

Articulating citizen science, semiautomatic identification and free web services for long-term acoustic monitoring: Vigie-Chiro SON Suivi des chauves-souris des orthoptères nocturnes examples from France and UK









Yves Bas, Stuart Newson, Kevin Barré, Jean-François Julien, Didier Bas and Christian Kerbiriou



- <u>Standardized recordings</u> (=repeatable measurement)
 - Same locations
 - Same periods
 - Same detectability
 - Trigger sensitivity
 - Microphone type

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Walk transects



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Walk transects





Car transects

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Walk transects



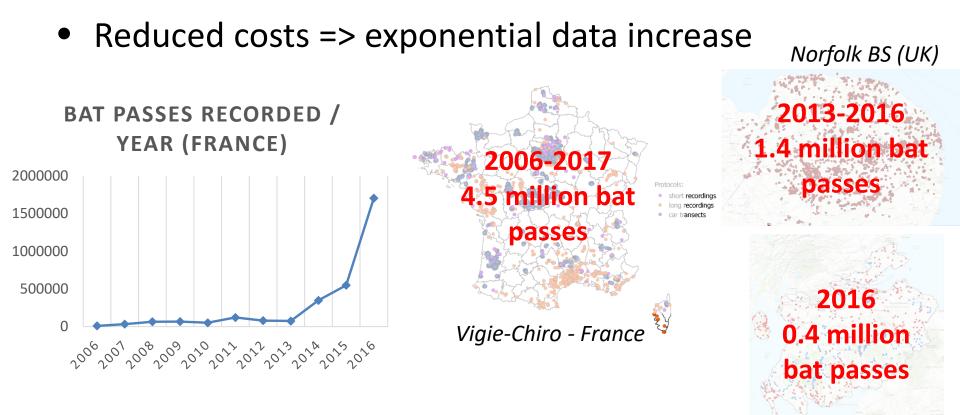


Car transects

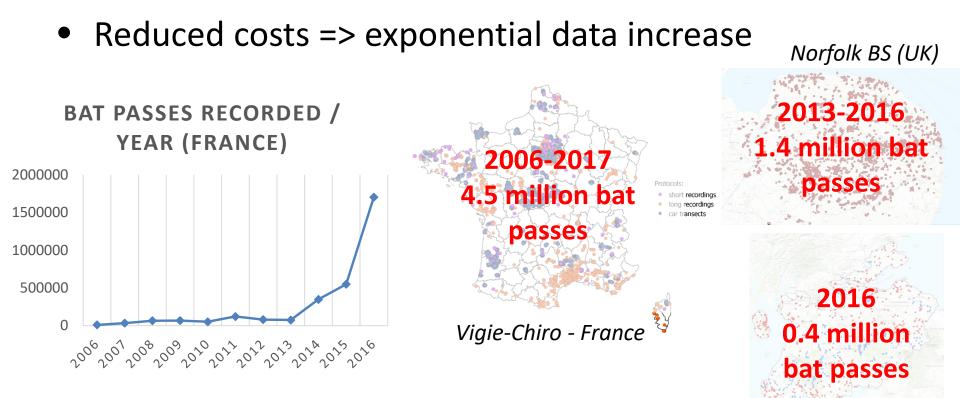
Whole-night recordings



• Reduced costs => exponential data increase



South Scotland BS (UK)



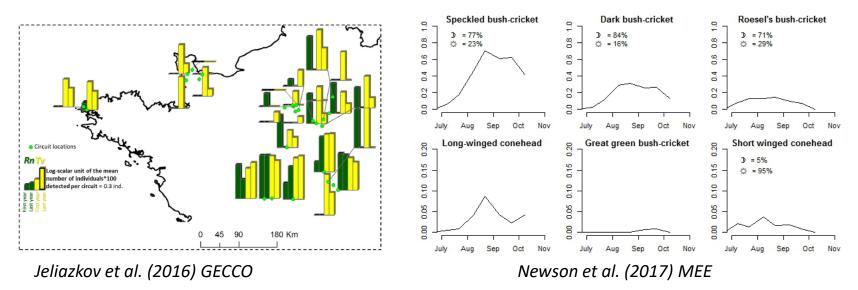
Complete manual checking impossible...
 There is just no other way than auto id!

South Scotland BS (UK)

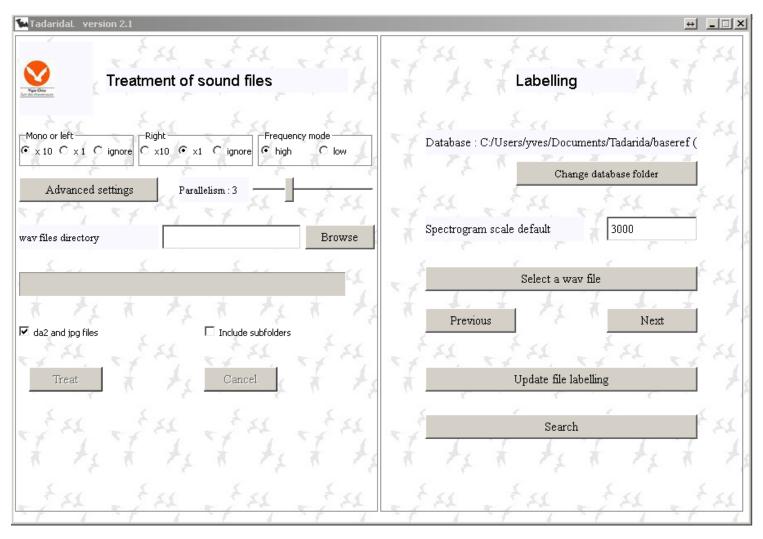
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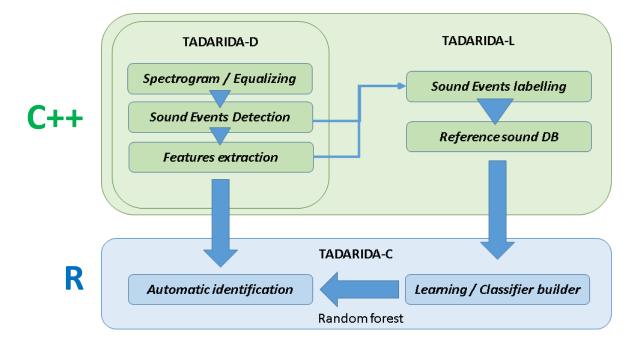
- Other less known good reasons:
 - 1) Manual checking error rate is decreasing over time! but biasing trends estimates... Solution: machines can easily re-analyse historic data and <u>control observer bias</u>
 - 2) You can get very good data on non-targeted taxa such as <u>bush-crickets</u>: spatial and temporal patterns, trends!!



