# The ecology of emerging diseases: a data mining approach

## Modeling the Complexity of Disease

**Chris Stephens**
C3 – Centro de Ciencias de la Complejidad y
Instituto de Ciencias Nucleares, UNAM
Talk LSHTM 23/07/2013

# Who are we?

**Complex systems and data mining group**

**Complexity and Public Health Program – C3, UNAM**

1.- Dr. Christopher R. Stephens
2.- M. en. C. Hugo Flores
3.- M. en C. Raúl Sierra Alcocer
4.- M. en C. Constantino González Salazar
5.- Dra. Ana Sanchez
6.- Dr. David Rosenblueth
7.- Dr. Manuel Beltran (U. of Arizona)

**Grupo del Laboratorio de sistemas de información geográfica del Instituto de Biología de la UNAM.**

8.- Dr. Víctor Sánchez-Cordero
9.- Dr. Ángel Rodríguez Moreno
10.- Dr. José Juan Flores Martínez
11.- Dr. Gabriel Granados Gutiérrez
12.- Dra. Camila González Rosas (Universidad de los Andes, Columbia)
13.- Dr. Carlos Napoleón Ibarra Cerdeña (INSP, Tapachula)
14.- Est. Biól. Ruth Areli Gómez Rodríguez
15.- Est. Biól. María Azucena Trinidad Flores

# Who are we?

**Grupo del laboratorio de inmunoparasitología del Departamento de Medicina Experimental de la Facultad de Medicina en la UNAM.**

16.- Dra. Ingeborg Becker

17.- Dra. Miriam Berzunza Cruz

18.- QFB. Dulce Jocelyn Bailón Martínez

19.- M. en C. Cristina Cañedo Guzmán

**El Centro Regional de Investigación del Instituto Nacional de Salud Pública (Tapachula, Chis.)**

20.- Dra. Janine M. Ramsey Willoquet

21.- Dr. Carlos Félix Marina Fernández

22.- Dra. Teresa Ordoñez

23.- Keynes De la Cruz Félix

# Who are we?

**Grupo de Tabasco: División Académica de Ciencias Biológicas. Universidad Juárez Autónoma de Tabasco**

24.- Dr. Mircea Gabriel Hidalgo Mihart
25.- Dra. Cristina Domingo Balcells

**Grupo de Monterrey: Laboratorio de Entomología médica, Depto. de Zoología de Invertebrados. Facultad de Ciencias Biológicas, Universidad Autónoma de Nuevo León**

26.- Dr. Eduardo A. Rebollar Téllez
27.- Estudiante Jorge Jesús Rodrìguez Rosas

**Grupo de Jalisco: Centro Universitario de la Costa Sur. Universidad de Guadalajara.**

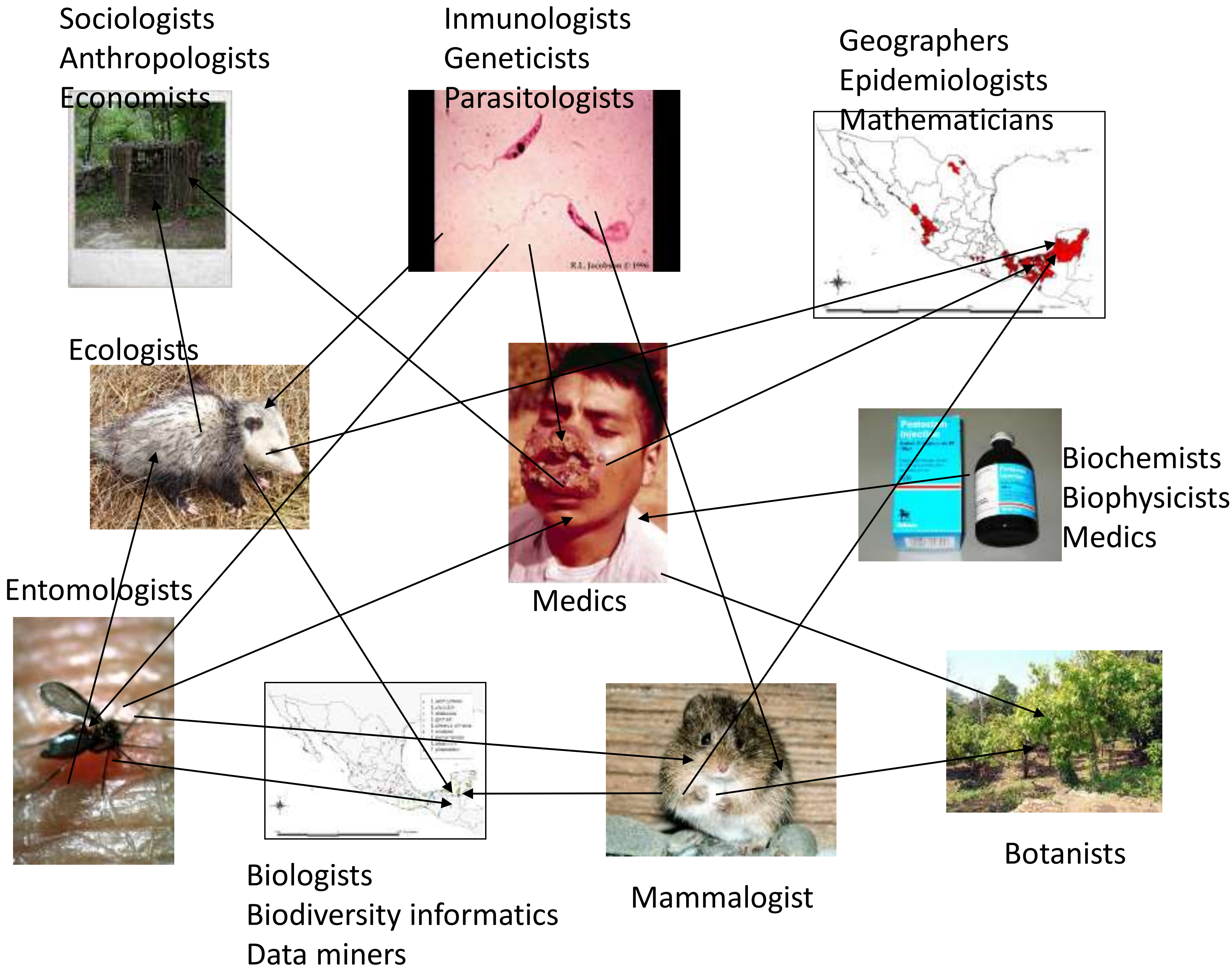
28.- Dr. Luis Ignacio Iñiguez Dávalos
29.- Biól. Pilar Ibarra
30.- Biól. María Magdalena Ramírez Martínez

**London School of Hygiene and Tropical Medicine**

31.- Dr. Michael Gaunt

# The Complexity of Disease and the Need for Transdisciplinarity

From the micro to the macro and back again


Sociologists
Anthropologists
Economists
Inmunologists
Geneticists
Parasitologists
Geographers
Epidemiologists
Mathematicians
Ecologists
Biochemists
Biophysicists
Medics
Medics
Entomologists
Biologists
Biodiversity informatics
Data miners
Mammalogist
Botanists

# What are our goals?
## The Santa Clause list

- Where will diseases emerge or re-emerge – why, when, what can we do about it and how do we know it's working?

- We want to predict, for instance
  - Disease reservoirs and vectors, their interactions and their relative importance
  - Spatio-temporal behaviour of disease and associated risk factors
  - Dispersal characteristics
  - Socio-demographic/economic risk factors
  - Genetic susceptibility (at all levels)

- We want an integrated systems analysis that takes into account the complex nature of disease and we want to *understand*

Known reservoirs
Known vectors
Known cases
Known risk factors

Unknown reservoirs
Unknown vectors
Unknown cases
Unknown risk factors

Known reservoirs
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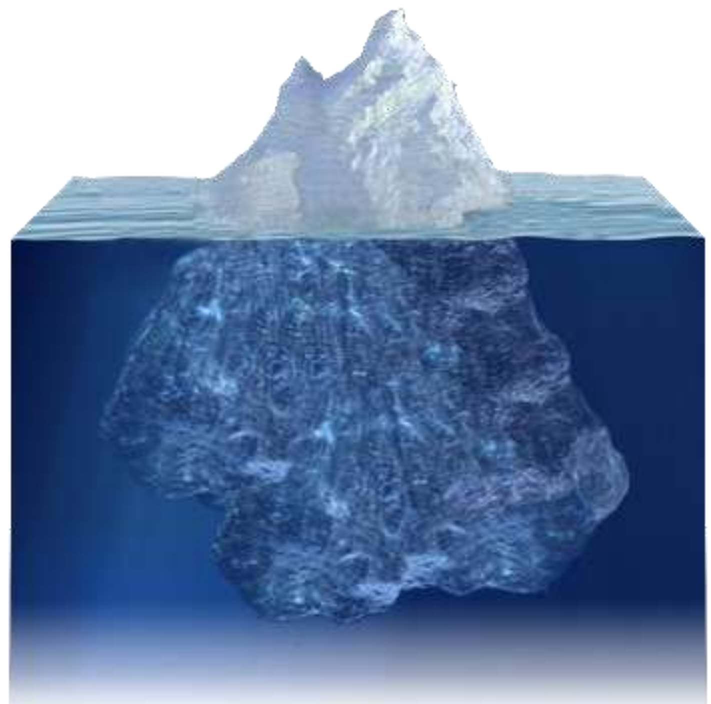
Known risk factors



