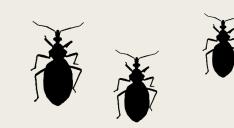
SPECIES IDENTIFICATION USING TENSORFLOW

Ali Khalighifar

(PhD Candidate in Ecology & Evolutionary Biology)







Outline

Introduction

Morphology-based Identification

- Project 1: Automated identification of Chagas disease vectors using statistical classifiers(Completed Project)
- Project 2: TensorFlow improves automated identification of Chagas disease vectors (Completed Project)
- Project 3: Marshalling diverse big data streams to understand risk of tick-borne diseases in the Great Plains (Future Project)

Signal-based Identification

- Project 1: Adapting TensorFlow to improve biodiversity assessment for Philippine frog species (Current Project)
- Project 2: TensorFlow helps surveillance of mosquito species using cell phone recordings of wingbeats (Current Project)

Conclusion

What is a Species?

- > At least 26 recognized species concepts
- > Ernst Mayr proposed the <u>biological species concept</u> as:

"Species are groups of actually or potentially interbreeding natural populations which are reproductively isolated from other such groups."

A biological species is a group of organisms that can reproduce with one another in nature and produce fertile offspring.



http://www.birds.cornell.edu

Hawaiian happy-face spider (Theridion grallator)

Western meadowlarks vs. Eastern meadowlarks(Sturnella neglecta)(Sturnella magna)



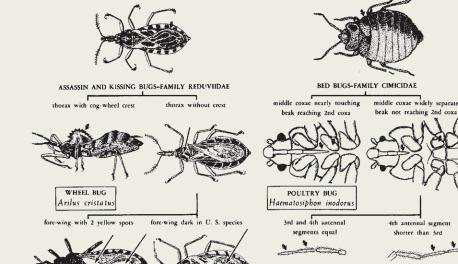
https://evolution.berkeley.edu

	Drimon comente de los entenes musiciais
	Primer segmento de las antenas muy pocas
	veces sobrepasando considerablemente el
	nivel del ápice del clípeo, en general apenas
	alcanzándolo, o aún más corto; pronoto di-
	ferente
14.	Primer segmento del rostro más largo que el
	tercero (figs. 36B; 93B; 131B; 148E; 180C,
	D; 188B) (en caso de duda pásase al 53) 15
	Primer segmento del rostro tan largo o aún más
	corto que el tercero (figs. 66A; 79B; 105E;
	146B; 158B; 165B)
15.	Cuerpo y corio de los hemélitros con pelos
	numerosos y bien perceptibles dorsalmente
	(figs. 16, 93D; 142A, B)16
	Cuerpo y corio prácticamente glabros, o con
	pelos muy breves y esparsos
16.	Cabeza fuertemente convexa dorsalmente (fig.
	93B); tubérculos anteníferos alargados, rela-
	tivemente próximos a los ojos (fig. 93B)
	lecticularia
	Cabeza no fuertemente convexa dorsalmente
	(fig. 142B); tubérculos anteníferos cortos,
	alejados de los ojos (fig. 142B)17
17	Corio de los hemélitros blanquecino-amarillento
17.	en su mayor parte, anaranjado en su base y
	negro en su ápice (fig. 130) . <i>.pallidipennis</i>
	Corio sin área blanca, preponderantemente
	negro, solo con manchas amarillas o rojo-
	anaranjadas en su base y subapicalmente
	(figs. 101, 109, 140, 141, 143)

untero interni (ing. 1110), intuitiente 100 deg mentos del conexivo dorsal negros y con mancha amarillo-anaranjada póstero-lateral (fig. 144D-F); mesosterno, metasterno y ventre del abdómen siempre con pelos suberectos largospicturata Genas con frecuencia sin atingir el nivel del ápice del clípeo (fig. 102D); pronoto con lóbulo posterior totalmente negro (fig. 101) o con 1+1 pequeñas manchas claras sobre los ángulos humerales (fig. 102D); segmentos del conexivo dorsal negros con mancha amarilla o amarillo-anaranjada en el tercio o en la mitad posterior, que se extiende o no hasta la sutura conexival (fig. 102B, C, D); mesosterno con pelos suberectos largos; metasterno y vientre del abdómen con pelos semejantes o con pelos cortos y acostadoslongipennis

21. Disco del escudete en la base con 1+1tubérculos salientes dirigidos hacia adelante y tocando el borde posterior del pronoto (figs. 70B; 126D); ángulos humerales ex-Disco del escudete sin los tubérculos mencionados, ángulos humerales no explanados

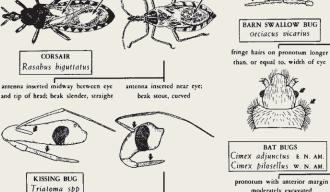
22. Color general castaño claro (fig. 70A); tubérculos discales y laterales del lóbulo anterior del pronoto muy salientes (fig. 70B); fémures anteriores y medianos con



wings usually well-developed; body elongate-oval

BUGS: PICTORIAL KEY TO SOME SPECIES THAT MAY BITE MAN Harry D. Pratt and Chester J. Stojanovich

wings reduced; body broadly-oval



MASKED HUNTER

Reduvius personatus

cted behind middle

BLACK BUG

Melanolestes picipes



Cimex hemipterus

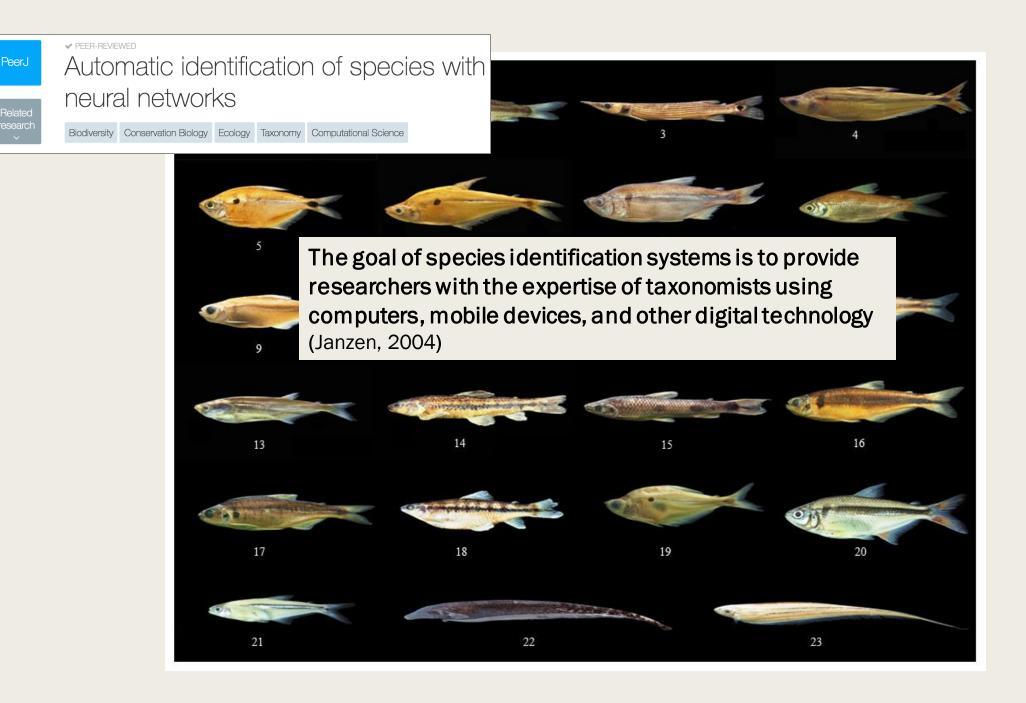
SO. U.S. & TROPICS

BED BUG Cimex lectularius

TEMPERATE AREAS

fringe hairs on pronotum

shorter than width of eye



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Conclusion

PROJECT 1: VIRTUAL VECTOR LAB

Spencer Art Museum, ITTC, Biodiversity Institute @ KU Universidade de Brasília Instituto Nacional de Salud Pública de Mexico

PeerJ

Automated identification of insect vectors of Chagas disease in Brazil and Mexico: the Virtual Vector Lab

Rodrigo Gurgel-Gonçalves¹, Ed Komp², Lindsay P. Campbell³, Ali Khalighifar³, Jarrett Mellenbruch⁴, Vagner José Mendonça^{1,5}, Hannah L. Owens^{3,6}, Keynes de la Cruz Felix⁷, A Townsend Peterson³ and Janine M. Ramsey⁷

⁴ Faculty of Medicine, Universidade de Brasília, Brasília, DF, Brazil
 ⁵ Information and Telecommunication Technology Center, University of Kansas, Lawrence, KS, United States
 ⁶ Biodiversity Institute, University of Kansas, Lawrence, KS, United States
 ⁶ Spencer Art Museum, University of Kansas, Lawrence, KS, United States
 ⁵ Centro de Cièncias da Saúde, Universidade Federal do Piauí, Brazil
 ⁶ Florida Museum of Natural History, University of Florida, Gainesville, FL, United States
 ⁷ Centro Regional de Investigación en Salud Pública, Instituto Nacional de Salud Publica, Tapachula, Chiapas, Mexico