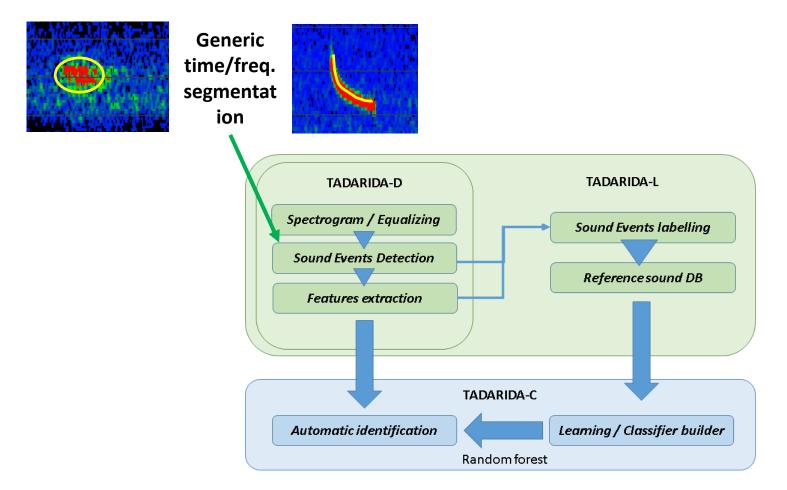
• The example of Tadarida open software



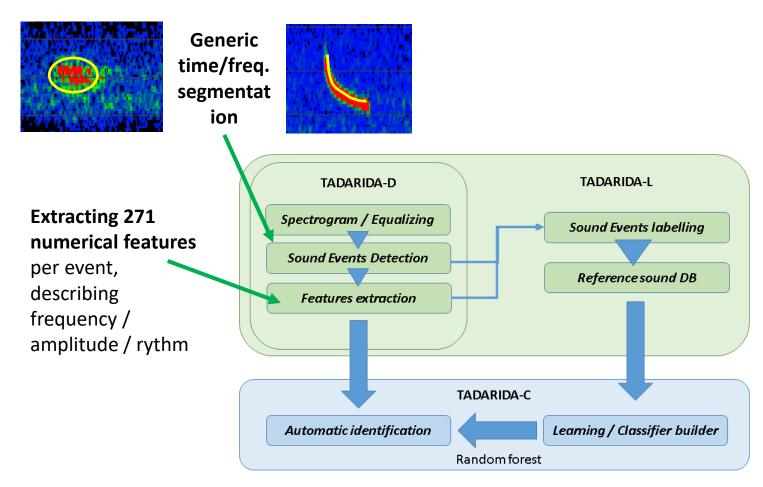
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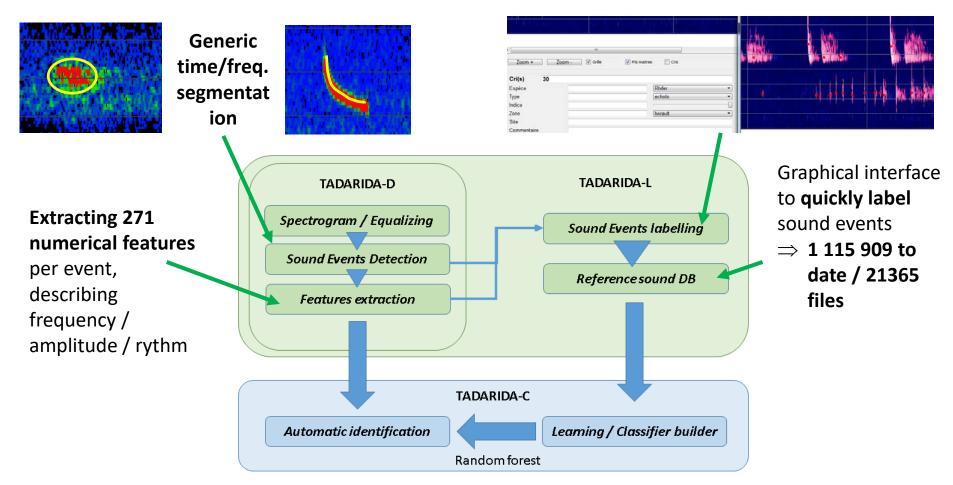
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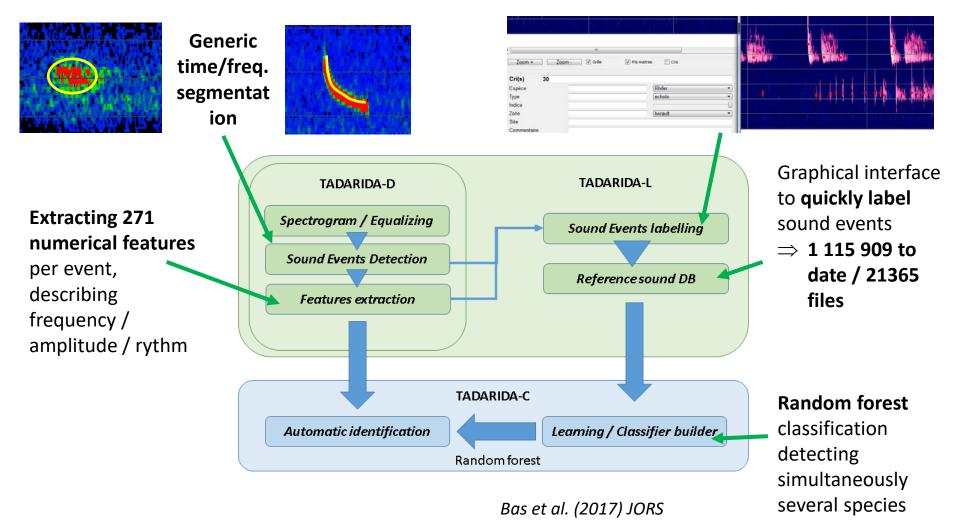
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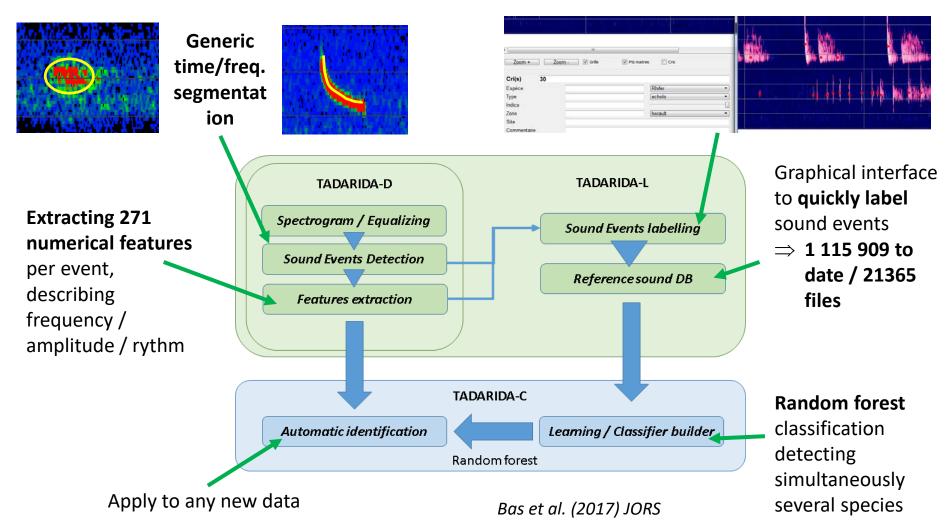
The example of Tadarida open software