***How do we model what's "under the water"?***

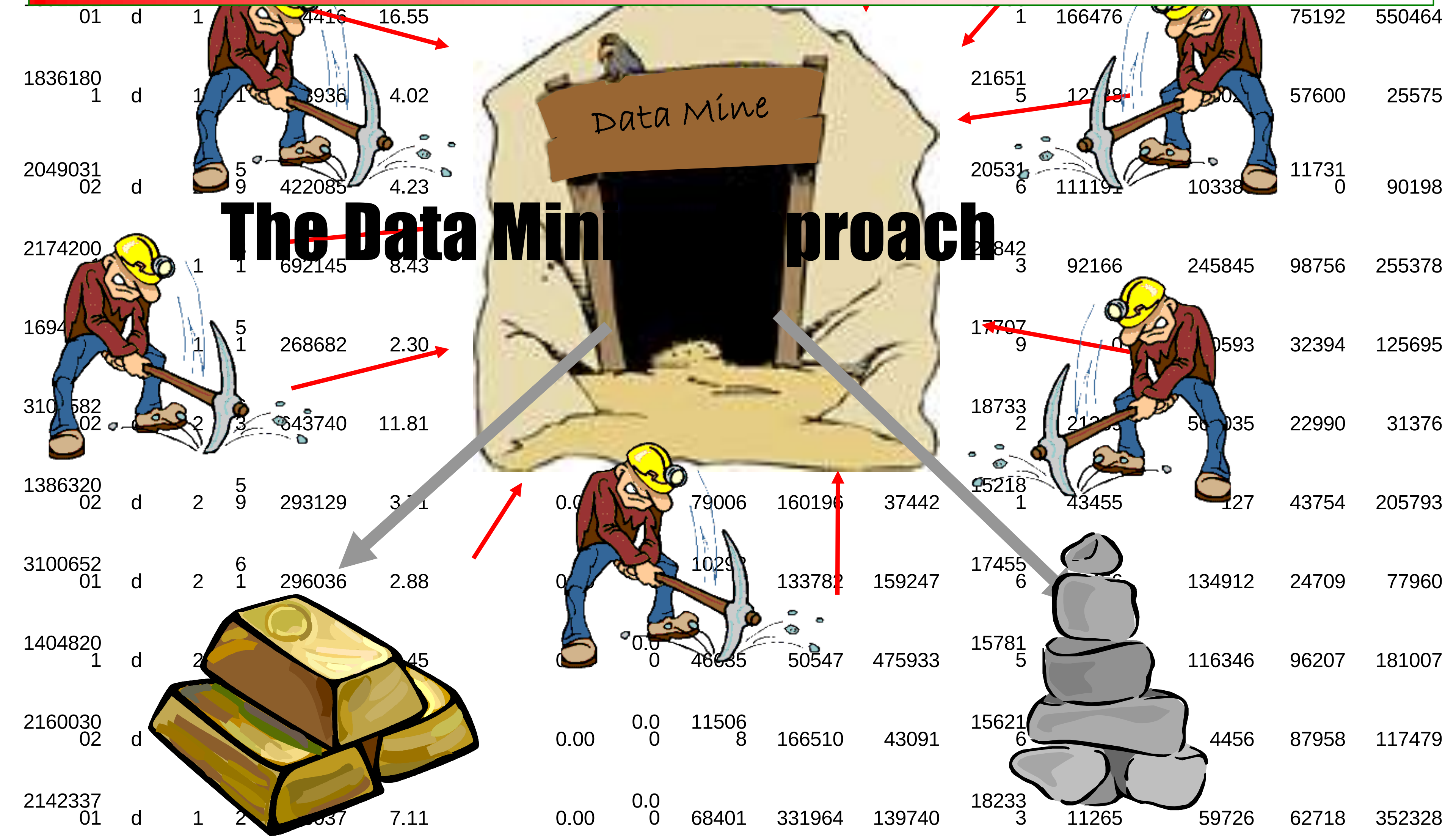
***Really, what is it?***

***Just good old fashioned modeling, statistical inference, but with a few twists…***

***Many variables/dimensions and multi-scale***

***Electronic format, “Unintentional” data***

***All necessary for modeling complex phenomena***

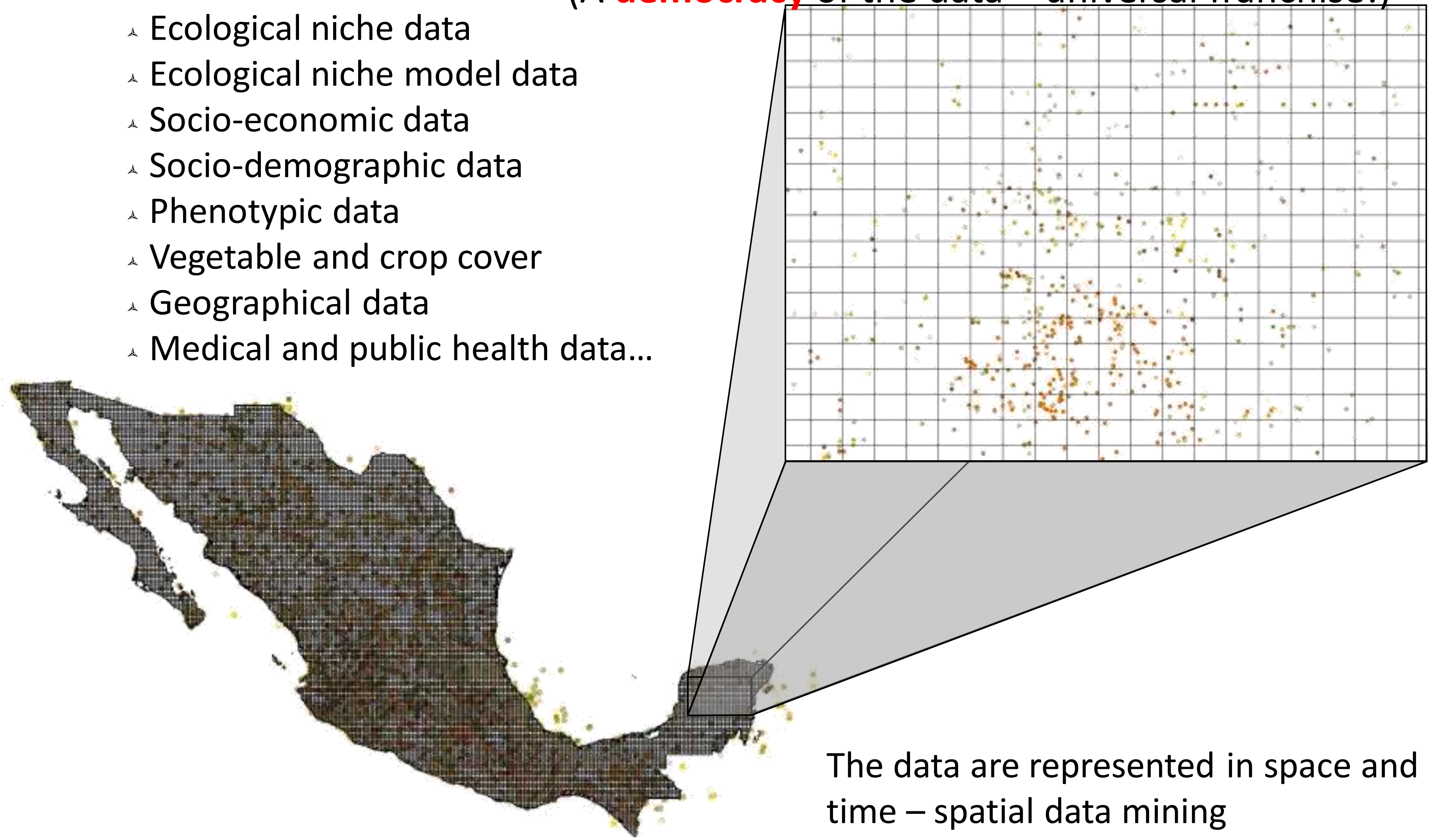


# But what are we going to mine…!

# Anything and everything!

(A **democracy** of the data – universal franchise!)

- Collection data
- Ecological niche data
- Ecological niche model data
- Socio-economic data
- Socio-demographic data
- Phenotypic data
- Vegetable and crop cover
- Geographical data
- Medical and public health data…