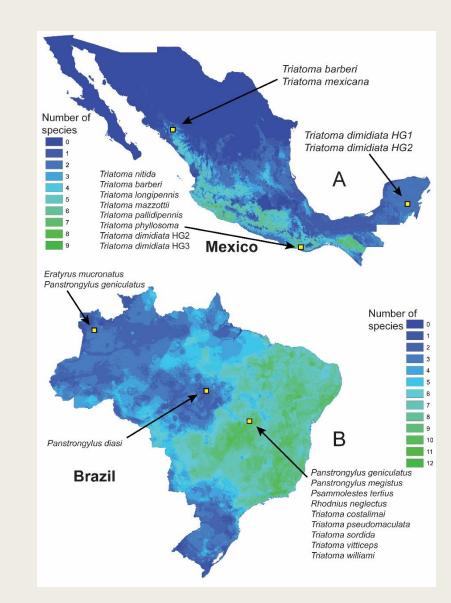
ABSTRACT

Identification of arthropods important in disease transmission is a crucial, yet difficult, task that can demand considerable training and experience. An important case in point is that of the 150+ species of Triatominae, vectors of *Trypanosoma cruzi*, causative agent of Chagas disease across the Americas. We present a fully automated system that is able to identify triatomine bugs from Mexico and Brazil with an accuracy consistently above 80%, and with considerable potential for further improvement. The system processes digital photographs from a photo apparatus into landmarks, and uses ratios of measurements that approximate aspects of coloration, as the basis for classification. This project has thus produced a working prototype that achieves reasonably robust correct identification rates, although many more developments can and will be added, and—more broadly—the project illustrates the value of multidisciplinary collaborations in resolving difficult and complex challenges.

Submitted 26 September 2016 Accepted 28 January 2017 Published 18 April 2017

Corresponding author A Townsend Peterson, town@ku.edu Subjects Entomology, Computational Science

Keywords Identification, Chagas disease, Triatominae, Automation, Primary occurrence data



- Vector-Borne Disease: Disease that results from an infection transmitted to humans and other animals by vectors (blood-feeding anthropods)
 - Vector-borne diseases account for more than 17% of all infectious diseases, causing more than 700,000 deaths annually.
- Vectors: Living organisms that can transmit infectious diseases between humans or from animals to humans. Vectors ingest disease-producing microorganisms during a blood meal from an infected host (human or animal) and later inject it into a new host during their subsequent blood meal.



Chagas Disease





For more information on Chagas www.cdc.gov/parasites/chagas



Triatoma phyllosoma pallidipennis Triatoma longipennis gerstaecker

1. http://www.who.int/mediacentre/factsheets/fs340/en/ 2.https://www.researchgate.net/publication/26703028_An_Estimate_of_the_Burden_of_Chagas_Disease_in_the_United_States





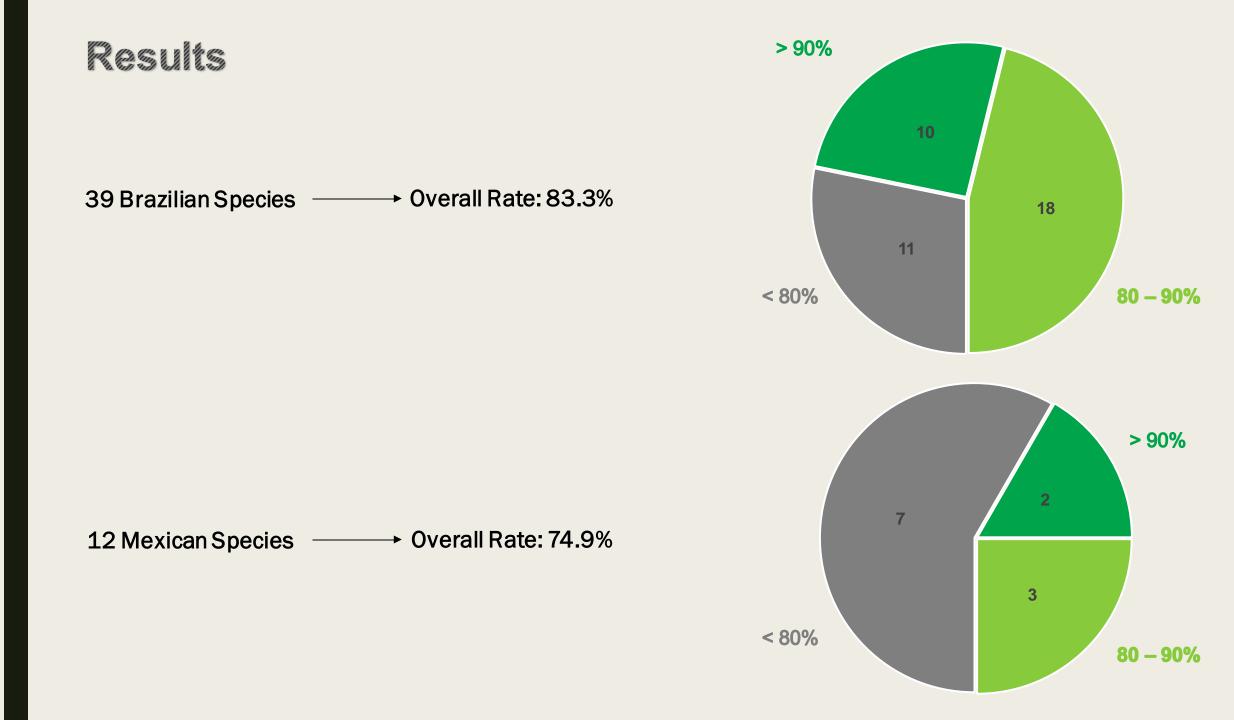












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Volume 56, Issue 5 September 2019

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Deep Learning Algorithms Improve Automated Identification of Chagas Disease Vectors

Ali Khalighifar ⊠, Ed Komp, Janine M Ramsey, Rodrigo Gurgel-Gonçalves, A Townsend Peterson

Journal of Medical Entomology, Volume 56, Issue 5, September 2019, Pages 1404–1410, https://doi.org/10.1093/jme/tjz065 Published: 23 May 2019 Article history v

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Abstract

Vector-borne Chagas disease is endemic to the Americas and imposes significant economic and social burdens on public health. In a previous contribution, we presented an automated identification system that was able to discriminate among 12 Mexican and 39 Brazilian triatomine (Hemiptera: Reduviidae) species from digital images. To explore the same data more deeply using machine-learning approaches, hoping for improvements in classification, we employed TensorFlow, an open-source software platform for a deep learning algorithm. We trained the algorithm based on 405 images for Mexican triatomine species and 1,584 images for Brazilian triatomine species. Our system achieved 83.0 and 86.7% correct identification rates across all Mexican and Brazilian species, respectively, an improvement over comparable rates from statistical classifiers (80.3 and 83.9%, respectively). Incorporating distributional information to reduce numbers of species in analyses improved identification rates to 95.8% for Mexican species and 98.9% for Brazilian species. Given the 'taxonomic impediment' and difficulties in providing entomological expertise necessary to control such diseases, automating the identification process offers a potential partial solution to crucial challenges.

Keywords: Chagas disease, TensorFlow, deep learning, Triatominae, automated species identification

Issue Section: Vector-Borne Diseases, Surveillance, Prevention

TensorFlow



- Transfer learning using Inception v3
- Google Brain Team designed Inception v3, a convolutional neural network for ILSVRC (ImageNet Large Scale Visual Recognition Competition) that is 48 layers deep and can classify images into 1000 object categories

"The Inception deep convolutional architecture was introduced as **GoogLeNet** in (Szegedy et al. 2015a), here named **Inception v1**. Later the Inception architecture was refined in various ways, first by the introduction of <u>batch normalization</u> (loffe and Szegedy 2015) (**Inception v2**). Later by additional <u>factorization</u> ideas in the third iteration (Szegedy et al. 2015b) which will be referred to as **Inception v3**."