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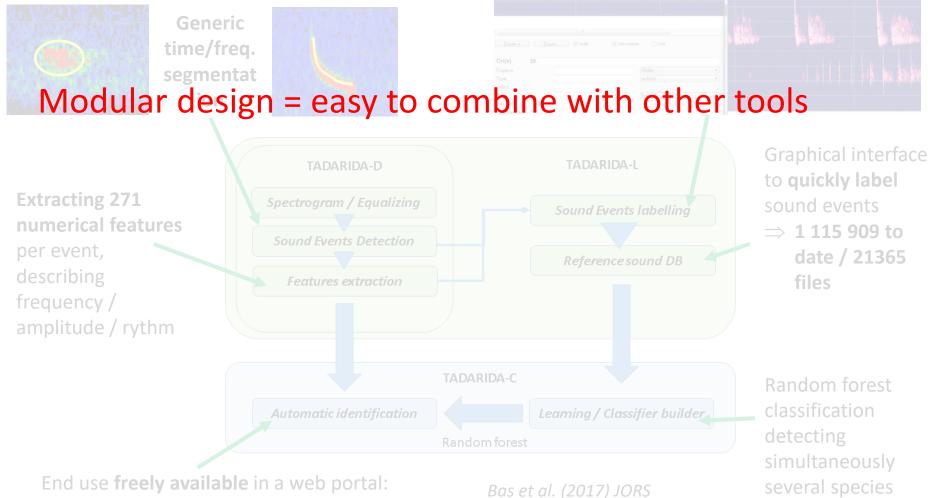
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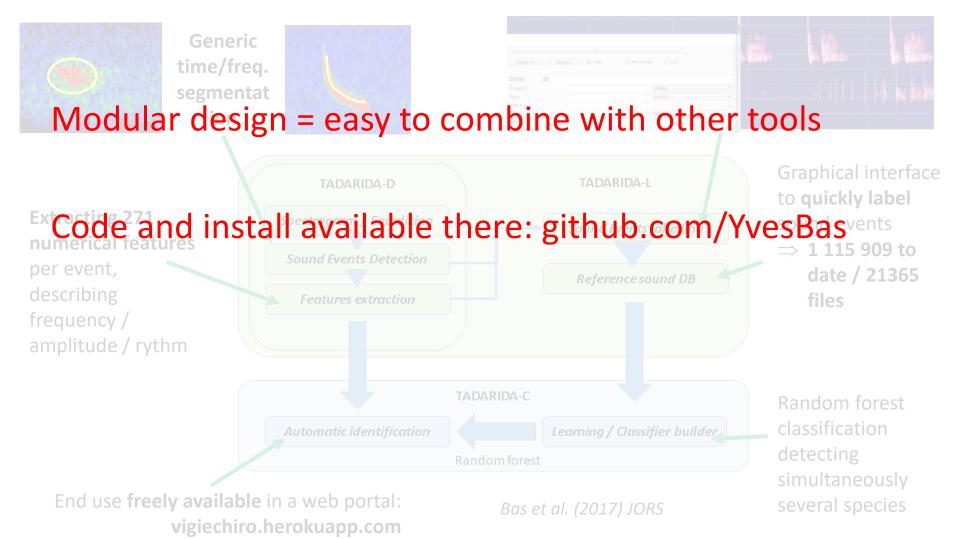


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vigiechiro.herokuapp.com

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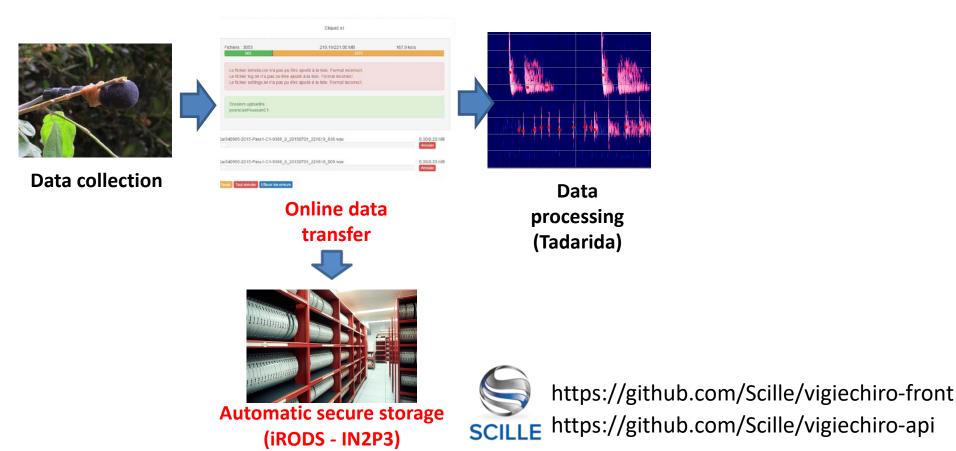


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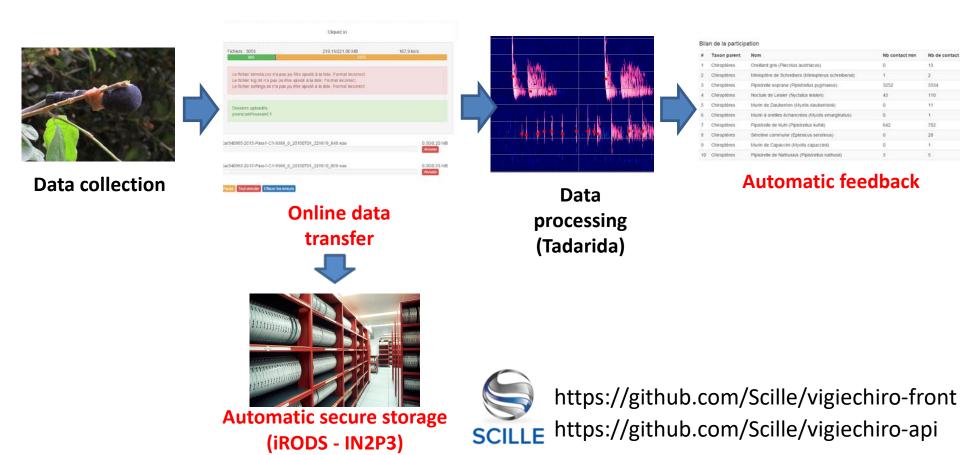




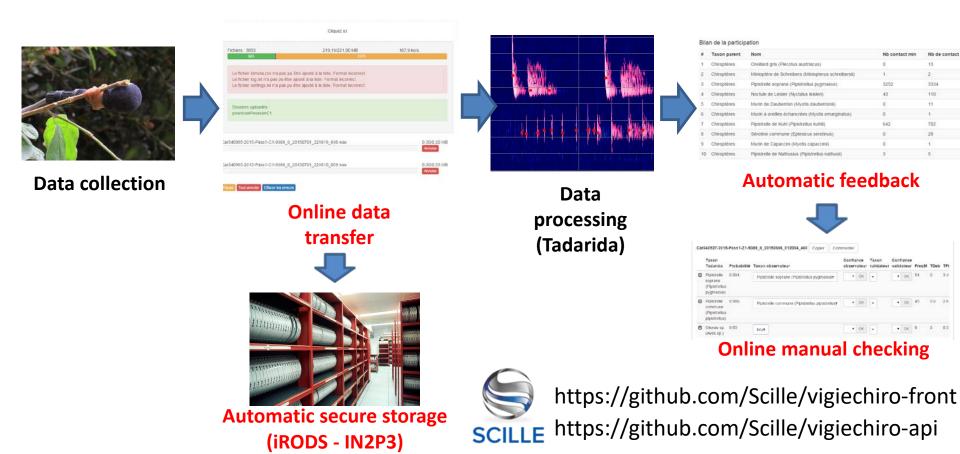
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• Norfolk Bat Survey

Table 2

Results showing the process involved in analysing and validating acoustic bat data collected through this project, and the number of recordings

Identity	Step 1. Initial analysis	ep 1. Initial analysis Step 2. Secondary recoding		Step 3. Manual analysis of recordings: re		
	Initially assigned to species	Recordings removed (confidence index < 3 and/or < 3 calls)	Confidence index at end of Step 2 (median, range)	Recordings manually checked	% unchanged	
Mdau	5403	3635	3 (3-6)	1768	90%	
Mmys/Mbra	3471	1950	3 (3-6)	1521	28%	
Mnat	1793	491	4 (3-10)	1302	85%	
Nnoc	8032	785	8 (3-10)	7247	88%	
Nlei	673	357	5 (3-10)	316	87%	
Eser	4053	1623	4 (3-9)	2430	99%	
Ppip	338,260	8969	10 (3-10)	1000 (sample)	99%	
Ppyg	179,482	6826	10 (3-10)	1000 (sample)	99%	
Pnat	1740	733	5 (3-10)	1007	91%	
Paur	4224	2264	5 (3-10)	1960	99%	
Bbar	2732	744	8 (3-10)	1988	100%	