The data are represented in space and time – spatial data mining

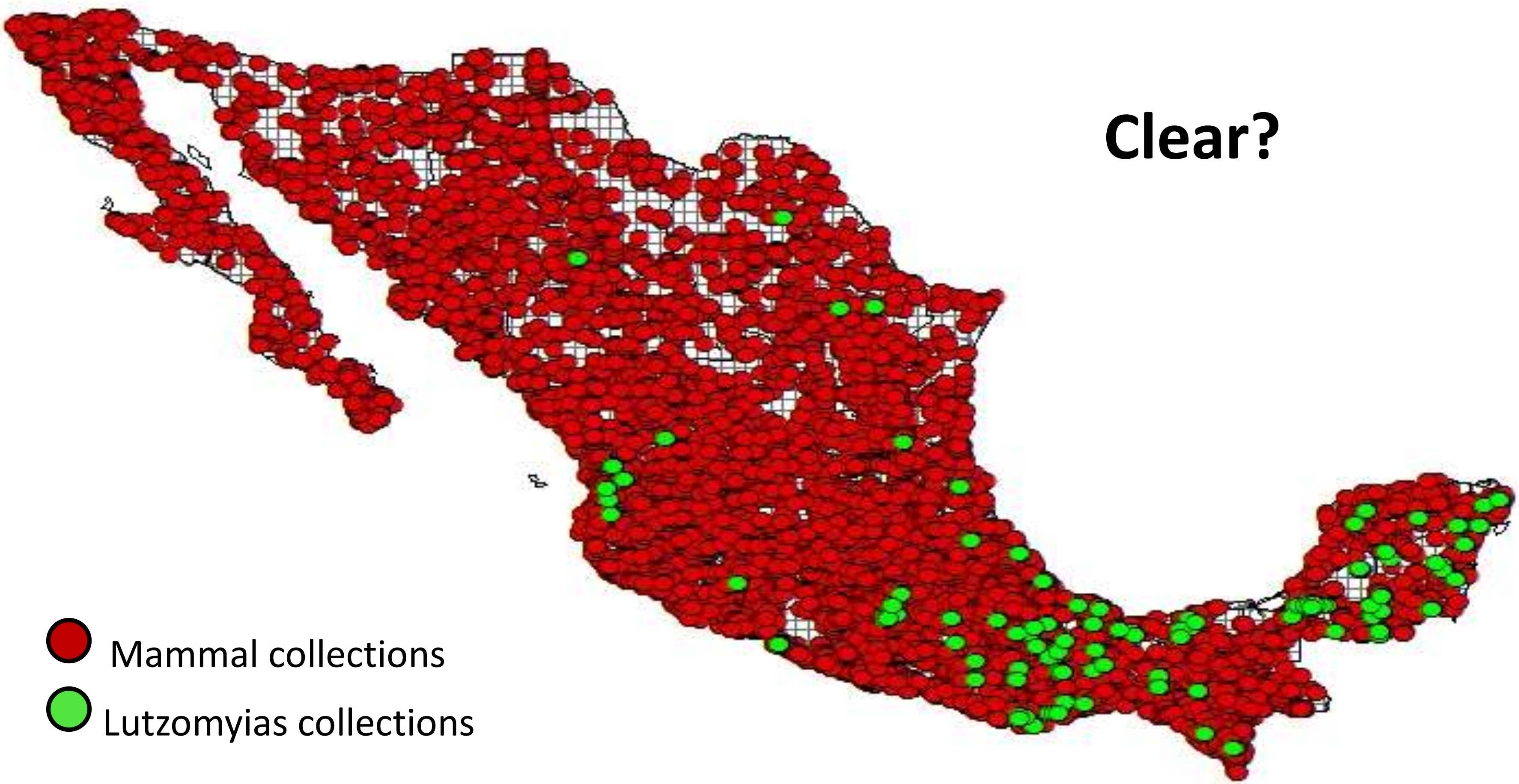
# But all data are not created equal…

- Different sources
  - Different location, data base, access,…
- Different data type – categorical, metric
- Different spatial resolution
  - Explicit – e.g., pixel by pixel in environmental layers
  - Implicit – 30,000,000 data points versus 30
    - Quality versus quantity
    - Abiotic versus biotic

Need to avoid the tyranny of the majority and protect minority rights!
Also, we need to be able to compare apples with apples!

- But the real Niche Space of a disease is VERY big!
- Where do we start?
- With the biotic…
- With the “ecological” part, reservoirs and vectors and all that…

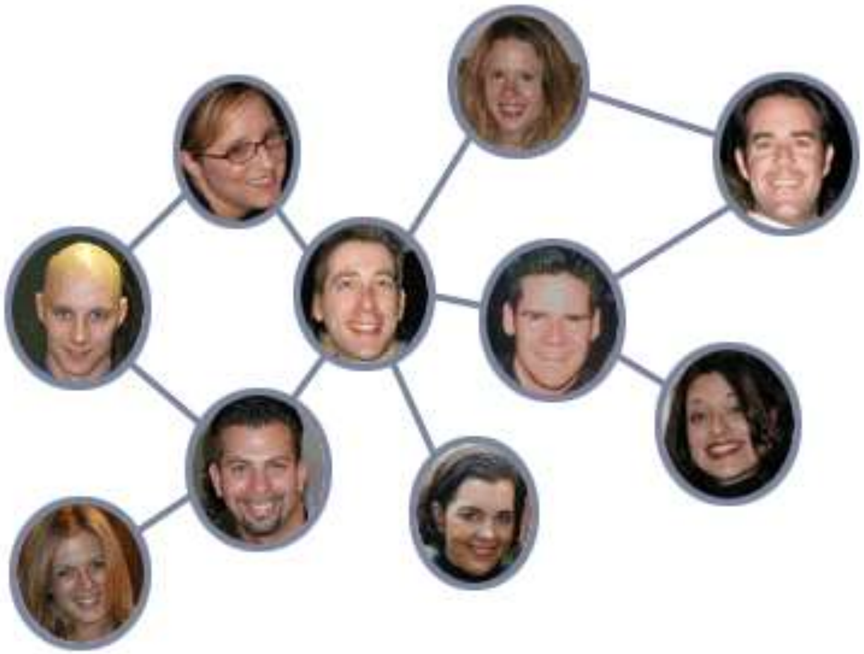
# Clear?



# You can judge a man

# by his “friends”

**or his “enemies”, or “parasites”,**
**or “prey” or “predators” or…**



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# Typical Ecological Network

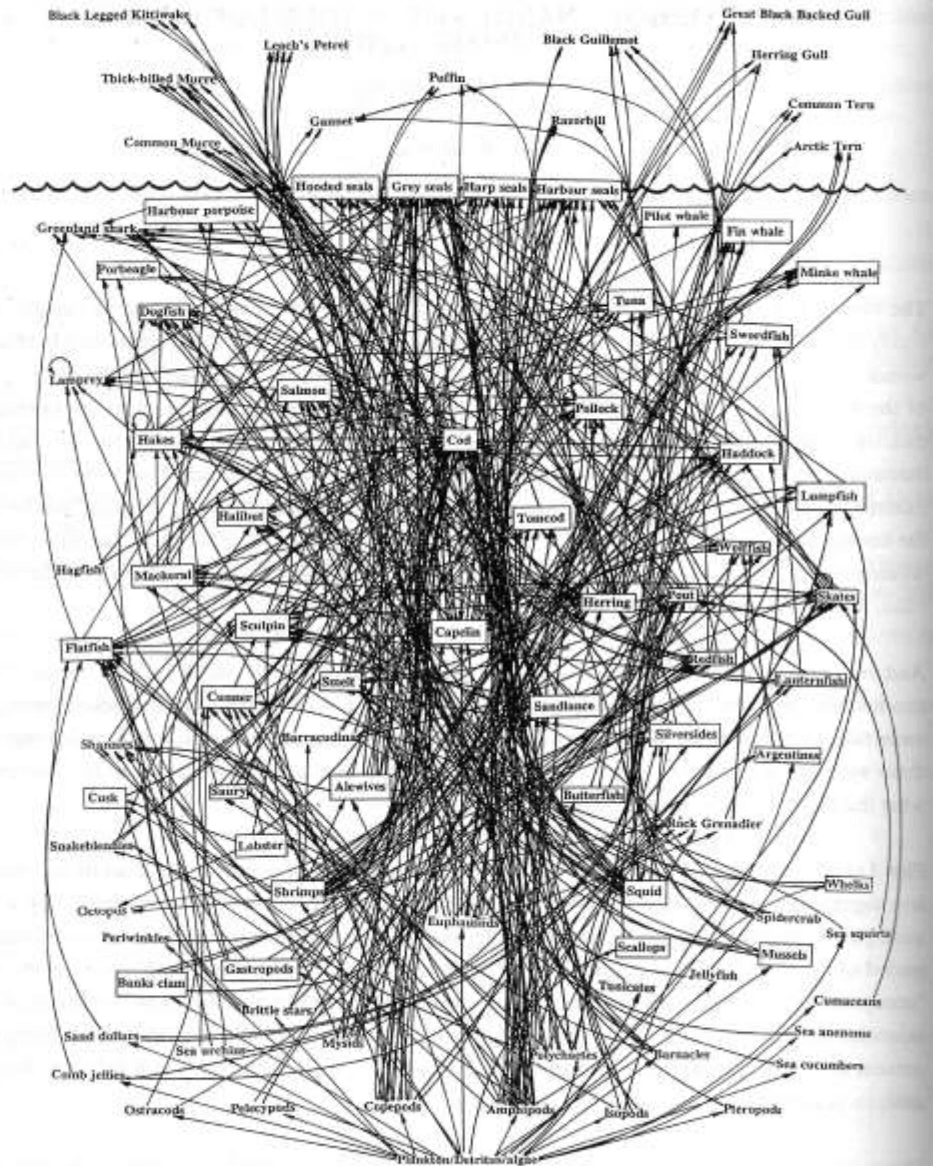
Food web associated with Cod for northwest Atlantic


Author(s):
Prof. David Lavigne

Institution:
Natural Sciences and Engineering Research Council


Visualization of ***known*** interactions at the species level

No spatio-temporal input



# Using Networks to Infer Reservoir-Vector Interactions

- Take nodes to be…
  - Species, other taxonomic or phylogenetic groupings, groupings by phenotypic characteristics,
- Take links to be a statistical measure of spatial (temporal) co-occurrence
  - P(Y|X), epsilon(Y|X), P(A,B|C,D), epsilon(Z|X,Y)
  - What is a high/low degree of co-occurrence?
  - What spatial (temporal) resolution? (When do things co-occur?)