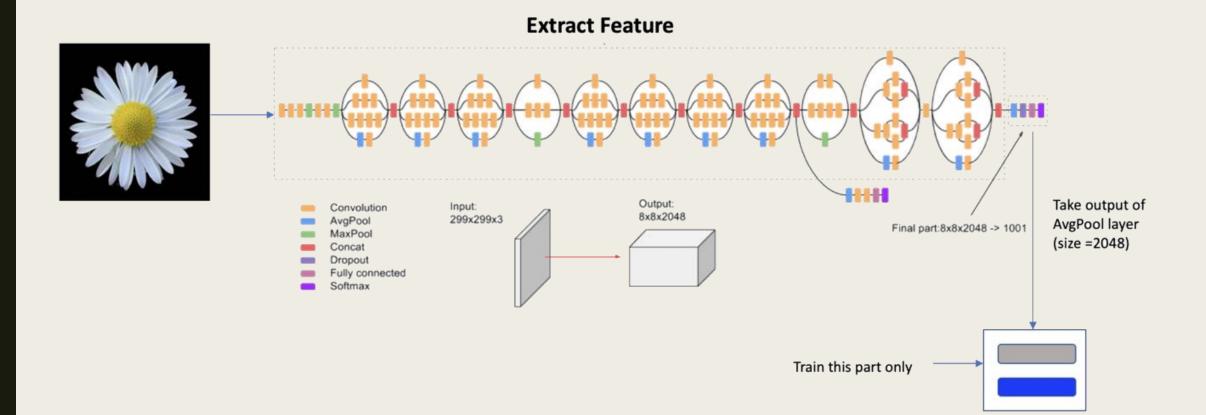




Methods

Leave-one-out cross validation

- Processed images vs non-processed images
- Distributional data



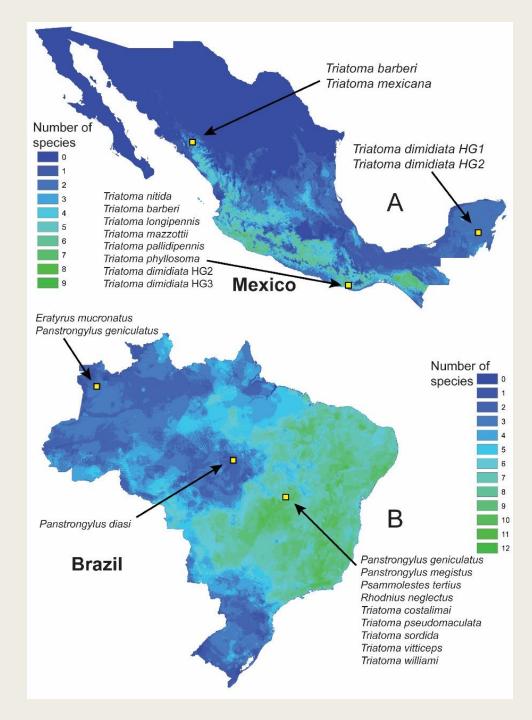
Methods

- Leave-one-out cross validation
- Processed images vs non-processed images
- > Distributional data



Methods

- Leave-one-out cross validation
- Processed images vs non-processed images
- Distributional data



Previous Results

12 Mexican Species ------ Overall Rate: 74.9%

TensorFlow

12 Mexican Species → Overall Rate: 83.0%



Previous Results

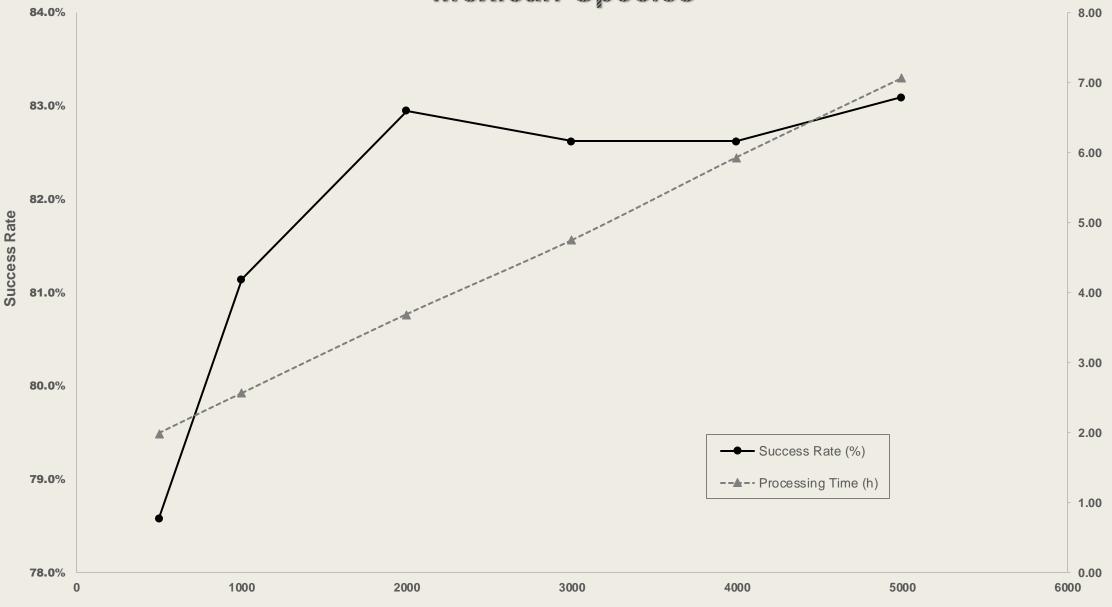
39 Brazilian Species → Overall Rate: 83.3%

TensorFlow

39 Brazilian Species → Overall Rate: 86.7%



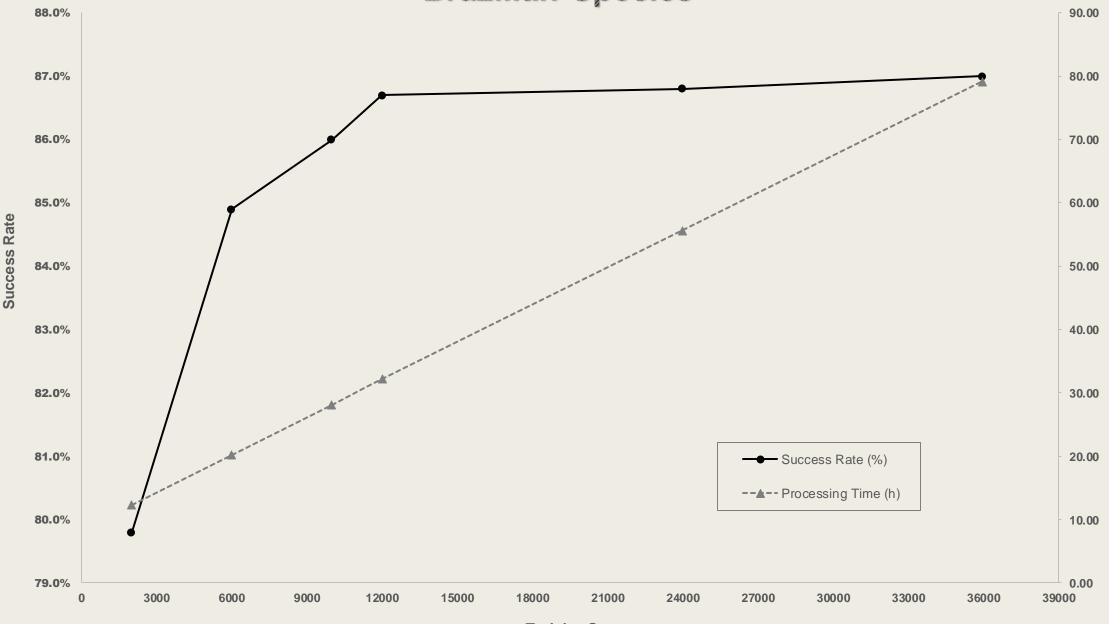




Processing Time (h)

Training Steps

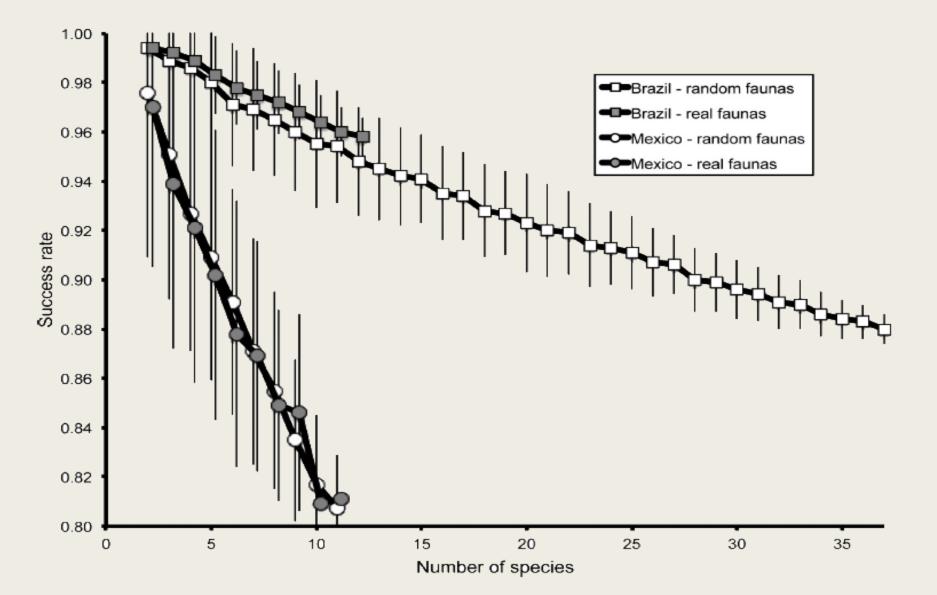
Brazilian Species



Processing Time (h)

Training Steps

Distributional Data



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Conclusion

Tick-borne diseases

***** Lyme disease

* Anaplasmosis

* Tick-borne relapsing fever

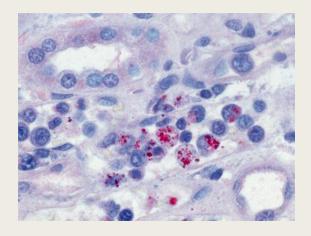
* Ehrlichiosis

* Babesiosis

* Tularemia

* Rocky Mountain spotted fever

Southern tick-associated rash illness









For the first time, this project marshals deployment, integration, pattern analysis and modeling of four big data streams in order to address emerging challenges of tick-borne diseases in the southern Great Plains:

- > Synthesize historic and current occurrence data for tick specimens
- Generate genomic data on ticks and pathogens to identify tick species and characterize the suite of pathogens that they carry
- > Gather remote sensing data to characterize the region's environmental landscapes
- Identify tick species using deep neural networks













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Conclusion

You may ask ...