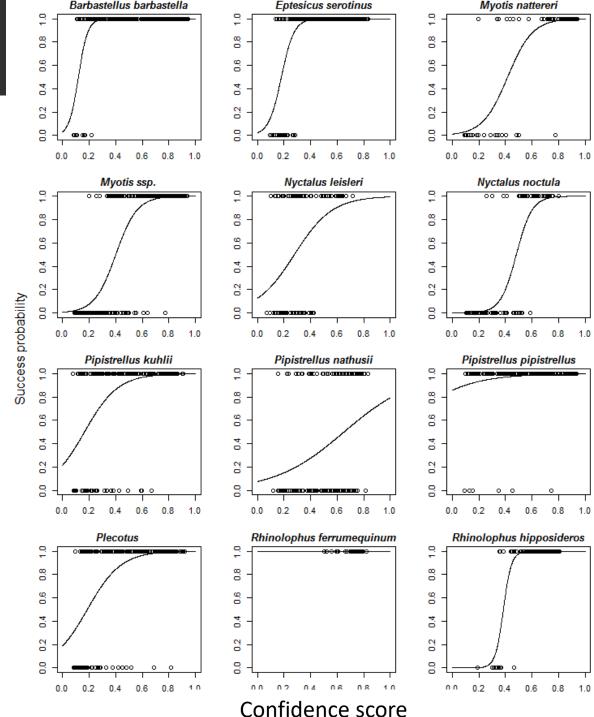
Low error rate for many species

Auto id: Score reliability

- Correlate error risk / confidence score
 - identify selection thresholds

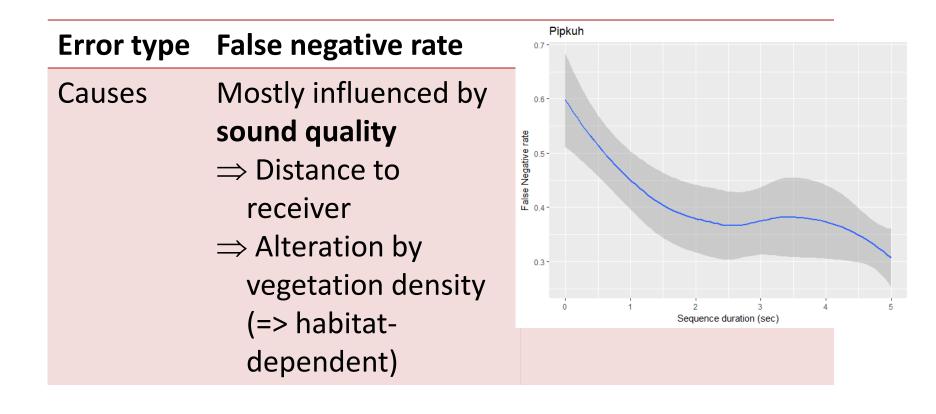
Confirmed id ~ software confidence

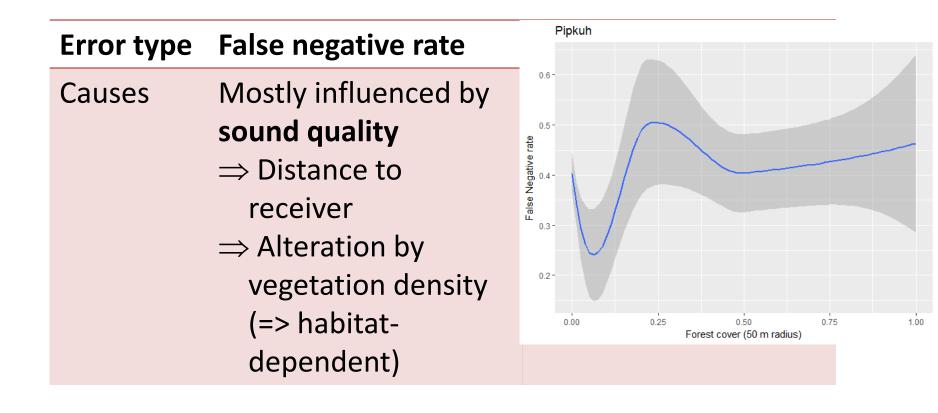
Barré et al. (in prep)



Error type	False negative rate	False positive rate

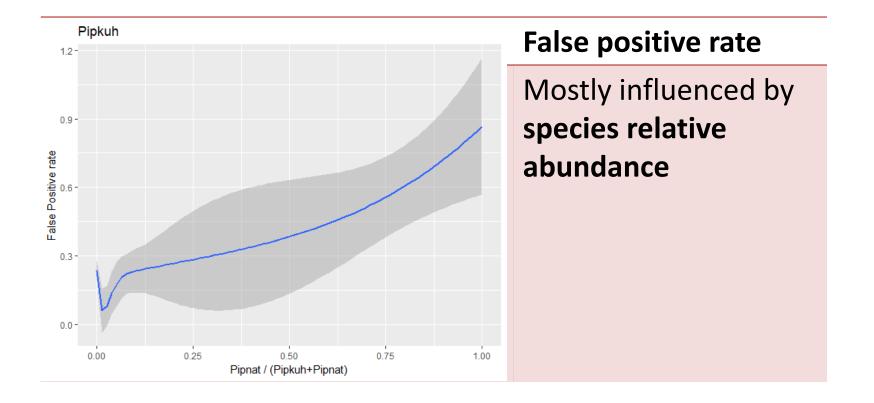
Error type	False negative rate	False positive rate
Causes		