No co-occurrences

a

b a

a

Two co-occurrences

a b a

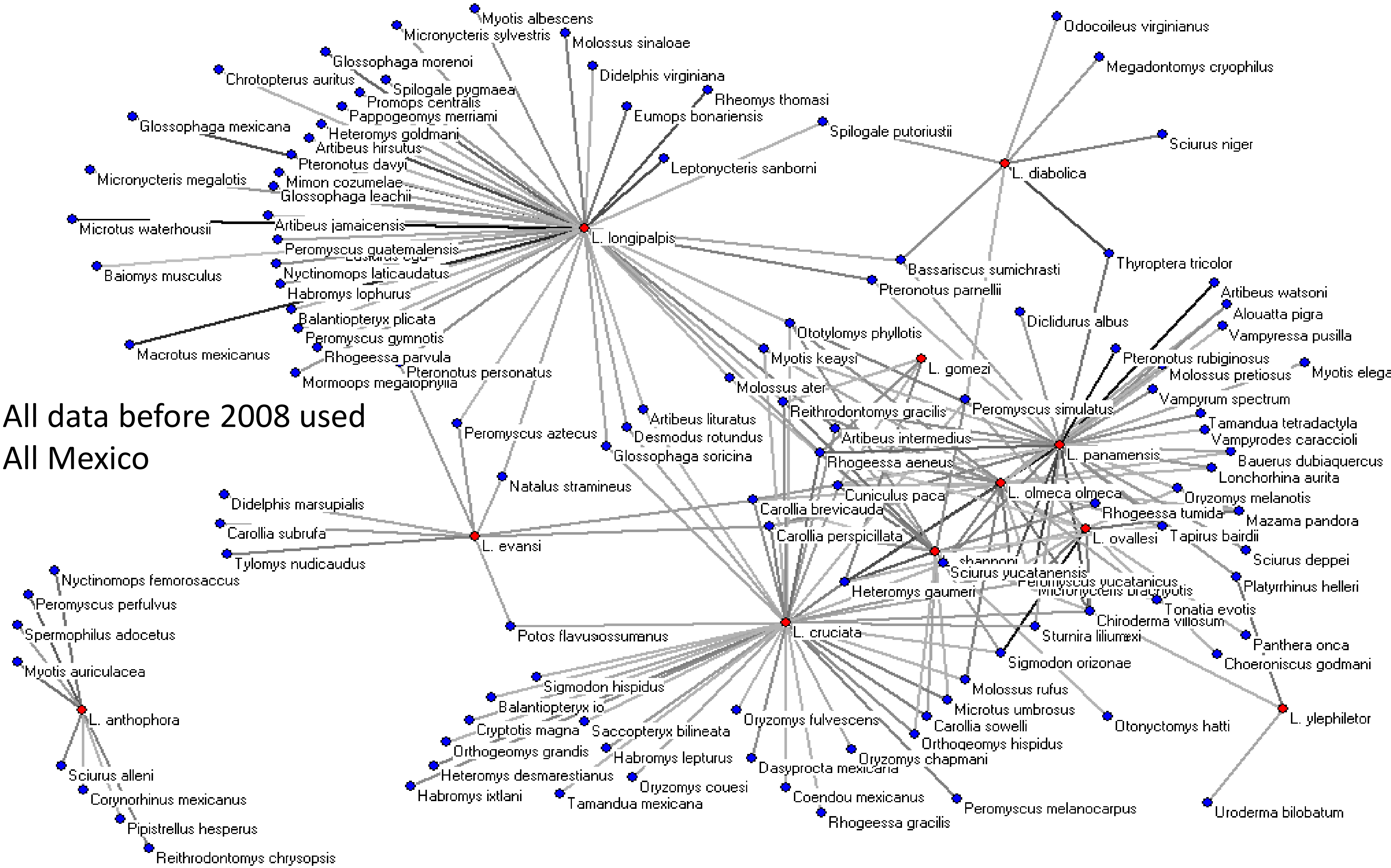
a

a b a

One co-occurrence

5 a 2b

# Who's friends with Lutzomyias?




All data before 2008 used

All Mexico

# Predicting Reservoirs

The 150 (out of 427) "best friends" of Lutzomyia as a genera.
The model works on known results.

| | Mammals | Epsilon | Conf. |
|---|---|---|---|
| 1 | Eira barbara | 10.1683 | |
| 2 | Rhogeessa aeneus | 9.3649 | |
| 3 | Artibeus intermedius | 9.1628 | |
| 4 | Reithrodontomys gracilis | 8.8921 | Yes |
| 5 | Carollia sowelli | 8.8303 | |
| 6 | Heteromys gaumeri | 8.8000 | Yes |
| 7 | Peromyscus mexicanus | 8.7859 | |
| 8 | Heteromys desmarestianu | 8.7164 | Yes |
| 9 | Molossus rufus | 8.6277 | |
| 10 | Glossophaga soricina | 8.5713 | |
| 11 | Carollia perspicillata | 8.5030 | |
| 12 | Orthogeomys hispidus | 8.3468 | |
| 13 | Pteronotus parnellii | 8.1632 | |
| 14 | Desmodus rotundus | 8.1519 | |
| 15 | Dasyprocta mexicana | 8.1128 | |
| 16 | Sturnira lilium | 8.0290 | |
| 17 | Dermanura phaeotis | 8.0055 | |
| 18 | Dasyprocta punctata | 7.9678 | |
| 19 | Oryzomys couesi | 7.7253 | |
| 20 | Potos flavus | 7.7246 | |
| 21 | Conepatus semistriatus | 7.6879 | |
| 22 | Ototylomys phyllotis | 7.5587 | Yes |
| 23 | Ateles geoffroyi | 7.4787 | |
| 24 | Cryptotis magna | 7.4207 | |
| 25 | Cuniculus paca | 7.3220 | |
| 26 | Lampronycteris brachyotis | 7.2852 | |
| 27 | Sigmodon hispidus | 7.2805 | Yes |
| 28 | Peromyscus yucatanicus | 7.2486 | Yes |
| 29 | Oryzomys chapmani | 7.1242 | |
| 30 | Didelphis virginiana | 7.1150 | |
| 31 | Peromyscus melanocarpu | 7.0260 | |
| 32 | Microtus umbrosus | 6.9630 | |
| 33 | Thyroptera tricolor | 6.9630 | |
| 34 | Nasua narica | 6.8953 | |
| 35 | Megadontomys cryophilus | 6.6830 | |
| 36 | Oryzomys alfaroi | 6.6816 | |
| 37 | Sorex veraepacis | 6.6797 | |
| 38 | Carollia subrufa | 6.6316 | |
| 39 | Peromyscus aztecus | 6.6173 | |
| 40 | Didelphis marsupialis | 6.4390 | Yes |
| 41 | Sciurus yucatanensis | 6.3865 | |
| 42 | Philander opossum | 6.2546 | |
| 43 | Habromys ixtlani | 6.1120 | |
| 44 | Microtus waterhousii | 6.1120 | |
| 45 | Pteronotus rubiginosus | 6.1120 | |
| 46 | Reithrodontomys microdor | 6.0967 | |
| 47 | Coendou mexicanus | 6.0268 | |
| 48 | Centurio senex | 6.0076 | |
| 49 | Artibeus jamaicensis | 5.9786 | |
| 50 | Glossophaga morenoi | 5.8847 | |

| | Mammals | Epsilon | Conf. |
|---|---|---|---|
| 51 | Molossus sinaloae | 5.8518 | |
| 52 | Artibeus lituratus | 5.8422 | |
| 53 | Mormoops megalophylla | 5.8374 | |
| 54 | Habromys lepturus | 5.7848 | |
| 55 | Myotis keaysi | 5.6148 | |
| 56 | Chiroderma villosum | 5.5562 | |
| 57 | Tamandua mexicana | 5.4845 | |
| 58 | Tylomys nudicaudus | 5.4510 | |
| 59 | Saccopteryx bilineata | 5.2984 | |
| 60 | Macrotus mexicanus | 5.2472 | |
| 61 | Sciurus aureogaster | 5.2267 | |
| 62 | Baiomys musculus | 5.2092 | |
| 63 | Rhogeessa tumida | 5.1950 | |
| 64 | Sciurus deppei | 5.1414 | |
| 65 | Dermanura watsoni | 5.1338 | |
| 66 | Otonyctomys hatti | 5.1338 | |
| 67 | Orthogeomys grandis | 5.0556 | |
| 68 | Alouatta palliata | 5.0457 | |
| 69 | Choeroniscus godmani | 5.0457 | |
| 70 | Peropteryx macrotis | 5.0457 | |
| 71 | Pteronotus personatus | 5.0266 | |
| 72 | Lontra longicaudis | 4.9330 | |
| 73 | Reithrodontomys mexicanu | 4.9120 | |
| 74 | Oryzomys rostratus | 4.8681 | |
| 75 | Mimon cozumelae | 4.8327 | |
| 76 | Pteronotus davyi | 4.7943 | |
| 77 | Herpailurus yagouaroundi | 4.7100 | |
| 78 | Glossophaga leachii | 4.6849 | |
| 79 | Rhogeessa gracilis | 4.6317 | |
| 80 | Sylvilagus brasiliensis | 4.6317 | |
| 81 | Hodomys alleni | 4.5155 | |
| 82 | Leopardus wiedii | 4.4420 | |
| 83 | Peromyscus simulatus | 4.4195 | |
| 84 | Sigmodon alleni | 4.3707 | |
| 85 | Bassariscus sumichrasti | 4.3110 | |
| 86 | Oryzomys fulvescens | 4.3110 | |
| 87 | Diphylla ecaudata | 4.3013 | |
| 88 | Oryzomys melanotis | 4.2907 | Yes |
| 89 | Micronycteris microtis | 4.2338 | |
| 90 | Mazama americana | 4.2274 | |
| 91 | Microtus oaxacensis | 4.2061 | |
| 92 | Rheomys thomasi | 4.2061 | |
| 93 | Oryzomys saturatior | 4.2061 | |
| 94 | Myotis elegans | 4.2024 | |
| 95 | Oligoryzomys fulvescens | 4.1984 | |
| 96 | Natalus stramineus | 4.0626 | |
| 97 | Balantiopteryx io | 4.0522 | |
| 98 | Nyctinomops laticaudatus | 4.0522 | |
| 99 | Tlacuatzin canescens | 4.0119 | |
| 100 | Odocoileus virginianus | 3.9265 | |

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| 101 | Balantiopteryx plicata | 3.8590 | |
| 102 | Peromyscus leucopus | 3.7994 | |
| 103 | Sturnina ludovici | 3.7888 | |
| 104 | Enchisthenes hartii | 3.6929 | |
| 105 | Vampyrodes caraccioli | 3.6929 | |
| 106 | Eptesicus furinalis | 3.6453 | |
| 107 | Liomys pictus | 3.6107 | |
| 108 | Glossophaga commissaris | 3.4861 | |
| 109 | Lonchorhina aurita | 3.4781 | |
| 110 | Phyllostomus discolor | 3.4781 | |
| 111 | Peromyscus gymnotis | 3.4516 | |
| 112 | Anoura geoffroyi | 3.4201 | |
| 113 | Platyrrhinus helleri | 3.3586 | |
| 114 | Eumops bonariensis | 3.3398 | |
| 115 | Sciurus variegatoides | 3.3398 | |
| 116 | Uroderma bilobatum | 3.3373 | |
| 117 | Lasiurus intermedius | 3.2197 | |
| 118 | Lasiurus ega | 3.1739 | |
| 119 | Peromyscus megalops | 3.1410 | |
| 120 | Eumops glaucinus | 3.0564 | |
| 121 | Urocyon cinereoargenteus | 2.9697 | |
| 122 | Procyon lotor | 2.9502 | |
| 123 | Hylonycteris underwoodi | 2.9343 | |
| 124 | Rhynchonycteris naso | 2.8580 | |
| 125 | Eptesicus brasiliensis | 2.8106 | |
| 126 | Myotis albescens | 2.8106 | |
| 127 | Lophostoma evotis | 2.8106 | |
| 128 | Tapirus bairdii | 2.8106 | |
| 129 | Vampyrum spectrum | 2.8106 | |
| 130 | Marmosa mexicana | 2.7731 | Yes |
| 131 | Peromyscus furvus | 2.7731 | |
| 132 | Myotis velifera | 2.5757 | |
| 133 | Spilogale putorius | 2.5411 | |
| 134 | Microtus mexicanus | 2.5268 | |
| 135 | Dasypus novemcinctus | 2.4725 | |
| 136 | Myotis nigricans | 2.4704 | |
| 137 | Lophostoma brasiliense | 2.4407 | |
| 138 | Diclidurus albus | 2.4407 | |
| 139 | Sciurus niger | 2.4407 | |
| 140 | Leptonycteris curasoae | 2.4268 | |
| 141 | Nyctomys sumichrasti | 2.4026 | |
| 142 | Sigmodon mascotensis | 2.3815 | |
| 143 | Alouatta pigra | 2.3374 | |
| 144 | Peromyscus melanophrys | 2.2204 | |
| 145 | Dermanura tolteca | 2.1920 | |
| 146 | Trachops cirrhosus | 2.1663 | |
| 147 | Bauerus dubiaquercus | 2.1612 | |
| 148 | Spilogale pygmaea | 2.1612 | |
| 149 | Leptonycteris nivalis | 2.1402 | |
| 150 | Sylvilagus floridanus | 2.1002 | |