> Why study frogs?

> Why study the Philippine biodiversity?

> Why analyze the calls/signals?

Why study frogs?

- Play an important role in the food chain
- Excellent bio-indicators
- Control insect populations

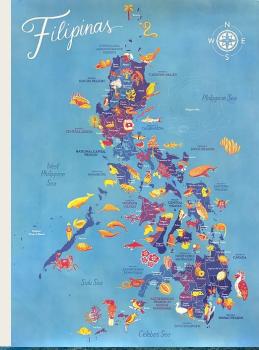
- > Why study the Philippine biodiversity?
- > Why analyze the calls/signals?



> Why study frogs?

- Why study the Philippine biodiversity?
 - Biodiversity hotspot
 - Ranked first in terms of amphibian endemism (98 out of 120 sp.)
 - High rate of species discovery
 - Availability of data

> Why analyze the calls/signals?





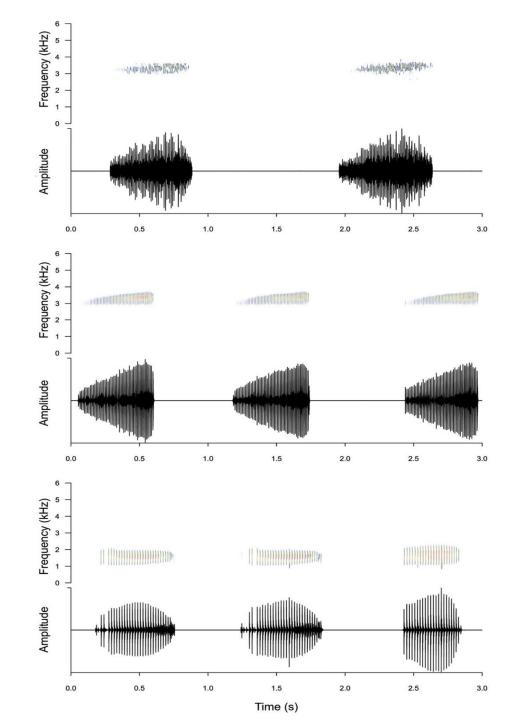
> Why study frogs?

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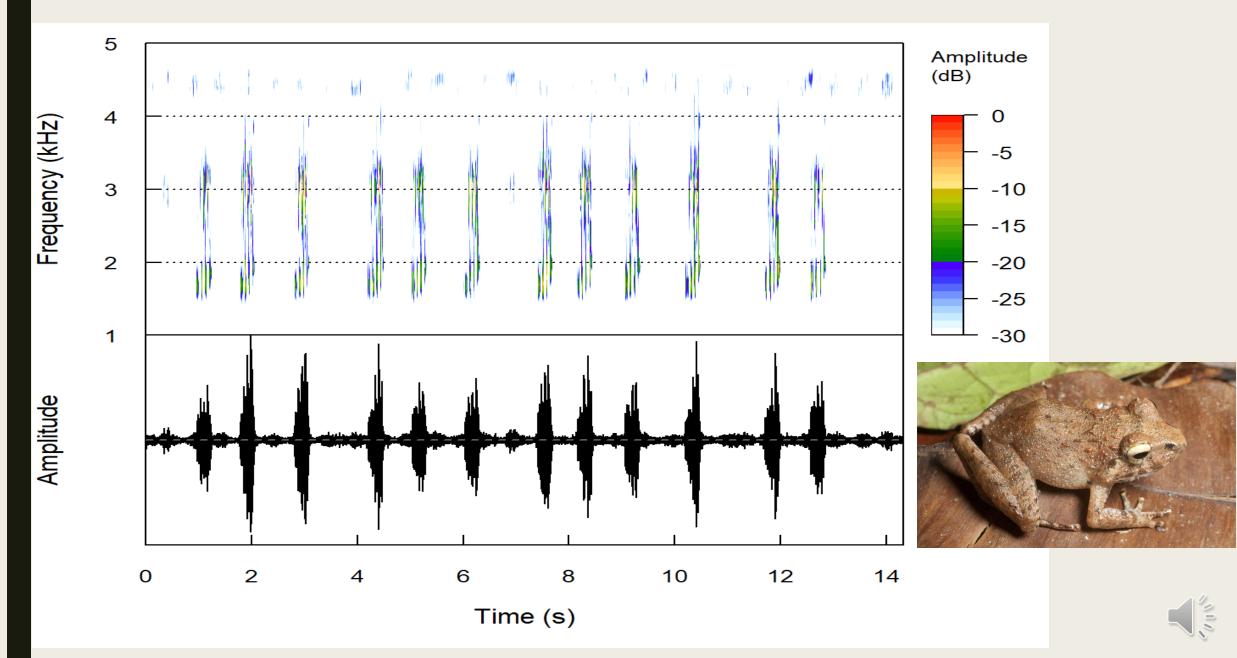
✤ Why analyze the calls/signals?

- Sexual selection: Sexual selection acts on an organism's ability to obtain (often by any means necessary!) or copulate successfully with a mate
- Advertisement calls