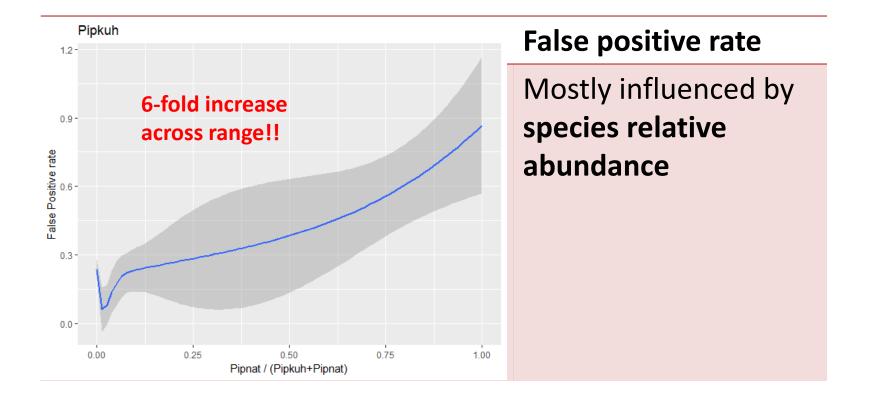


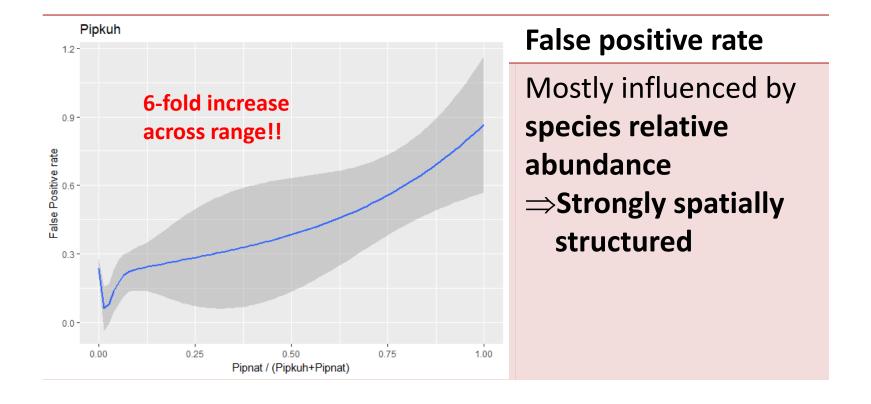


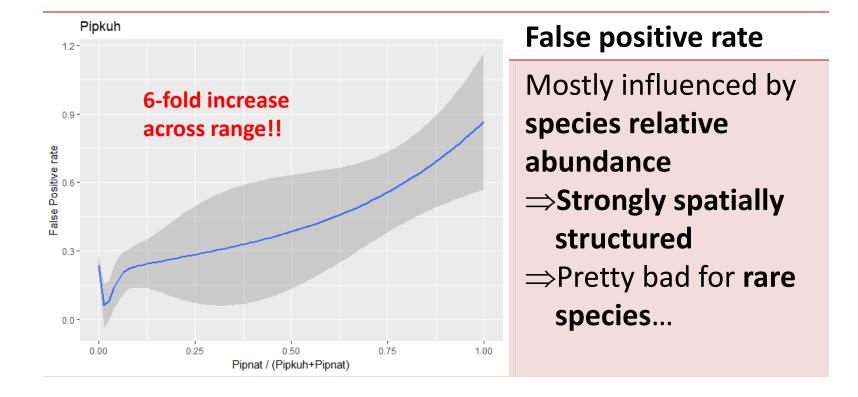
Error type False negative rate		False positive rate	
Causes	Mostly influenced by		
	sound quality		
	\Rightarrow Distance to		
	receiver		
	\Rightarrow Alteration by		
	vegetation density		
	(=> habitat-		
	dependent)		

Error type False negative rate		False positive rate	
Causes	Mostly influenced by sound quality ⇒ Distance to receiver ⇒ Alteration by vegetation density (=> habitat- dependent)	Mostly influenced by species relative abundance	









• Are errors biased / ecological patterns?

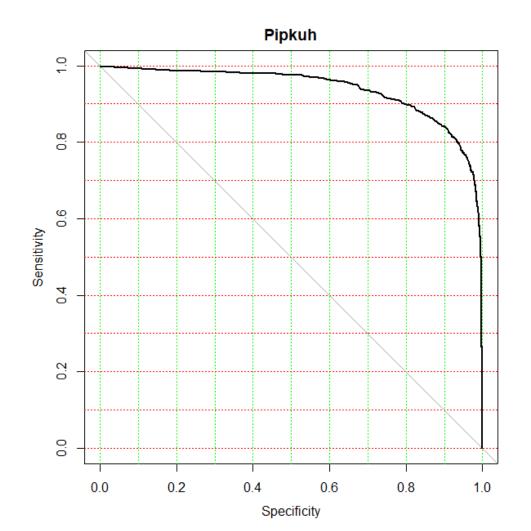
Error type	False negative rate	False positive rate
Causes	Mostly influenced by	Mostly influenced by
	sound quality	species relative
	\Rightarrow Distance to	abundance
	receiver	\Rightarrow Strongly spatially
	\Rightarrow Alteration by	structured
	vegetation density	⇒Pretty bad for rare
	(=> habitat-	species
	dependent)	

Biased?

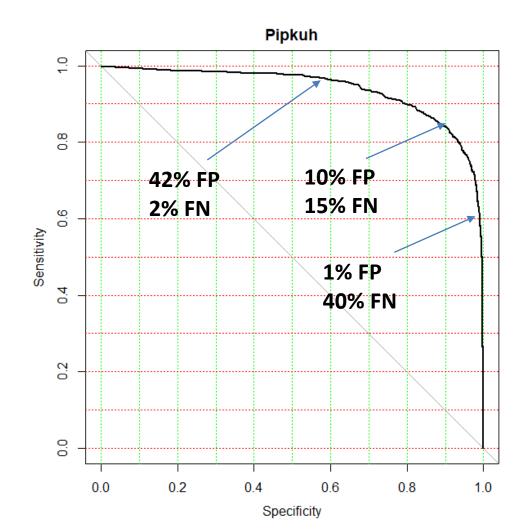
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Biased?	may be a little	Often heavily!

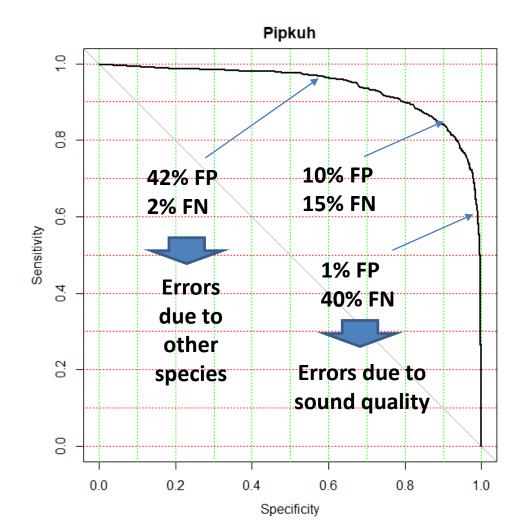
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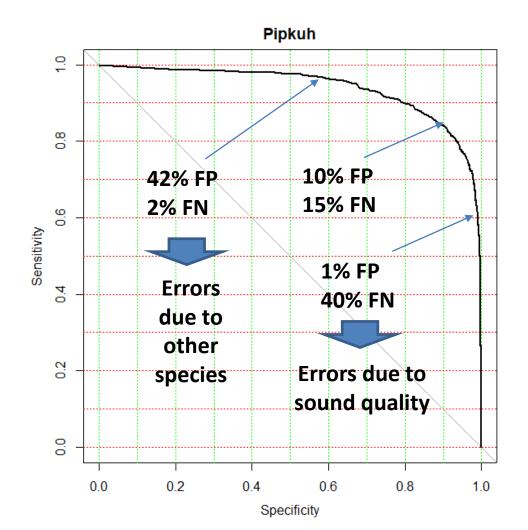


• A threshold to minimise bias?



All thresholds will lead to potentially biased measures but sources of bias differ

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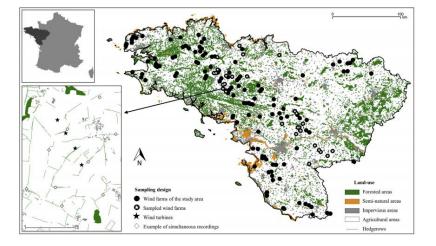


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Solution: checking consistency of ecological inference with varying thresholds (FP/FN rates)

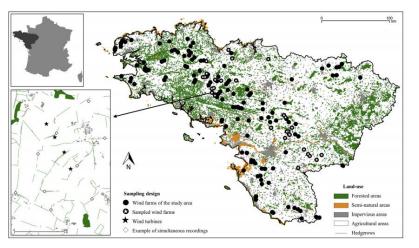
Varying thresholds

• A study of the effect of distance to wind turbine on bats (Barré et al. 2018 Biol Cons)



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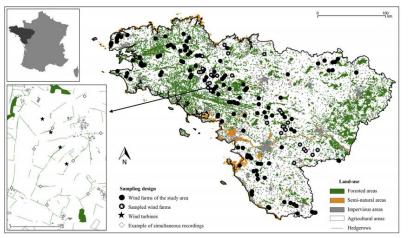


• Estimates vary little!