# But how to test it…? The Emerging Disease production line

Links to IMSS and INSP

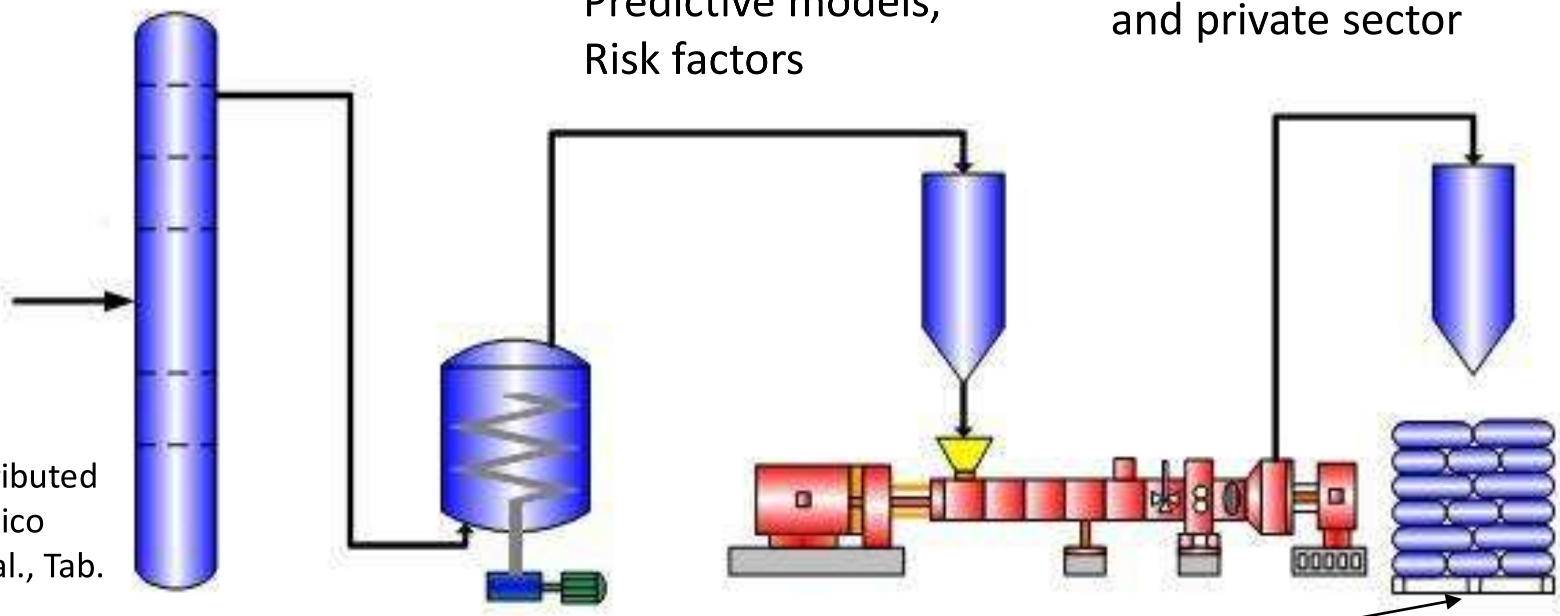
Requires large, well-organized interdisciplinary team

Data Mining:
Predictive models,
Risk factors

Close relationship with public health authorities and private sector

Field work : samples

Five groups distributed throughout Mexico
DF, Chiap., NL, Jal., Tab.



Laboratory analysis

Solutions:

- Decision support systems
- Treatments
- Intelligent software

Over 1200 mammals collected from over 70 species

Two laboratories

PCR tests on samples for different diseases

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| 107 | Liomys pictus | 3.6107 | |
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| 109 | Lonchorhina aurita | 3.4781 | |
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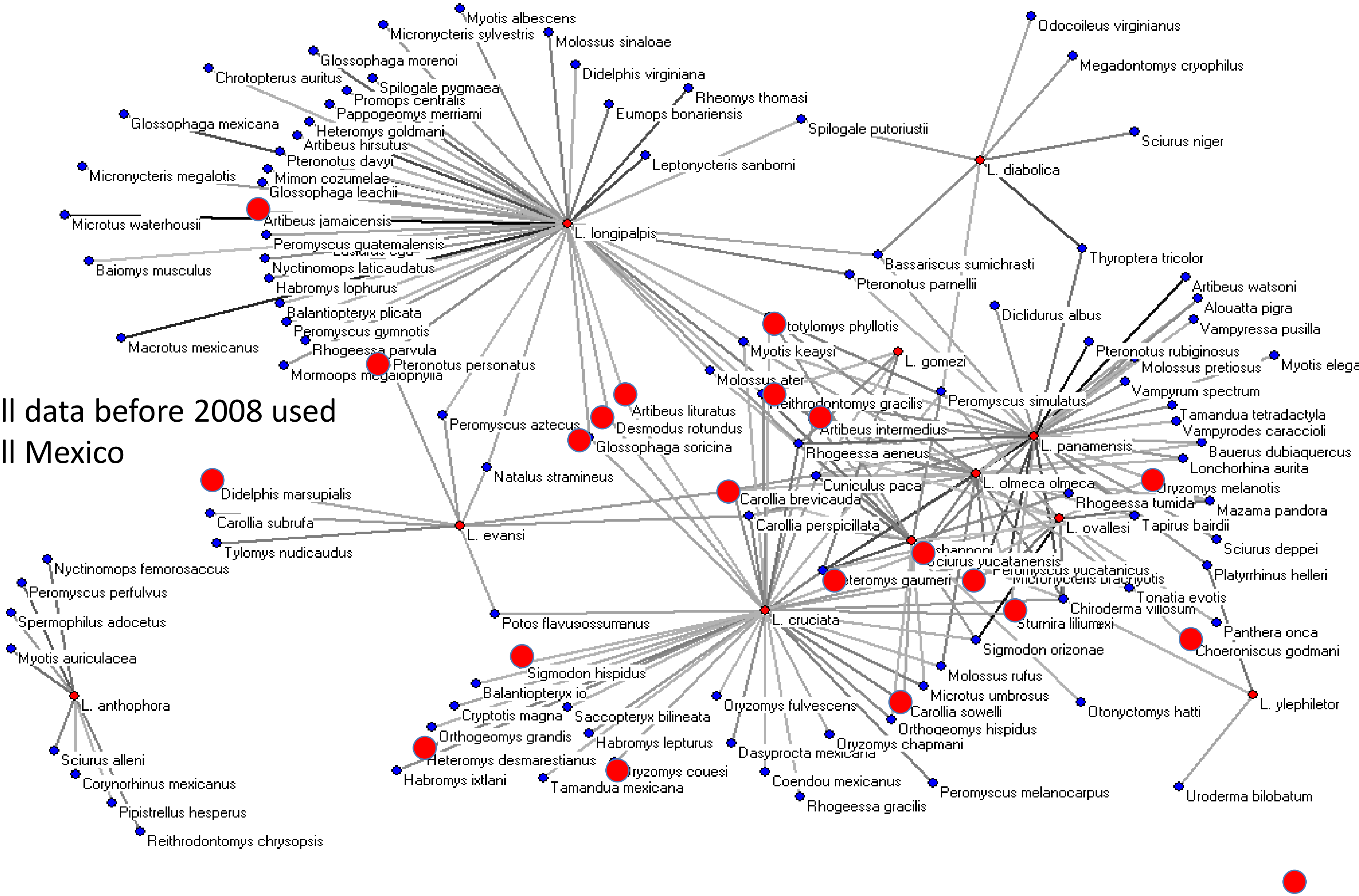
| 114 | Eumops bonariensis | 3.3398 | |
| 115 | Sciurus variegatoides | 3.3398 | |
| 116 | Uroderma bilobatum | 3.3373 | |
| 117 | Lasiurus intermedius | 3.2197 | |
| 118 | Lasiurus ega | 3.1739 | |
| 119 | Peromyscus megalops | 3.1410 | |
| 120 | Eumops glaucinus | 3.0564 | |
| 121 | Urocyon cinereoargenteus | 2.9697 | |
| 122 | Procyon lotor | 2.9502 | |
| 123 | Hylonycteris underwoodi | 2.9343 | |
| 124 | Rhynchonycteris naso | 2.8580 | |
| 125 | Eptesicus brasiliensis | 2.8106 | |
| 126 | Myotis albescens | 2.8106 | |
| 127 | Lophostoma evotis | 2.8106 | |
| 128 | Tapirus bairdii | 2.8106 | |
| 129 | Vampyrum spectrum | 2.8106 | |
| 130 | Marmosa mexicana | 2.7731 | Yes |
| 131 | Peromyscus furvus | 2.7731 | |
| 132 | Myotis velifera | 2.5757 | |
| 133 | Spilogale putorius | 2.5411 | |
| 134 | Microtus mexicanus | 2.5268 | |
| 135 | Dasypus novemcinctus | 2.4725 | |
| 136 | Myotis nigricans | 2.4704 | |
| 137 | Lophostoma brasiliense | 2.4407 | |
| 138 | Diclidurus albus | 2.4407 | |
| 139 | Sciurus niger | 2.4407 | |
| 140 | Leptonycteris curasoae | 2.4268 | |
| 141 | Nyctomys sumichrasti | 2.4026 | |
| 142 | Sigmodon mascotensis | 2.3815 | |
| 143 | Alouatta pigra | 2.3374 | |
| 144 | Peromyscus melanophrys | 2.2204 | |
| 145 | Dermanura tolteca | 2.1920 | |
| 146 | Trachops cirrhosus | 2.1663 | |
| 147 | Bauerus dubiaquercus | 2.1612 | |
| 148 | Spilogale pygmaea | 2.1612 | |
| 149 | Leptonycteris nivalis | 2.1402 | |
| 150 | Sylvilagus floridanus | 2.1002 | |

