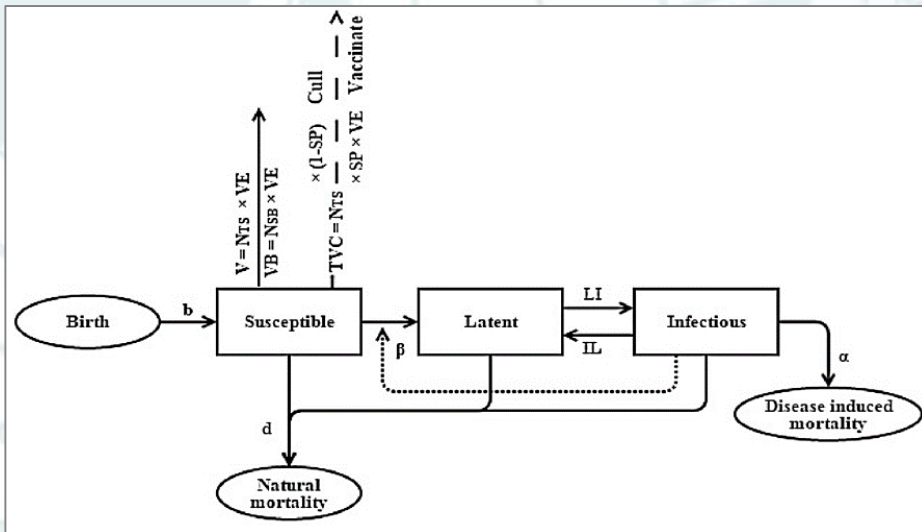




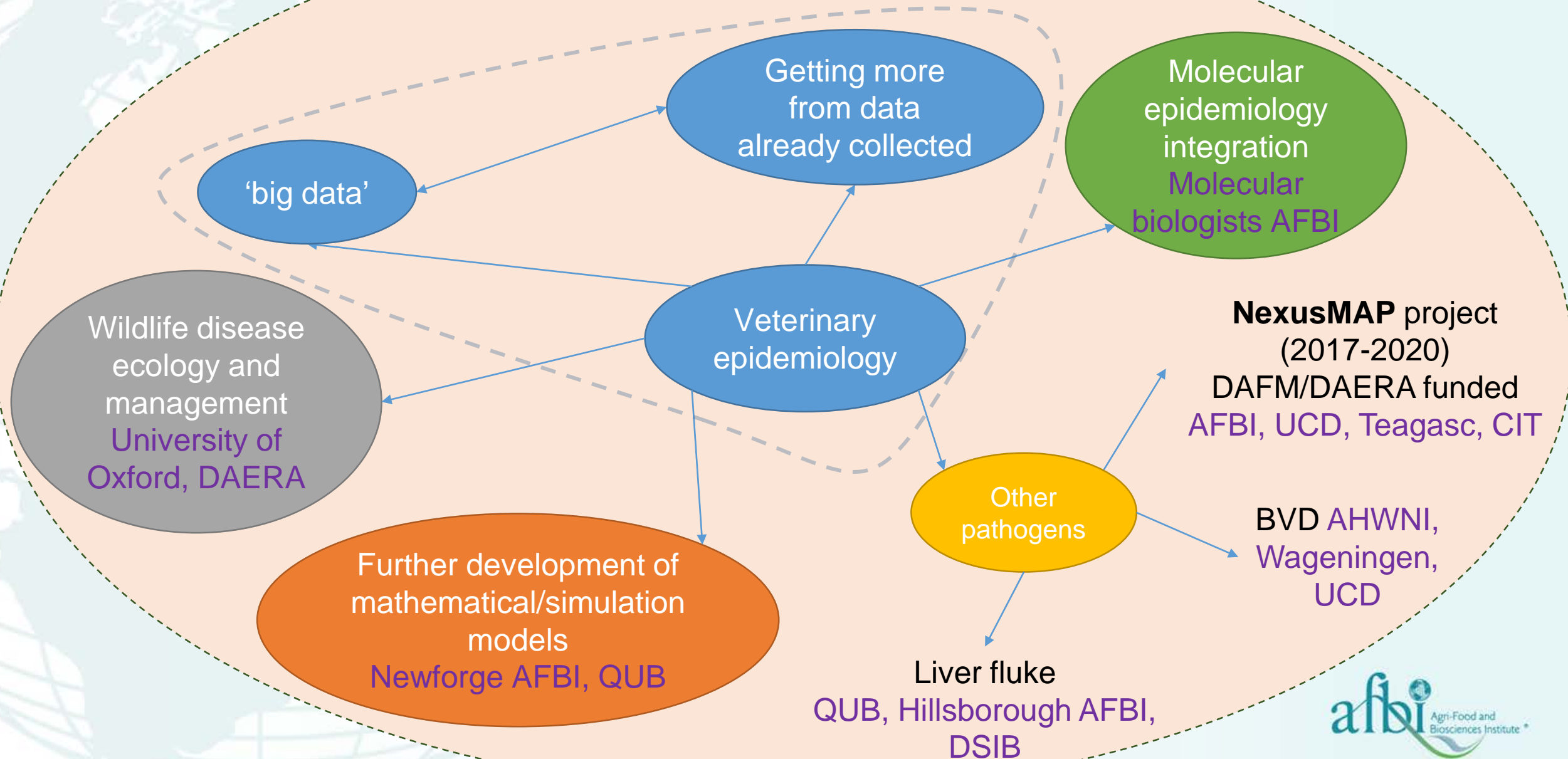
# Veterinary Epidemiology – Wildlife

## Simulation modelling

- Using fundamental parameters, create a *in silico* model to test 'what if' scenarios



# Veterinary Epidemiology – the future vision?





Department of  
**Agriculture, Environment  
and Rural Affairs**

[www.daera-ni.gov.uk](http://www.daera-ni.gov.uk)



**Farmers and Unions**

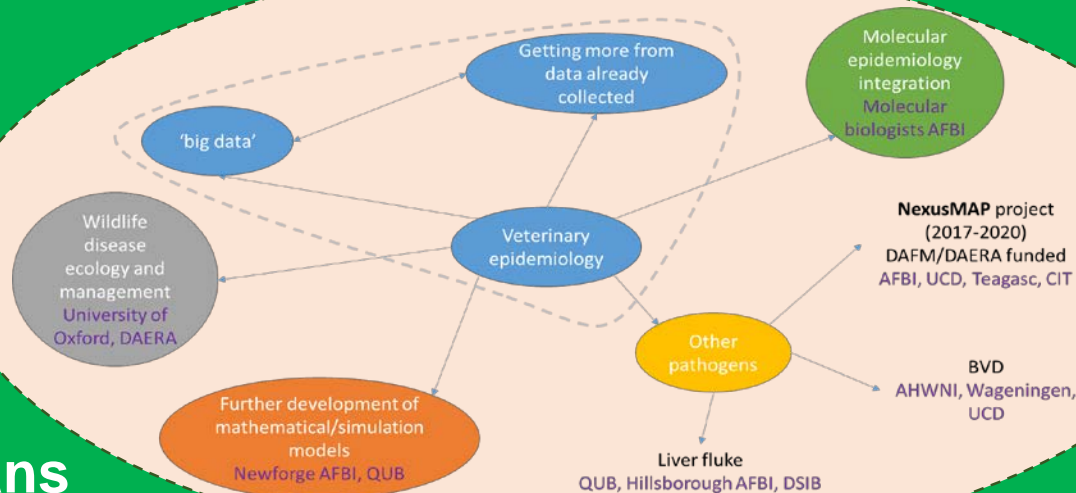
**Academia**

**Industry**

**Public & other stakeholders**

**Veterinarians**

**Policy stakeholders**



**Northern Ireland  
Badger Group**





# Acknowledgements

## *Collaborators/institutions (2014-2018):*

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Dr. Christina Buesching (ecology, Oxon)  
Prof. David Macdonald (ecology, Oxon)



**Dr. Sam Strain** (BVDV/Johne's disease, AHWNI)



**Dr. James O'Keeffe** (veterinary medicine, DAFM/UCD)  
Prof. Simon More (epidemiology, University College Dublin)



**Prof. Wayne Martin** (veterinary epidemiology, University of Guelph)



Prof. John Quinn (ecology; University College Cork)  
Dr. Paddy Sleeman (wildlife; UCC)



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Emma Campbell (wildlife disease ecology; QUB)



Laura Rosen (wildlife disease ecology; Colorado State University)



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