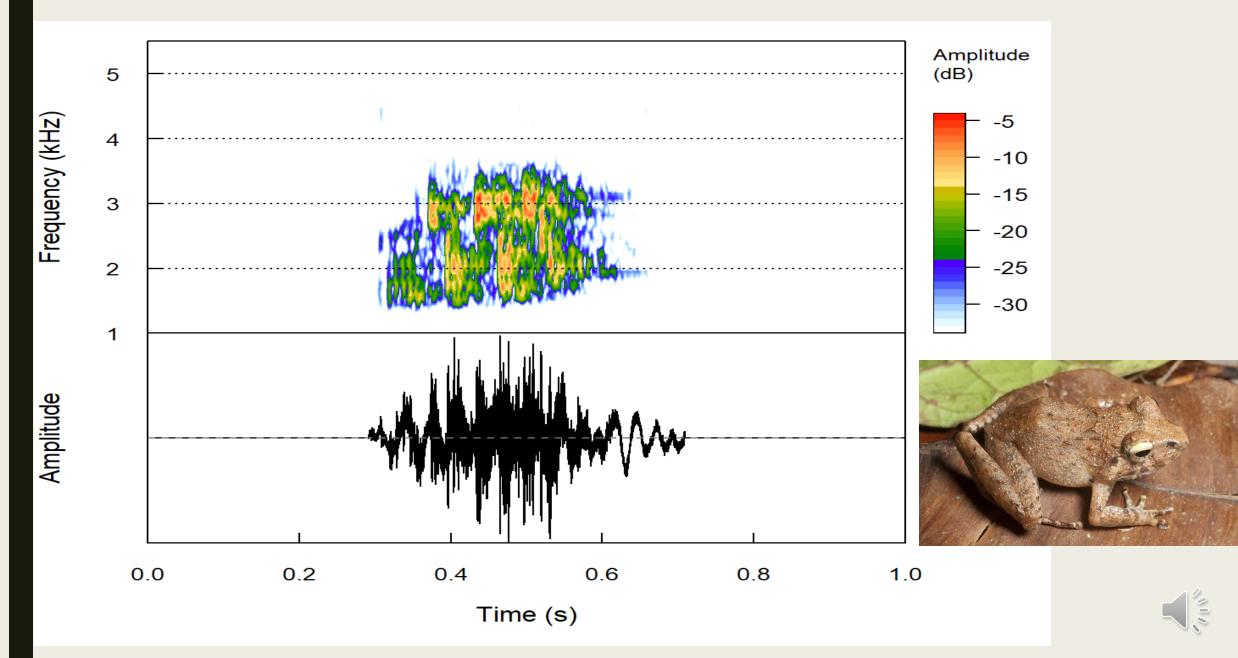




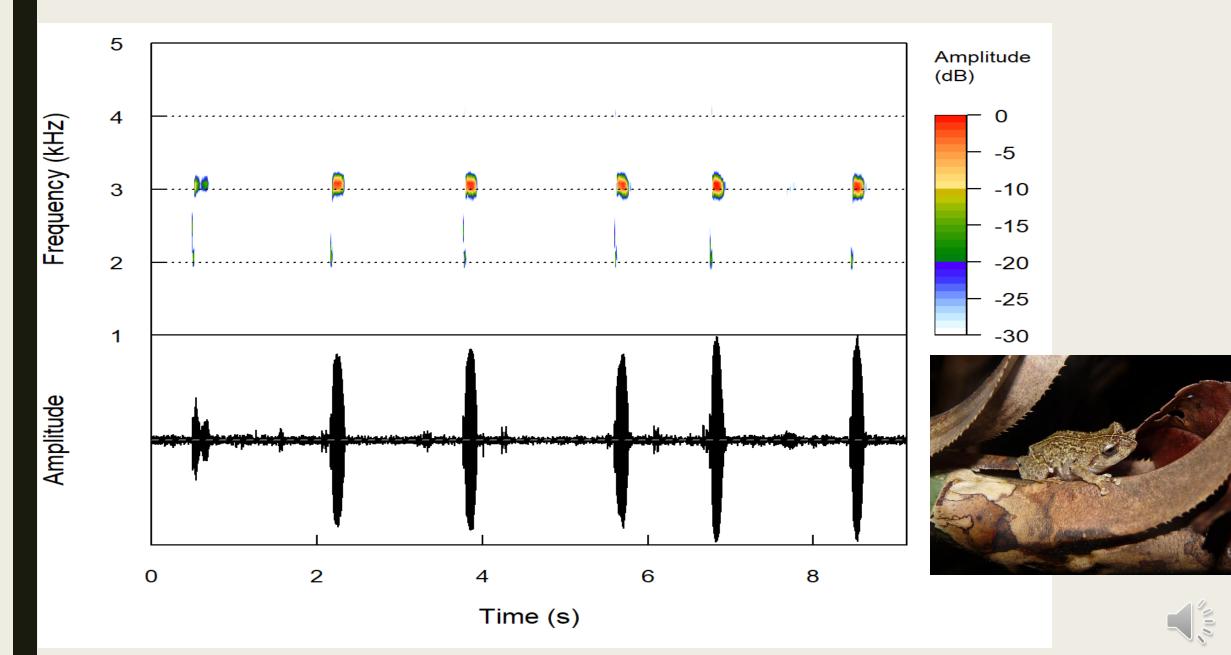
Platymantis cagayanensis (bout)



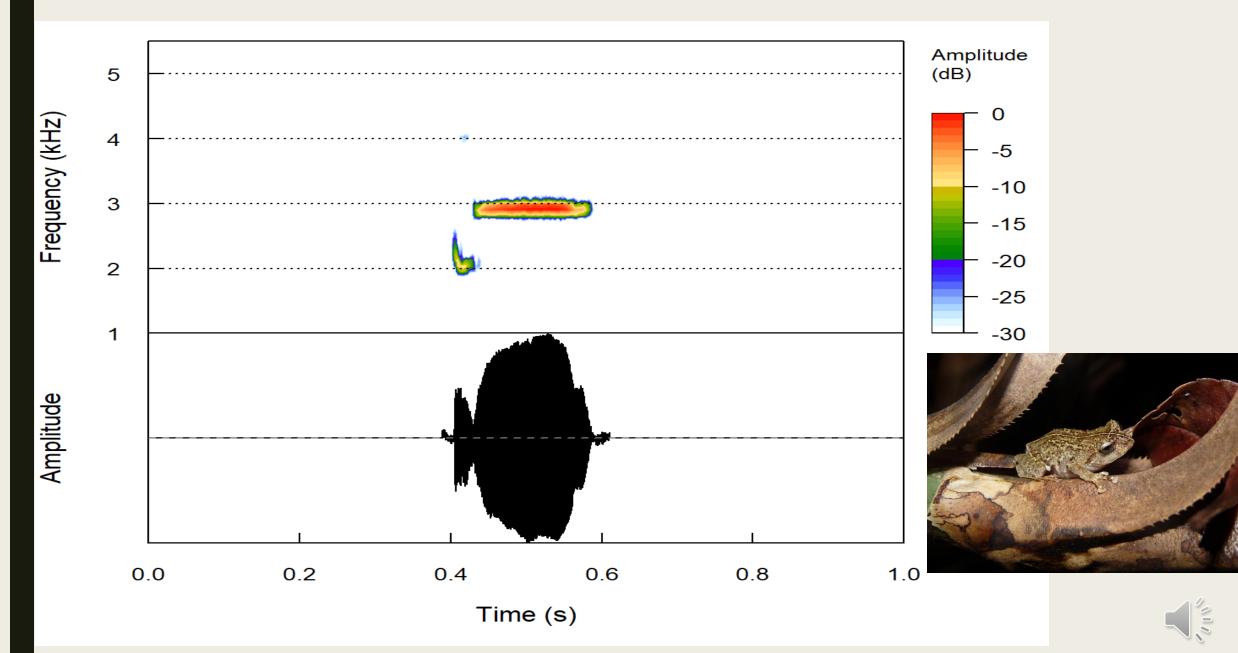
Platymantis cagayanensis (call/single note)



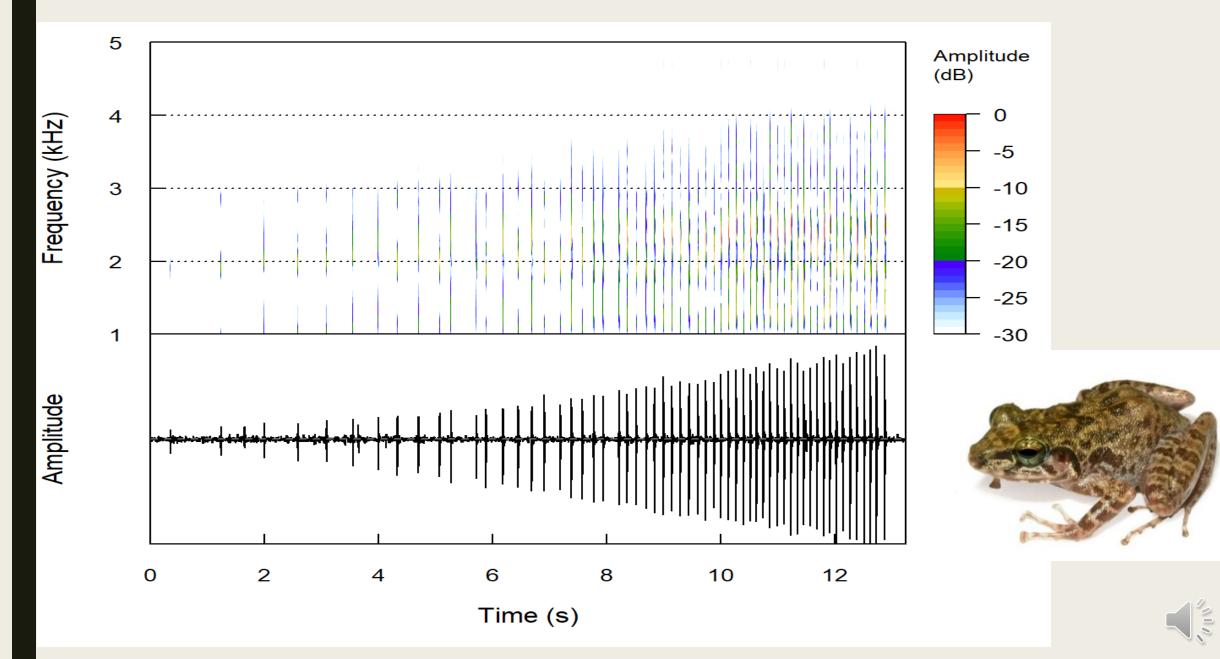
Platymantis isarog (random bout)



Platymantis isarog (call/single note)