All data before 2008 used

All Mexico



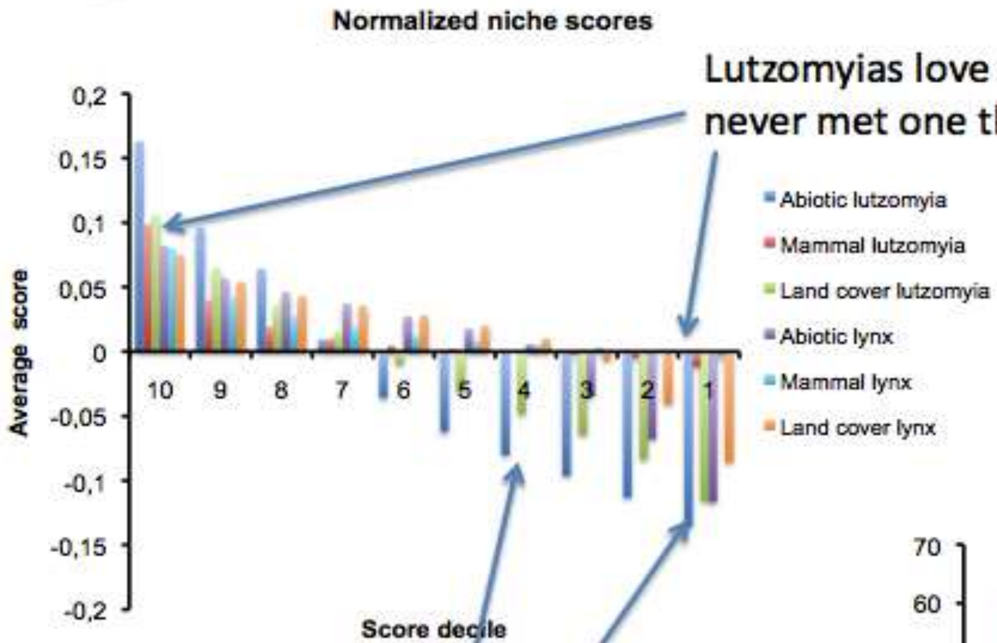
# Modelling Works!

- Predicted and confirmed 21 new species of mammal as carriers of Leishmania in Mexico (about 30% of those tested)
- 12 of them are bats, identified for the first time in Mexico
- Squirrels identified as carriers
- Changes the picture for control of Leishmania totally; Leishmania and Lutzomyias are eclectic in their host source. Linnean classification is NOT ecologically relevant
- So we can see that the biotic (mammals/food)part of the Niche Space for Leishmaniasis is important. What about other factors?
  - Abiotic – Worldclim
  - Vegetation/landcover

# Modelling the Niche Space of Leishmaniasis (well, Lutzomyias really)

| TOP DECILE<br>Optimal niche conditions for *Lutzomyia* | | | | BOTTOM DECILE<br>Suboptimal niche conditions for *Lutzomyia* | | | |
|---|---|---|---|---|---|---|---|
| ABIOTIC VARIABLES | RANGE | Epsilon | Score contribution | ABIOTIC VARIABLES | RANGE | Epsilon | Score contribut |
| BIO17 | 88-219 | *8.960* | *5.013* | BIO12 | 42-507 | *-5.604* | *-2.279* |
| BIO1 | 23.3-26.4 | *8.938* | *1.006* | BIO16 | 18-218 | *-5.001* | *-2.328* |
| BIO11 | 22.2-25.3 | *8.873* | *2.322* | BIO18 | 1-249 | *-3.839* | *-3.799* |
| BIO14 | 26-63 | *8.782* | *4.916* | BIO6 | 3.1-3.4 | *-3.761* | *-2.931* |
| BIO4 | 25.35-33.09 | *7.543* | *2.152* | BIO7 | 26.3-28.4 | *-3.544* | *-8.853* |
| BIO6 | 13.4-16.6 | *7.524* | *3.293* | BIO2 | 16.5-18.4 | *-3.535* | *-2.997* |
| BIO13 | 392-774 | *7.107* | *12.913* | BIO11 | 2.9-12.5 | *-3.271* | *-4.482* |
| BIO7 | 28.5-30.6 | *7.012* | *3.803* | BIO4 | 3310-7184 | *-2.971* | *-9.551* |
| BIO16 | 1019-2019 | *6.925* | *12.175* | BIO19 | 192-383 | *-2.940* | *-0.448* |
| BIO19 | 192-383 | *6.618* | *4.157* | BIO10 | 28.9-32.3 | *-2.669* | *-0.916* |
| BIO12 | 1906-3302 | *6.314* | *8.701* | BIO1 | 10.3-19.9 | *-2.189* | *-1.033* |
| BIO2 | 9.8-10.8 | *6.130* | *4.458* | BIO3 | 3.7-5.5 | *-2.130* | *-3.576* |
| BIO18 | 623-746 | *5.748* | *1.260* | BIO8 | 28.4-31.7 | *-1.964* | *-0.731* |
| **RESERVOIRS** | | | | **RESERVOIRS** | | | |
| *Reithrodontomys gracilis* | | *8.892* | *2.640* | *Sigmodon hispidus* | | *6.946* | *1.244* |
| *Heteromys gaumeri* | | *8.800* | *2.234* | | | | |
| *Heteromys desmarestianus* | | *8.716* | *2.381* | | | | |
| *Ototylomys phyllotis* | | *7.559* | *2.028* | | | | |
| *Peromyscus yucatanicus* | | *7.249* | *2.116* | | | | |
| *Sigmodon hispidus* | | *6.946* | *1.244* | | | | |
| *Didelphis marsupialis* | | *5.774* | *1.662* | | | | |
| *Oryzomys melanotis* | | *3.494* | *1.387* | | | | |
| *Marmosa mexicana* | | *2.773* | *1.541* | | | | |
| **LAND COVER** | | | | **LAND COVER** | | | |
| Cloud forest | | *6.642* | *1.408* | Subtropical scrub | | *-1.675* | *-1.527* |
| Tropical evergreen forest | | *6.603* | *4.476* | Subtropical scrub with secondary vegetation | | *-1.849* | *-1.658* |
| Cloud forest with secondary vegetation | | *6.028* | *1.459* | Xeric scrub with secondary vegetation | | *-2.092* | *-3.640* |
| Tropical evergreen forest with secondary vegetation | | *6.007* | *4.344* | Xeric scrub | | *-2.924* | *-4.044* |
| Agriculture areas | | *5.966* | *1.736* | Mesquite | | *-3.337* | *-1.714* |
| Human settlement | | *4.947* | *0.577* | Grassland | | *-3.734* | *-1.874* |
| Deciduous tropical forest with secondary vegetation | | *4.081* | *1.013* | Mangroves | | *-4.063* | *-2.000* |

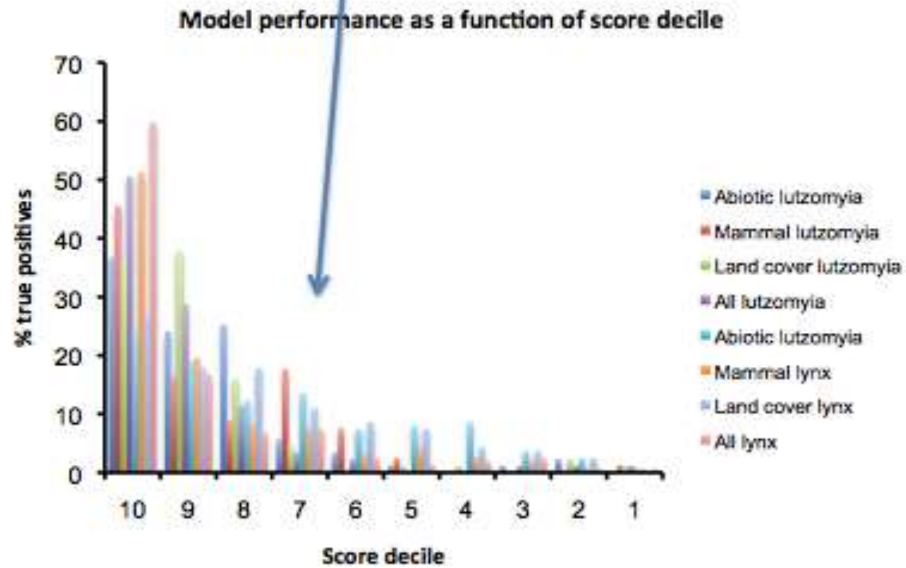
# Modelling the Niche Space of Leishmaniasis (well, Lutzomyias really)




Lutzomyias love mammals, never met one they didn't like

Including in a fuller, richer Niche Space leads to more predictive models (less false positives/negatives)

Climatic factors are more important for determining where Lutzomyias aren't rather than where they are