	Threshold type	
Species	FP = FN	FP << FN
Barbastella barbastellus	0.237 ± 0.107	0.237 ± 0.107
Eptesicus serotinus	0.132 ± 0.169	0.141 ± 0.179
Myotis nattereri	0.132 ± 0.106	0.038 ± 0.044
Myotis spp.	0.260 ± 0.091	0.245 ± 0.096
Pipistrellus kuhlii	-0.004 ± 0.100	-0.005 ± 0.103
Pipistrellus pipistrellus	0.413 ± 0.100	0.413 ± 0.100
Plecotus spp.	0.309 ± 0.096	0.233 ± 0.102

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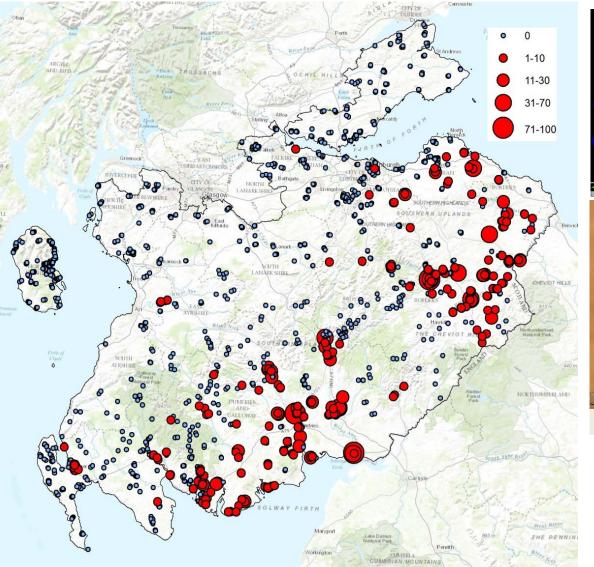


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 ⇒ Inferences are robust against id errors!

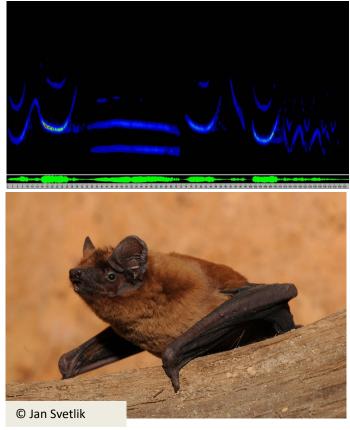
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Method replicated for artifical light (Pauwels et al. in review), motorways (Claireau et al. in review), etc

Accurate data: spatial

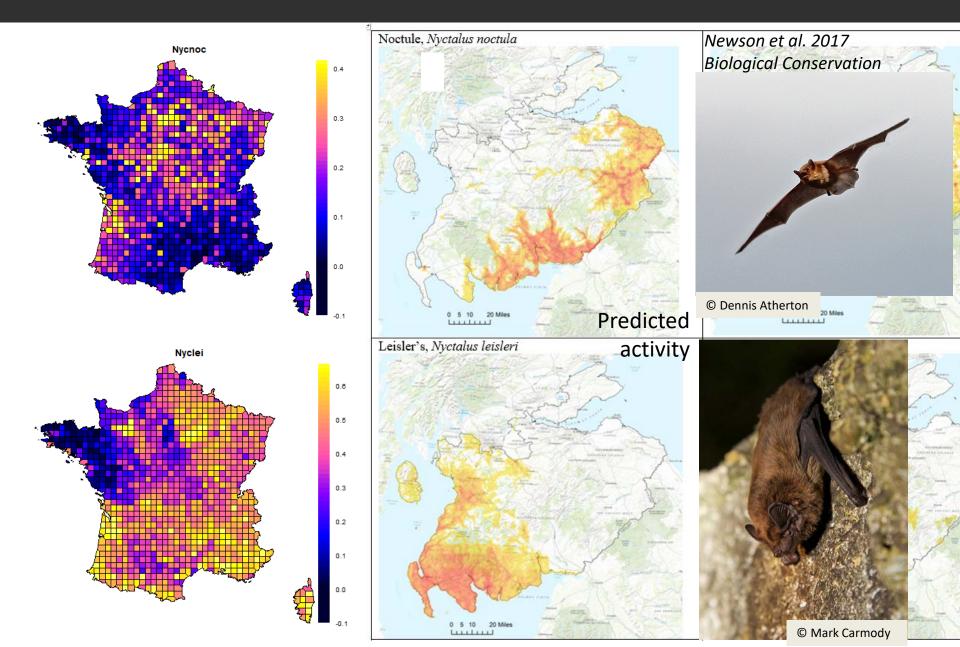


Southern Scotland Bat Survey



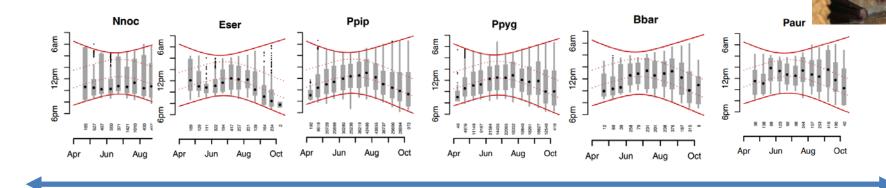
Raw data Nyctalus noctula

Accurate data: spatial

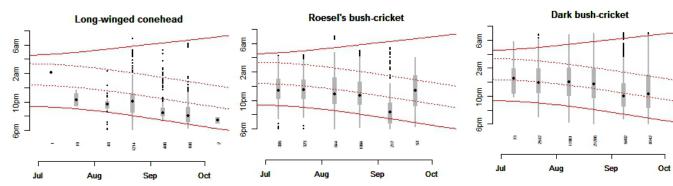


Accurate data: phenology

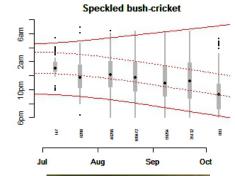
Newson et al. (2015) Biological Conservation



Crepuscular activity



Whole-night activity





Newson et al. (2017) Methods in Ecology and Evolution

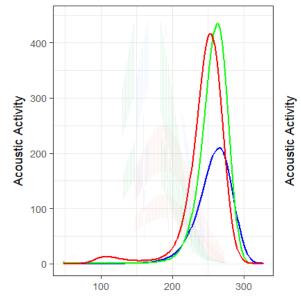
Accurate data: phenology

Bas et al. (in prep)

Detecting seasonal phenological shifts

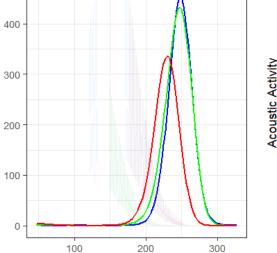


./VigieChiro/GLMs/GLMnonselect



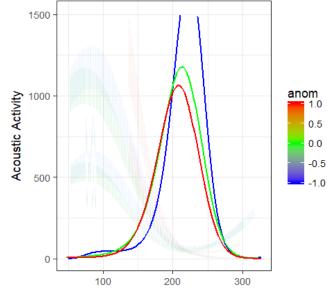


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./VigieChiro/GLMs/GLMnonselect_interAT



Date

And already some species trends

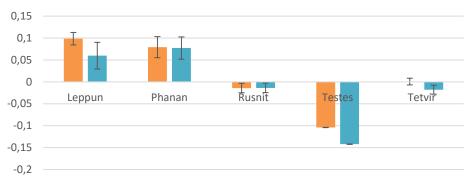
Strongly declining in France



...declines not previously suspected...

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Estimated trends (2006-2016)



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Thank you for your attention! And many thanks to participants of Vigie-Chiro, Norfolk Bat Survey and South Scotland Bat Survey!!



Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

The use of automated identification of bat echolocation calls in acoustic monitoring: A cautionary note for a sound analysis

Danilo Russo^{a,b,*}, Christian C. Voigt^{c,d}

^a Wildlife Research Unit, Laboratorio di Ecologia Applicata, Sezione di Biologia e Protezione dei Sistem Università degli Studi di Napoli Federico II, Via Università 100, 1-80055 Portici, Napoli, Italy ^b School of Biological Sciences, Life Sciences Building, University of Bristol, 24 Tyndall Avenue, Bristol I ^c Department of Evolutionary Ecology, Leibniz Institute for Zoo and Wildlife Research, Alfred-Kowalke ^d Department of Animal Behaviour, Institute of Zoology, Freie Universitat Berlin, Takustr. 6, 14195 Bet



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Testing the performances of automated identification of bat echolocation calls: A request for prudence



Jens Rydell^{a,*}, Stefan Nyman^b, Johan Eklöf^c, Gareth Jones^d, Danilo Russo^{d,e}

^a Biology Department, Lund University, SE-223 62 Lund, Sweden

^b Skarpskyttevägen 30D, SE-226 42 Lund, Sweden ^c Krokdalsvägen 88, SE-51734 Bollebygd, Sweden

⁴ School of Biological Sciences, Life Sciences Building, University of Bristol, 24 Tyndall Avenue, Bristol BS8 1TQ, UK

* Wildlife Research Unit, Laboratorio di Ecologia Applicata, Sezione di Biologia e Protezione dei Sistemi Agrari e Forestali, Dipartimento di Agraria, Università degli Studi di Napoli Federico II, Via Università 100, Portici (Napoli), Italy



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Testing the performances of automated identification of bat echolocation calls: A request for prudence



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 Well, it's obviously not perfect, so you cannot neglect error rates!



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- Well, it's obviously not perfect, so you cannot neglect error rates! You still NEED to:
 - 1) Estimate error rates
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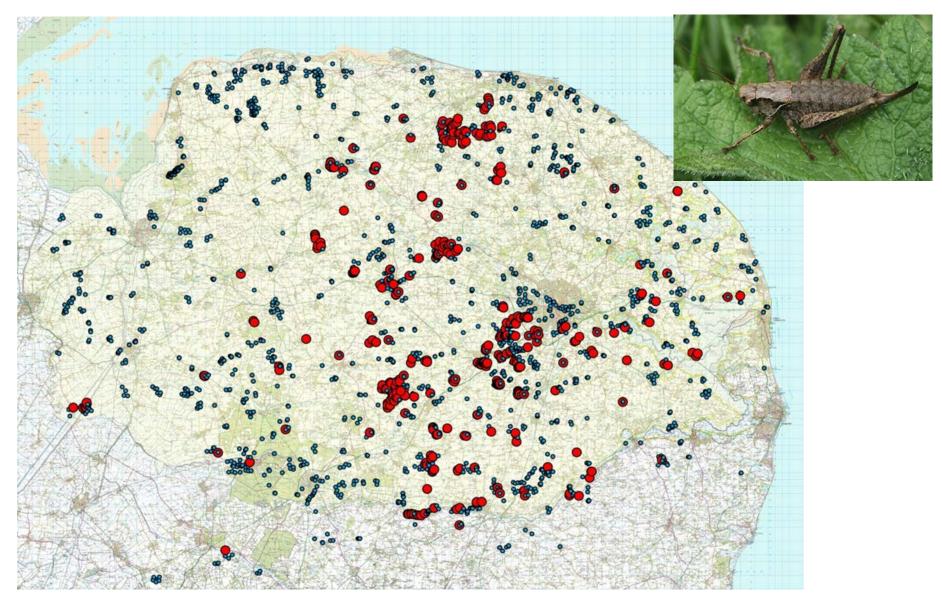
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 ^b Skarpskyttevidgen 300, SE-226 42 Lund, Sweden
 ^c KrokalasVigen 88, SE-5173 Bollebygd, Sweden
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- Well, it's obviously not perfect, so you cannot neglect error rates! You still NEED to:
 - 1) Estimate error rates
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=> That's what we call « semi-automatic id »

 Correlate error risk / confidence score

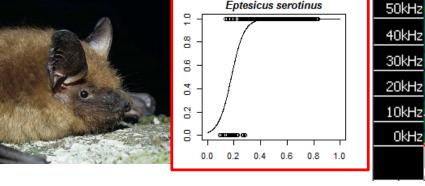
Also works for bush-crickets: Dark Bush-cricket (42,132 recordings)



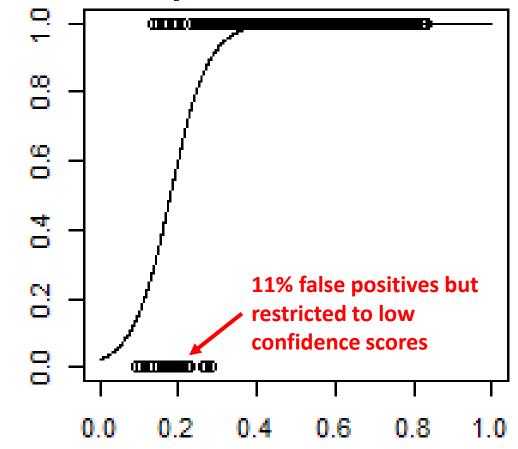
Norfolk Bat Survey

- Correlate error risk / confidence score
 - identify
 selection
 thresholds

Confirmed id ~ software confidence Success probability



Eptesicus serotinus

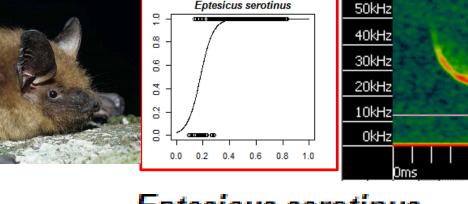


Confidence score

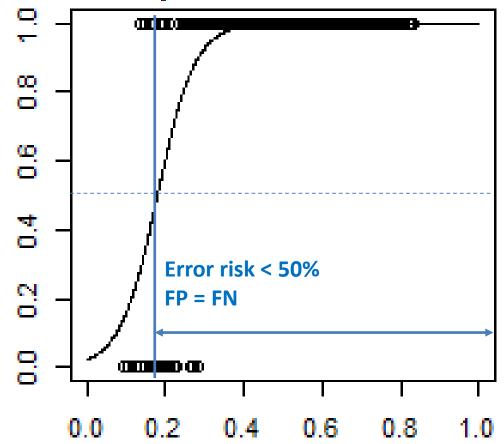
Barré et al. (in prep)

- Correlate error risk / confidence score
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Eptesicus serotinus

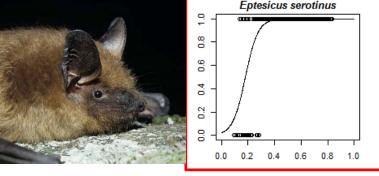


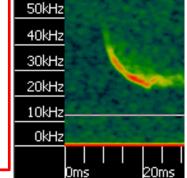
Barré et al. (in prep)

Confidence score

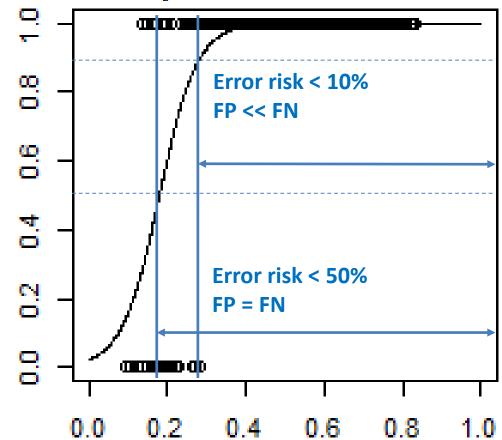
- Correlate error risk / confidence score
 - identify
 selection
 thresholds