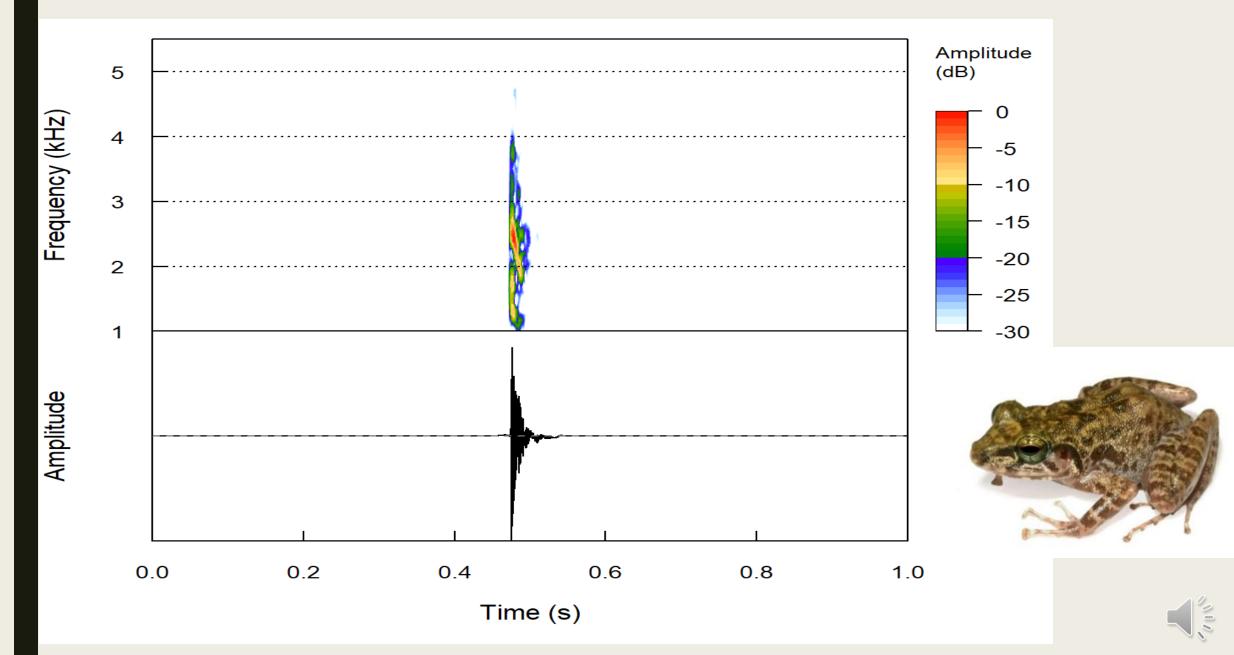


Platymantis insulatus (bout/call)

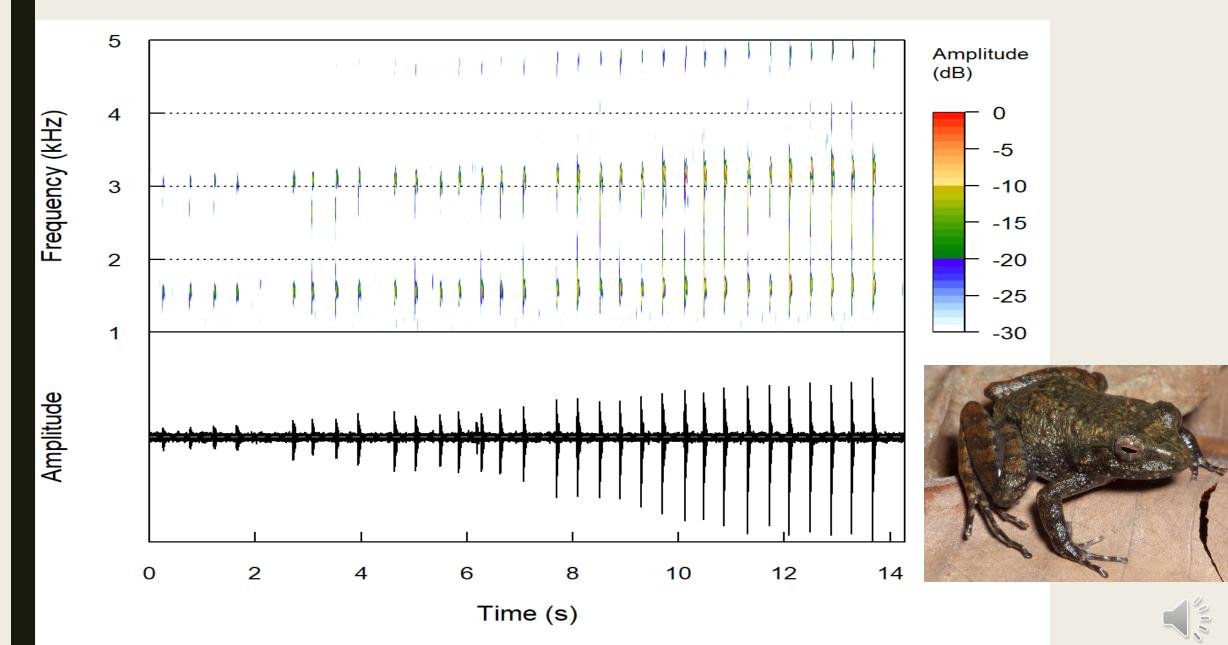


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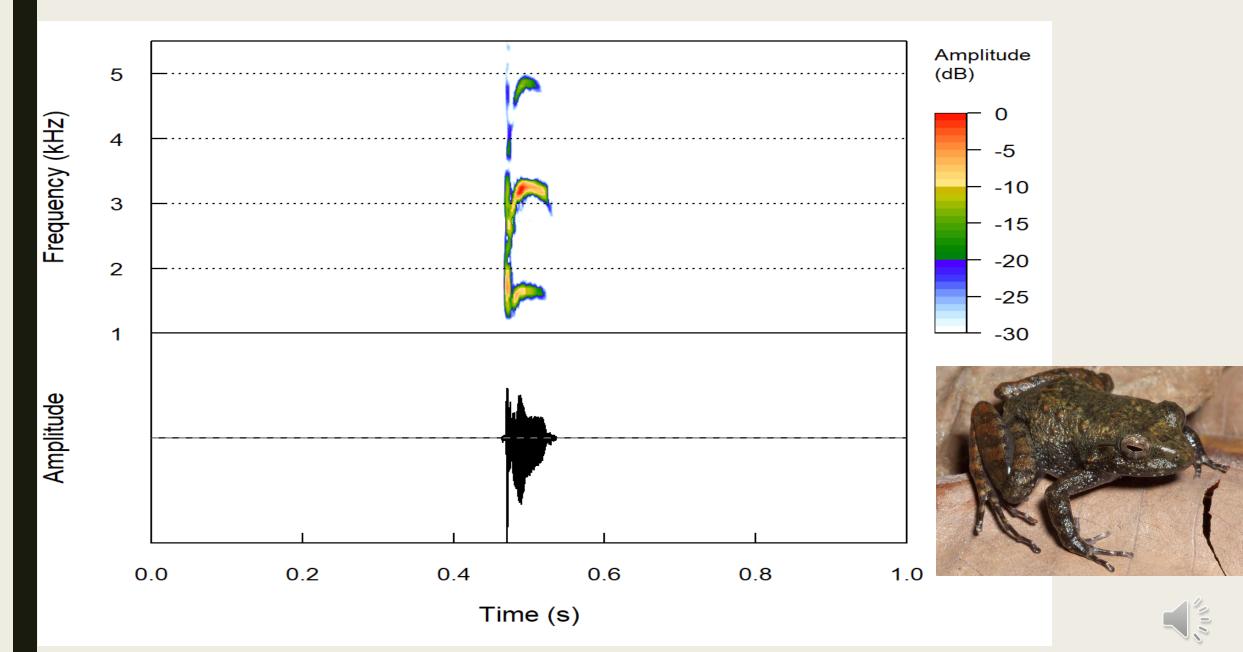
Platymantis insulatus (single note)



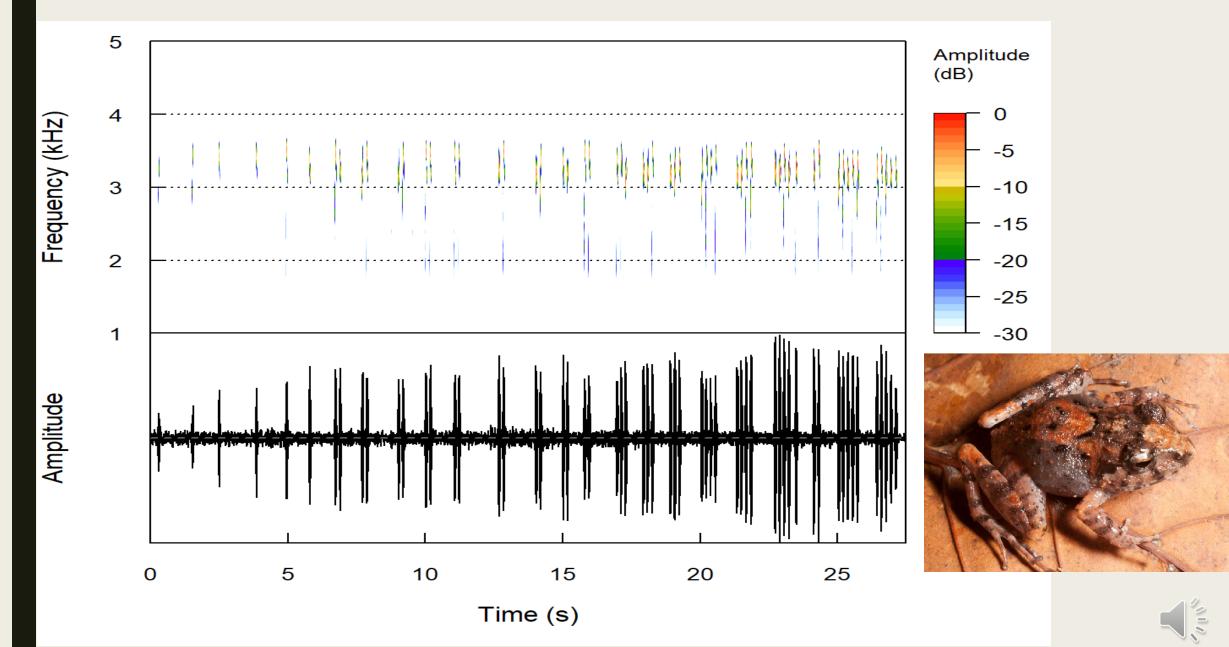
Platymantis levigatus (bout/call)