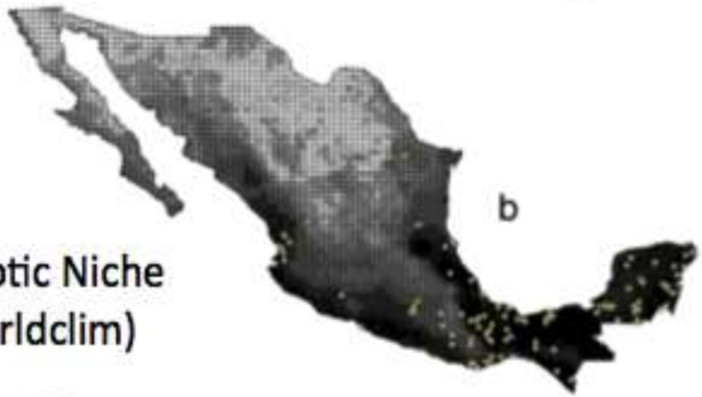


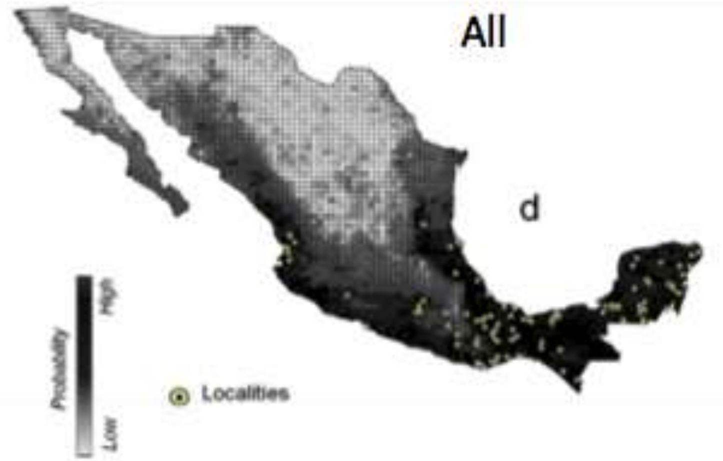
# Lutzomyia Risk Maps from Different Niche models

Biotic Niche (Mammals)

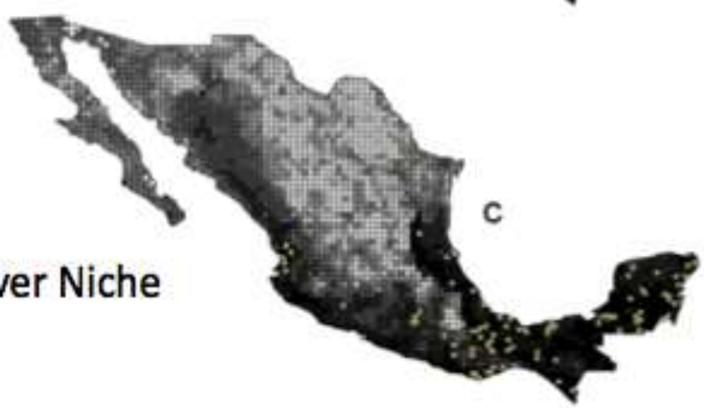

Relatively higher probability to find Lutzomyias in the north of Mexico from the biotic model than the abiotic one. Are Lutzomyias more common in the north of Mexico than previous data or models would suggest?

Abiotic Niche (Worldclim)




Landcover Niche



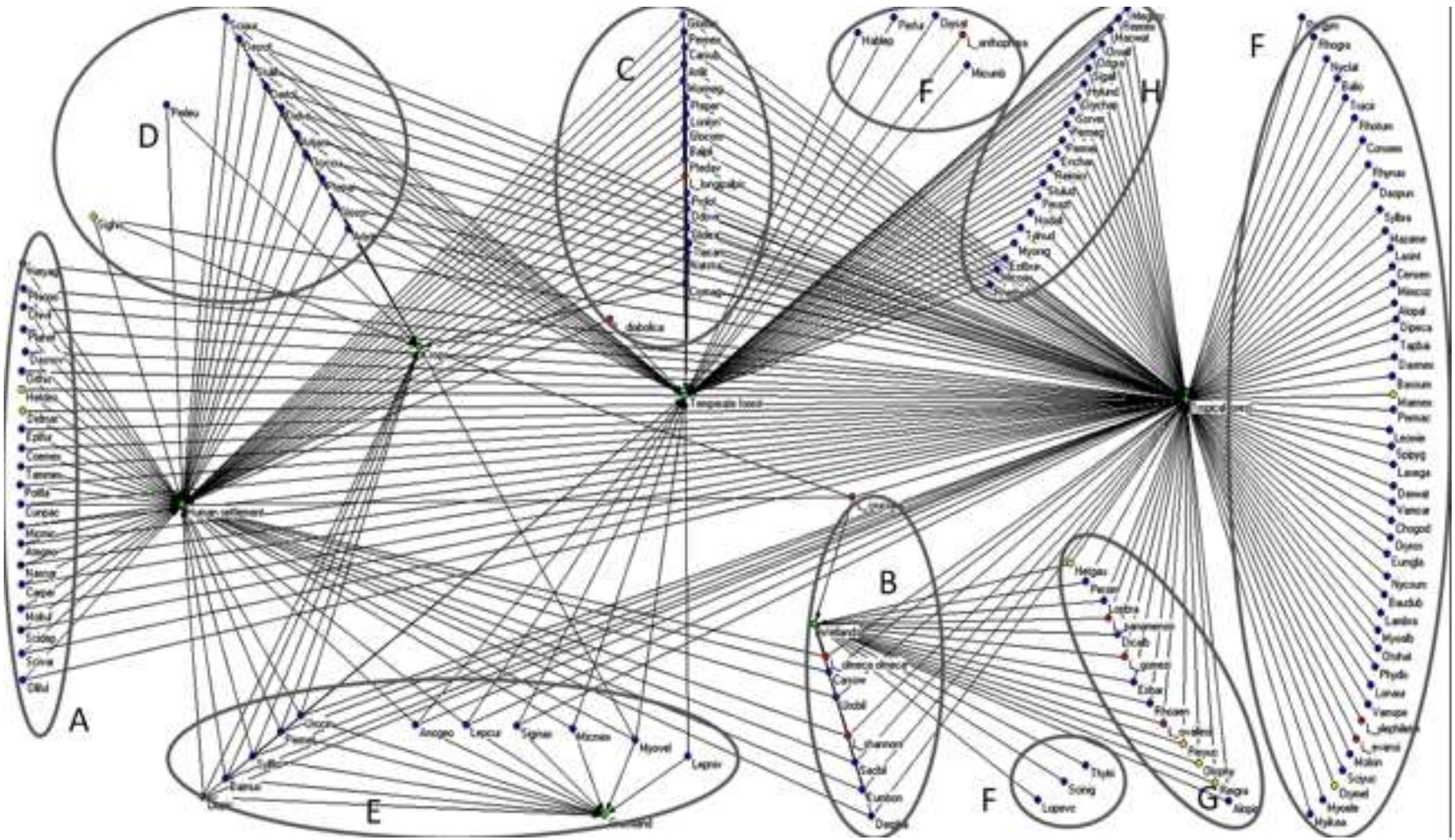

Results: 51 individuals from 5 sites in Nuevo Leon collected from 10 species of Lutzomyia. Also positive resultads from Tamaulipas.

centro de ciencias de la complejidad

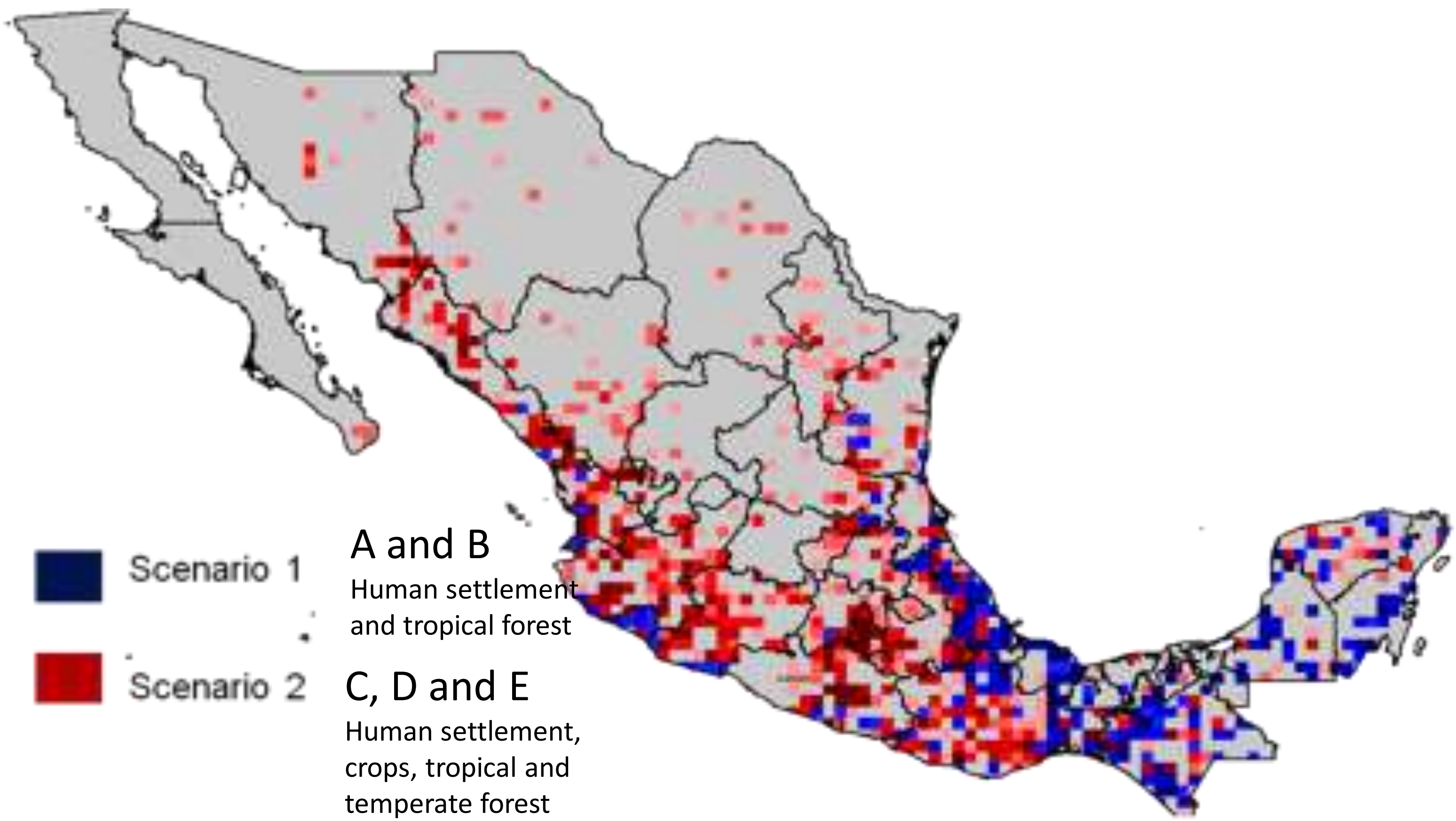
# Lutzomyia Risk Maps from Mammals and Landcover


Biased Lutzomyia collections. Our modeling indicated that there were potential biases.