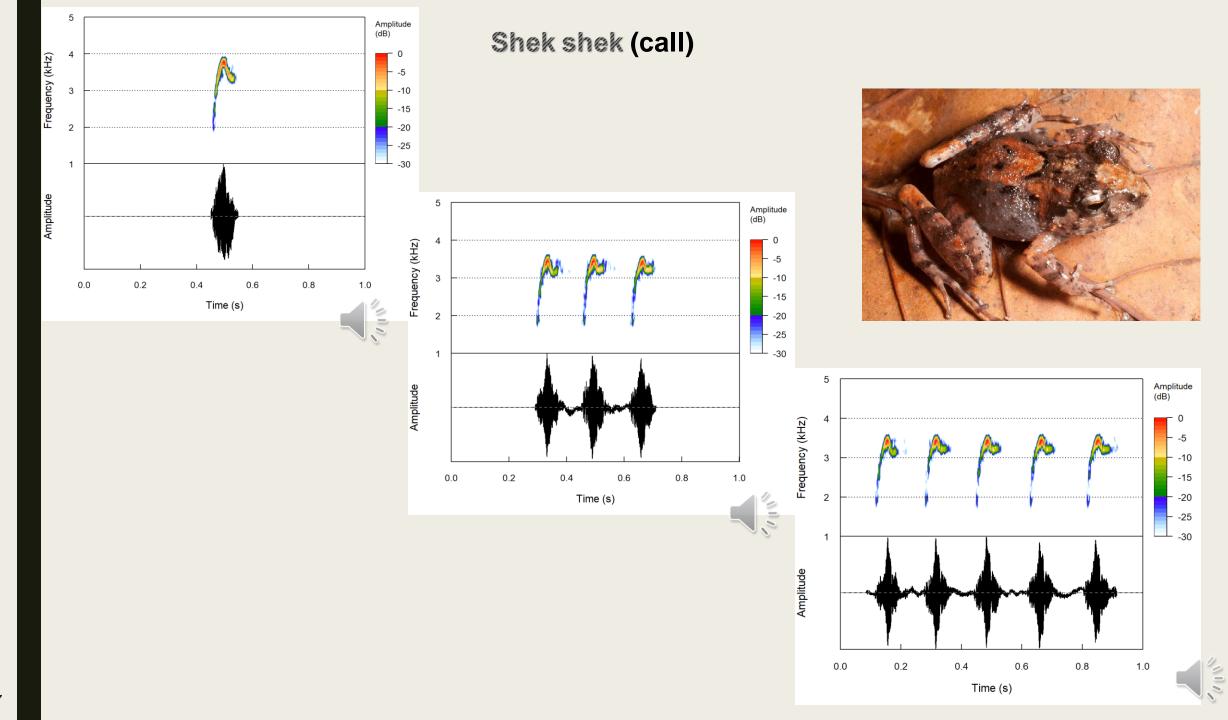
Platymantis levigatus (single note)



Shek shek (bout)

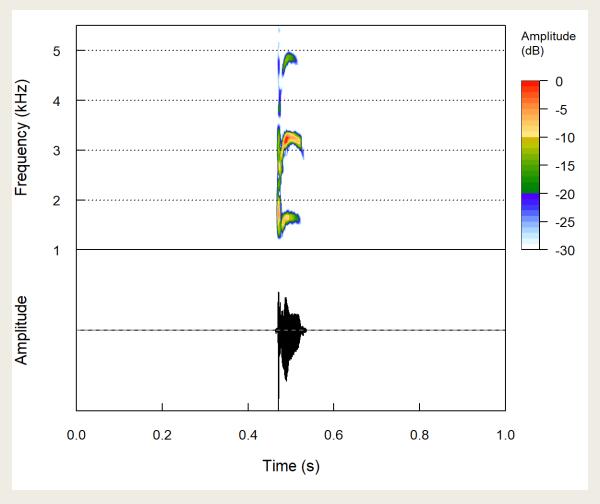


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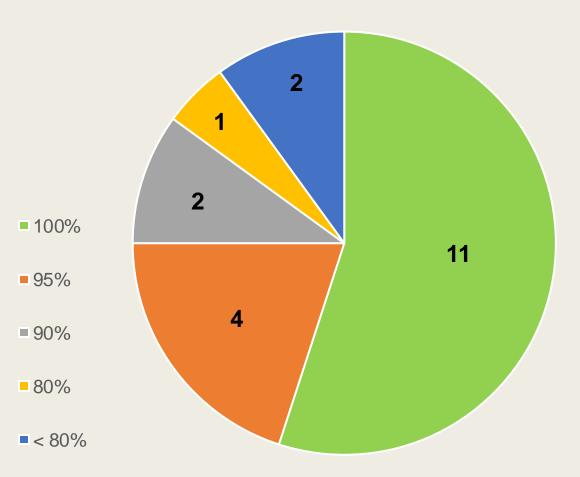
Methods

- > Clipped single notes (20 samples per sp.)
 - Added silence to have the same time length
 - Same frequency range to cover all species
- Trained TensorFlow on 20 described species
- > 20 described sp. Vs 21 undescribed sp.
- Island-based identification



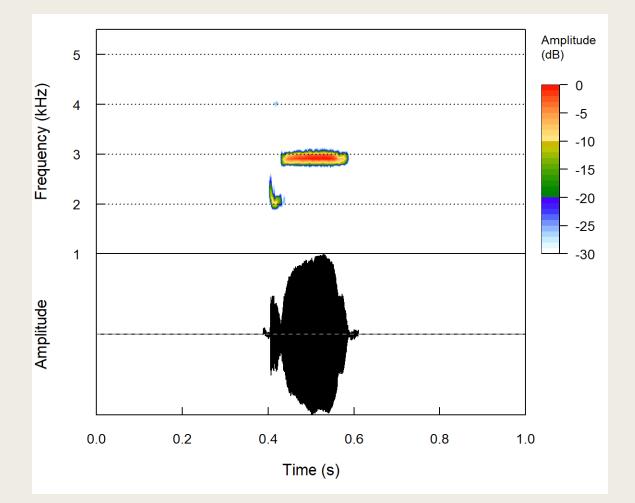
Results

20 described species → Overall Rate: 94.3%



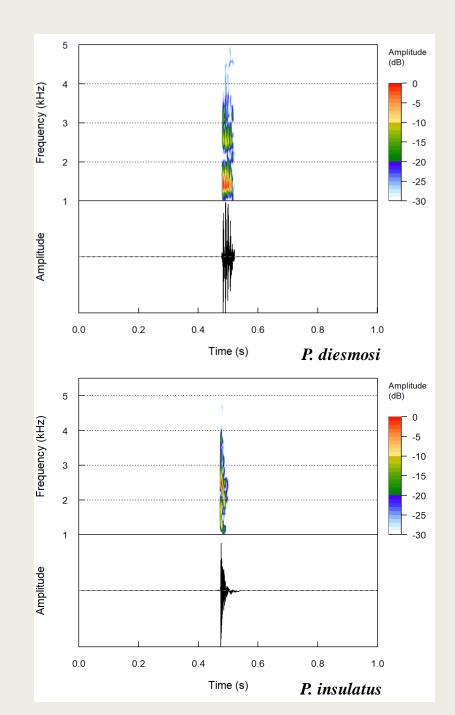
Described vs undescribed species

- > TF identified all 20 *P. isarog* calls as isarog
 - **• TF** certainty = **98.1%**
- TF identified all 20 P. diesmosi calls as P. insulates
 - **• TF certainty = 94.3%**
- TF confused "churink redori" with 10 different species
 - **TF certainty = 38.4%**