# Making the Network more complex: Potential patterns of dispersal



# Generating dispersal scenarios



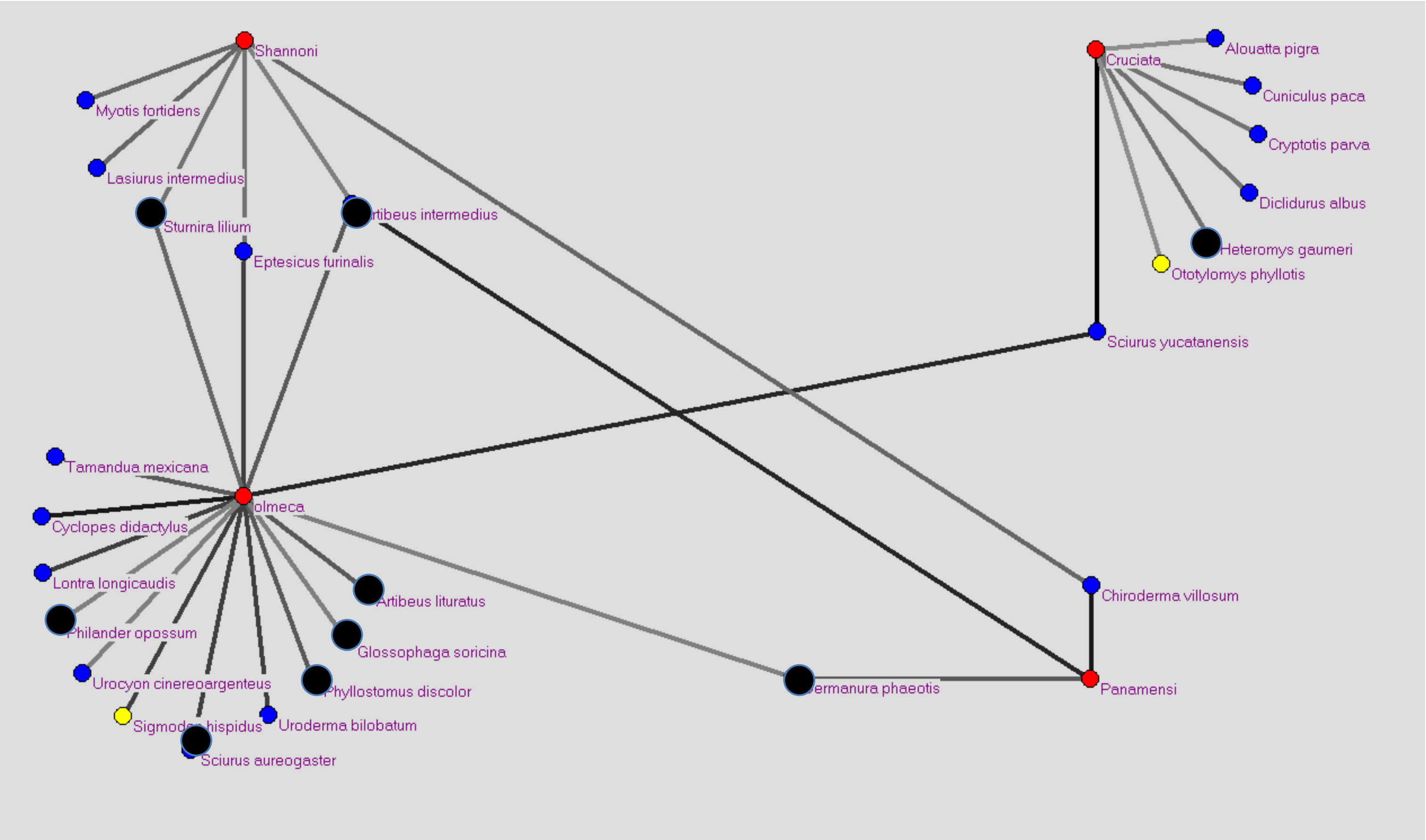

A and B

Human settlement and tropical forest

C, D and E

Human settlement, crops, tropical and temperate forest

# Drilling down to a more local level…
# The biotic network for Tabasco



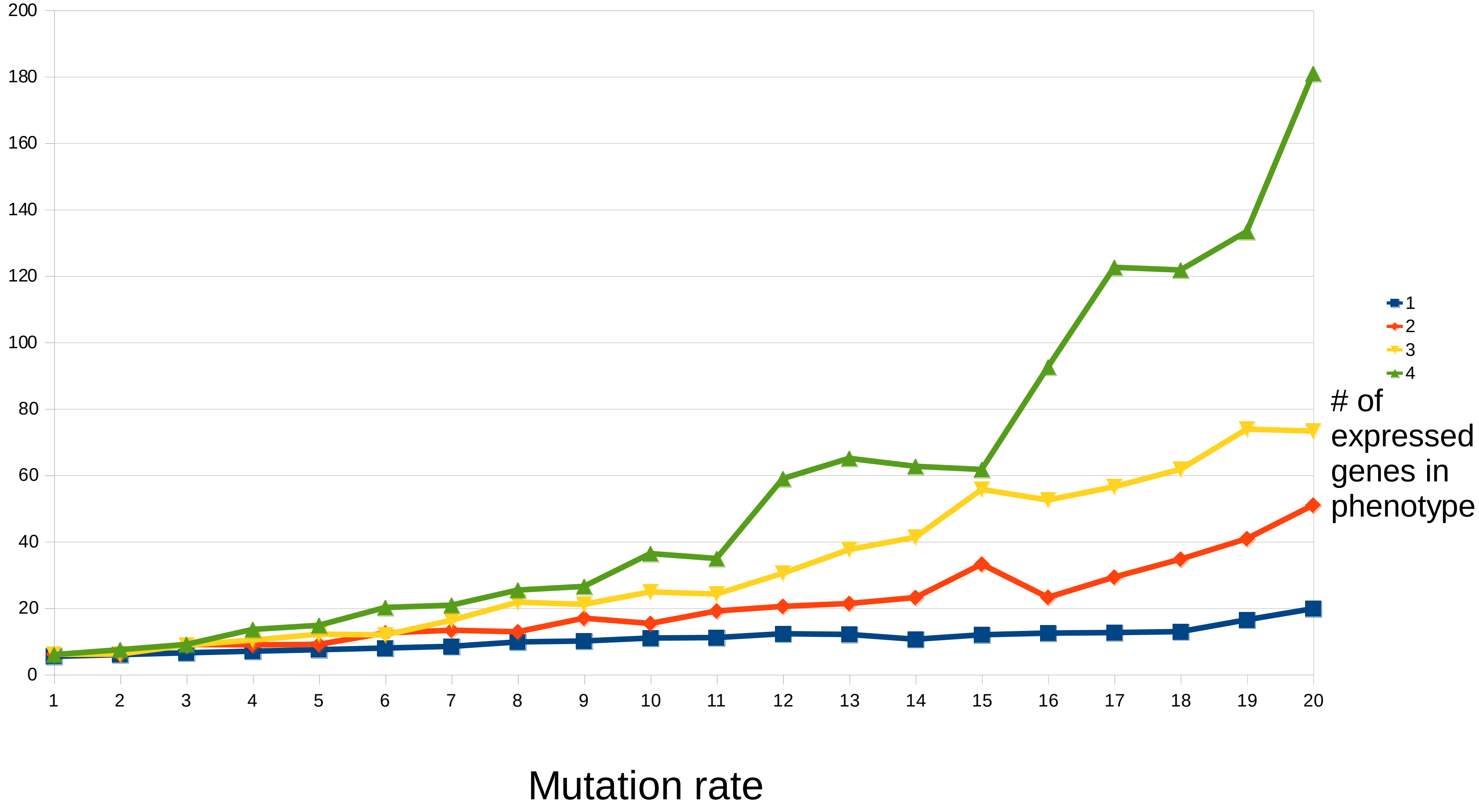

C. Gonzalez, Universidad de los Andes, Bogota

# And now from macro to micro...

# How do pathogens manage to thrive in a large range of hosts?

# How do they generate and maintain phenotypic diversity?

Infection lifetime



# Conclusions

- **Emerging zoonoses are complex SYSTEMS**
  - They are also composed of complex SUB-SYSTEMS
  - Many variables are relevant and the micro and the macro are intimately related
  - Their study requires potentially large, interdisciplinary teams
- **We CANNOT do "science" (separate, controlled experiments) to determine the effect of every variable (No PV=RT)**
- **The world is awash with data**
  - Much of this data can be used to (indirectly) infer interactions/relationships/risk factors
  - E.g. Predicting the distribution of Lutzomyia, a model with about 500 variables, using point collection data
  - Inference networks are a great way of understanding and visualising potential biotic/abiotic/other interactions

# Conclusions

- **Modeling at a true systems level IS possible**

Difference between prediction and understanding

Correlation versus causation

Phenomenological versus “fundamental” models

# Relevant Publications


Stephens, Christopher R., et al. "Using biotic interaction networks for prediction in biodiversity and emerging diseases." *PloS one* 4.5 (2009): e5725.

González-Salazar, C., and C. R. Stephens. "Constructing Ecological Networks: A Tool to Infer Risk of Transmission and Dispersal of Leishmaniasis." *Zoonoses and Public Health* 59.s2 (2012): 179-193.

Sánchez-Cordero, Víctor, et al. "Competitive interactions between felid species may limit the southern distribution of bobcats Lynx rufus." *Ecography* 31.6 (2008): 757-764.

González-Salazar, Constantino, Christopher R. Stephens, and Pablo A. Marquet. "Comparing the relative contributions of biotic and abiotic factors as mediators of species' distributions." *Ecological Modelling* 248 (2013): 57-70.