Described vs undescribed species

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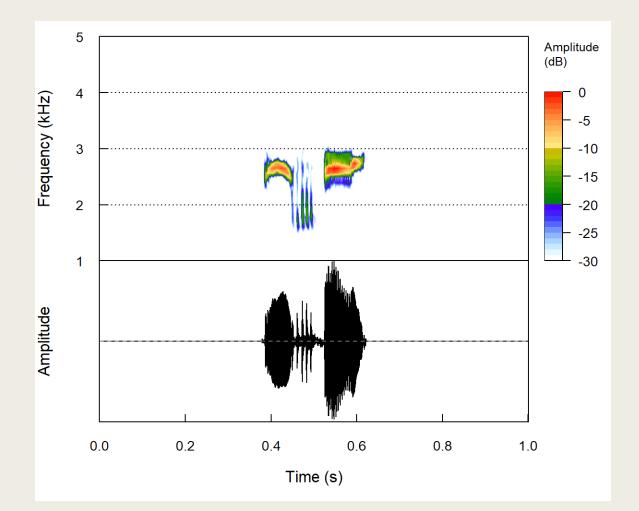


Described vs undescribed species

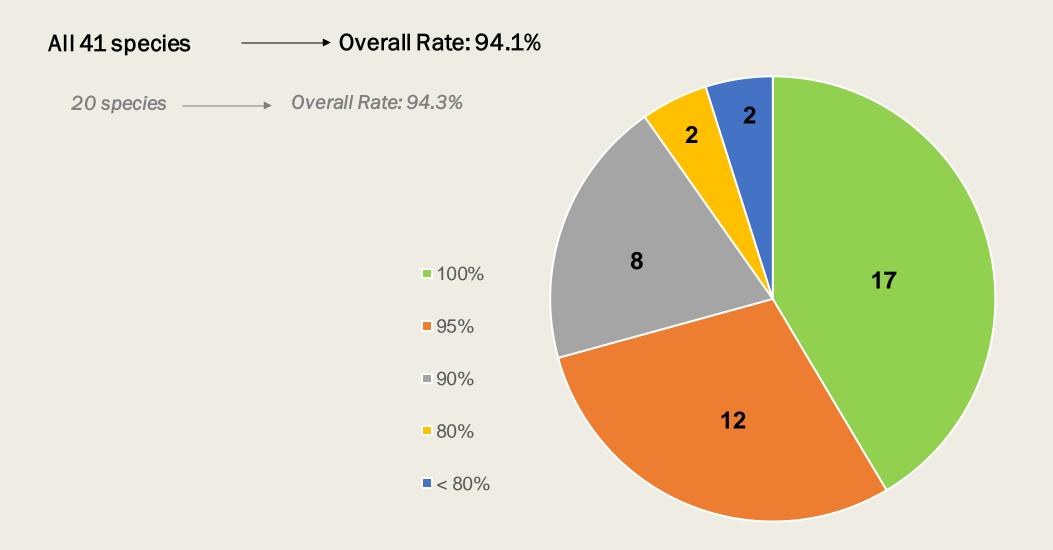
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Results



Island-based Identification

Island names	Number of species	Overall ID rate
Luzon	27	94.60%
Mindanao	б	100%
Sibuyan Tablas	6	100%
Polillo	б	99.20%
Samar Leyte Bohol	5	98.00%
Catanduanes	4	100%
Negros	4	100%
Dinagat Siargao	4	96.30%
Gigante	3	100%
Panay	3	100%
Romblon	3	100%

Luzon Polillo Catanduanes Marinduque TablasSibuyan Busuanga Samar Culion Biliran Panav Dumaran Guimaras Dinagat Siargao Siguijor Camiguin Mindanao 2

Basilan

The overall average ID rate across all islands = 98.7%

Jolo

Balabac

GeoCurrents Map

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Conclusion

Mosquito-borne diseases

* Malaria

✤ Zika virus

***** West Nile virus

* Chikungunya virus

* Dengue fever



Mosquito wingbeats

* Helps to identify species

***** Gives information about the sex

Helps surveillance of mosquito species



Provides the opportunity to control mosquito populations

Methods

~300 recordings over the past mosquito seasons

40 samples of Aedes aegypti from Mexico

16 samples of Anopheles gambiae from Ghana

Collecting instruction videos in English and Spanish

Goals

1) Identifying species in Kansas mosquito community

2) Detecting the presence of two alien species





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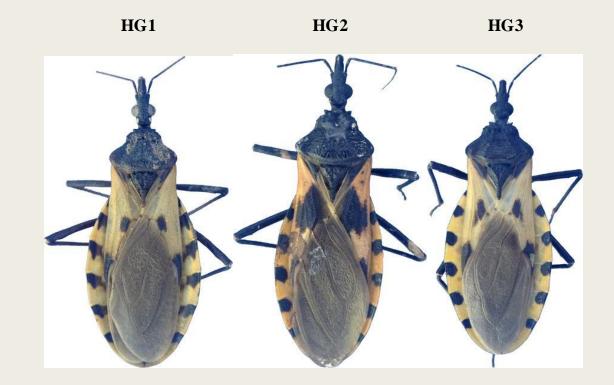
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Conclusion

***** Achievements

- *T. dimidiata* HG1, HG2, HG3
- *P. dorsalis* vs *P. guntheri*
- Citizen-scientists

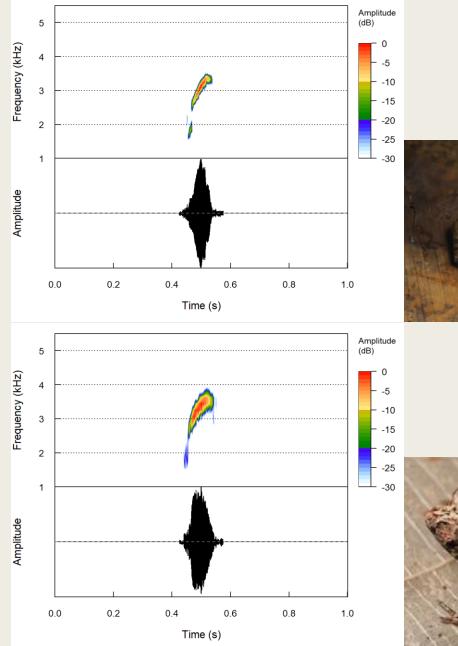
- > Challenges
- > Caveats



***** Achievements

- *T. dimidiata* HG1, HG2, HG3
- *P. dorsalis* vs *P. guntheri*
- Citizen-scientists

ChallengesCaveats



P. dorsalis



P. guntheri



***** Achievements

- *T. dimidiata* HG1, HG2, HG3
- P. dorsalis vs P. guntheri
- Citizen-scientists

- > Challenges
- > Caveats



Achievements

* Challenges

- Correct identification of species
- Availability of data

Record your observations

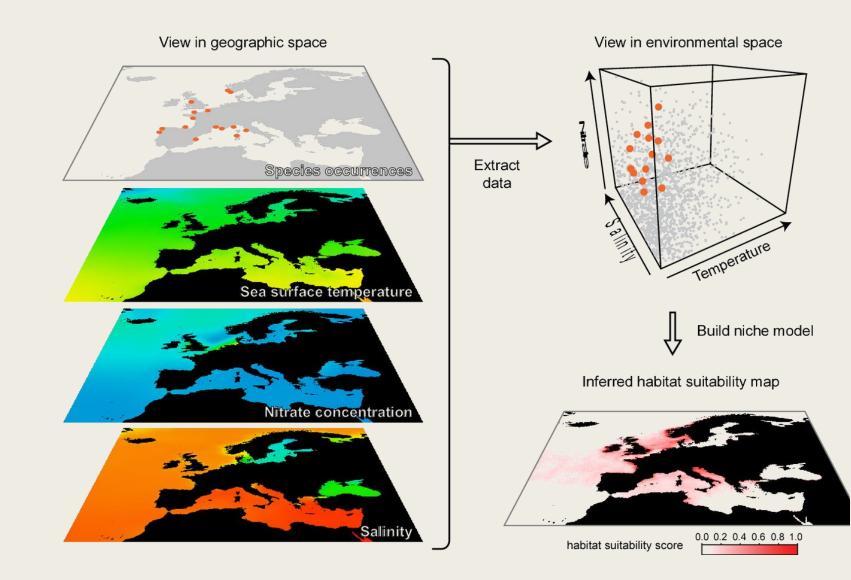
> Caveats



Exploring and Conserving Nature

Macaulay Library

- > Achievements
- > Challenges
- * Caveats
 - Number of images
 - Concepts vs tools



Acknowledgement

* <u>Co-authors</u>

- Town Peterson
- Ed Komp
- Janine Ramsey
- Rodrigo Gurgel-Gonçalves,
- Rafe Brown
- Johana Goyes
- Nathan Burkett-Cadena

* <u>Collaborators</u>

- Daniel Jiménez-García
- Lindsay Campbell
- Spencer Mattingly