Confirmed id ~ software confidence Success probability





Eptesicus serotinus



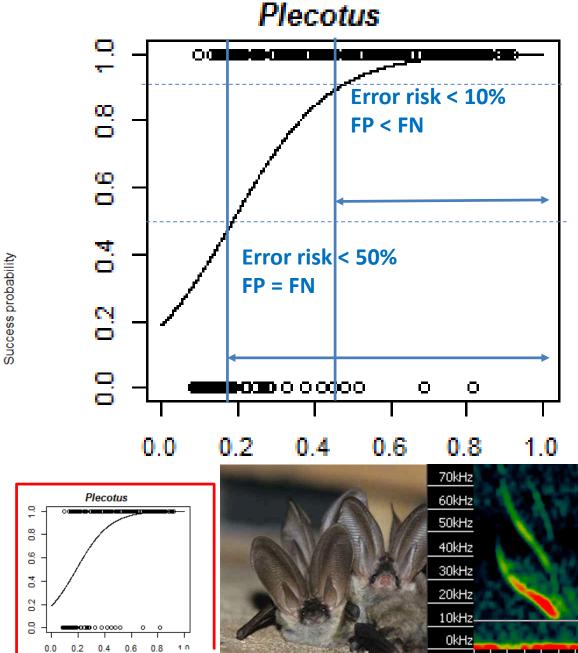
Barré et al. (in prep)

Confidence score

- Correlate error risk / confidence score
 - identify
 selection
 thresholds

Confirmed id ~ software confidence

Barré et al. (in prep)



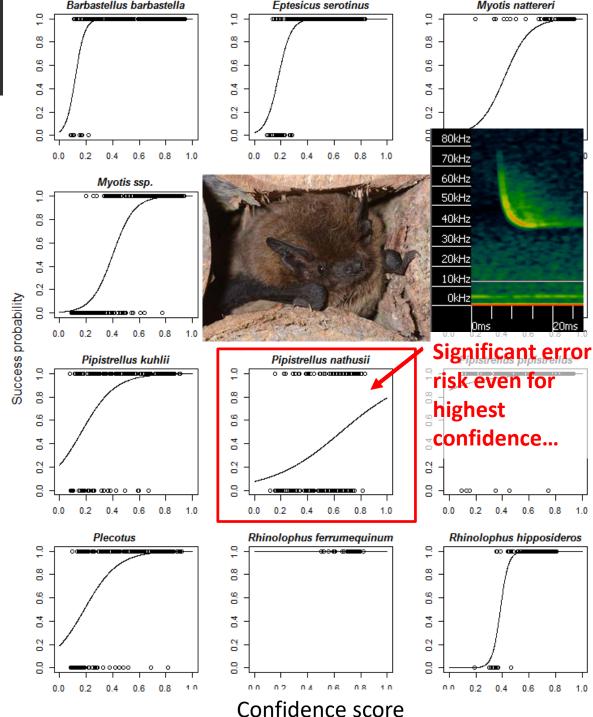
Oms

10ms

- Correlate error risk / confidence score
 - identify selection thresholds

Confirmed id ~ software confidence

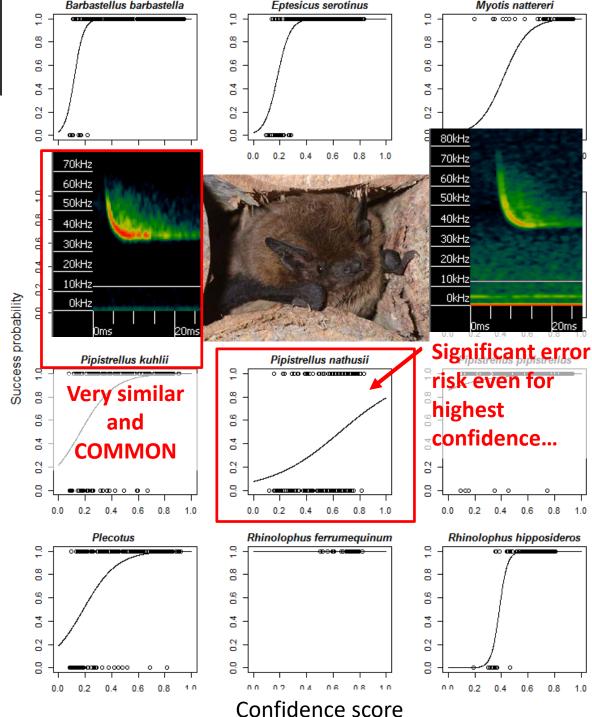
Barré et al. (in prep)



- Correlate error risk / confidence score
 - identify selection thresholds

Confirmed id ~ software confidence

Barré et al. (in prep)

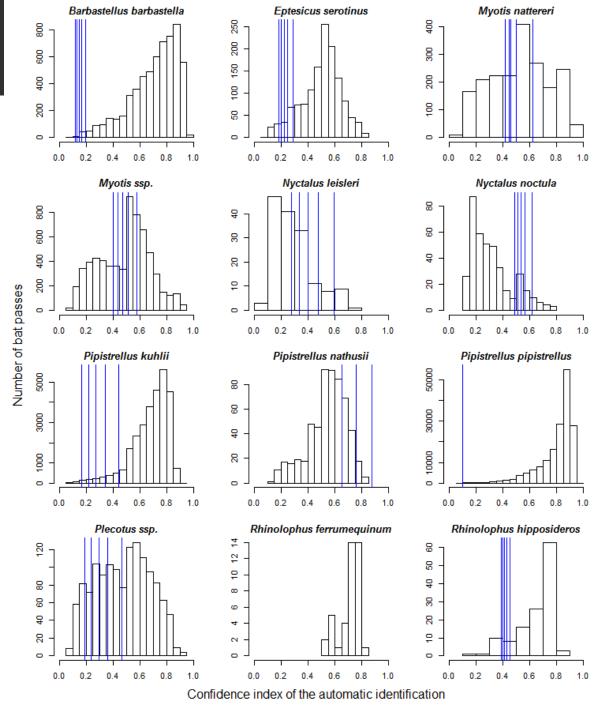


- Correlate error risk / confidence score
 - identify
 selection
 thresholds

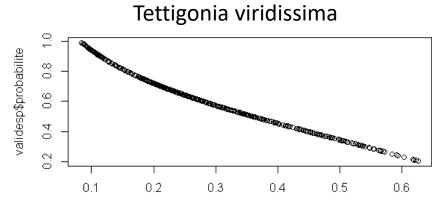
Confirmed id ~ software confidence



Barré et al. (in prep)

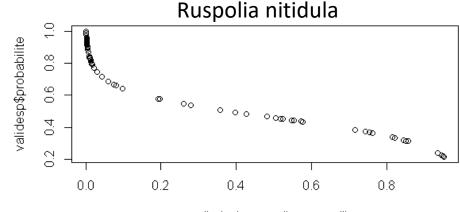


- Correlate error risk / confidence score
 - identify
 selection
 thresholds



predict(m1, type = "response")

Confirmed id ~ software confidence



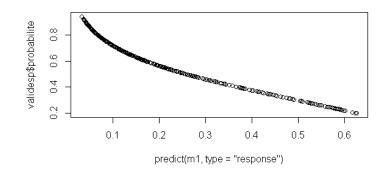
predict(m1, type = "response")



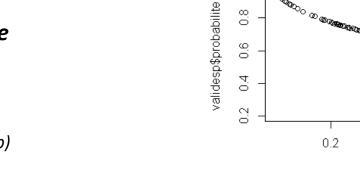
Barré et al. (in prep)

- Correlate error risk / confidence score
 - identify selection thresholds

Leptophyes punctatissima



Confirmed id ~ software confidence



0.0

Pholidoptera griseoaptera CONTRACTOR OF THE CONTRACTOR OF CONTRACTOR OF THE CONTRACTOR OF TH AND COLORIDAN COLORIDA



Barré et al. (in prep)

predict(m1, type = "response")

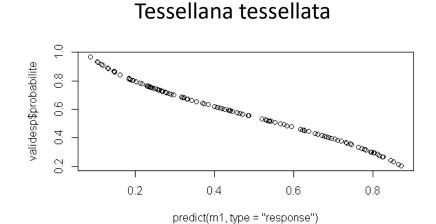
0.6

0.8

1.0

0.4

- Correlate error risk / confidence score
 - identify
 selection
 thresholds

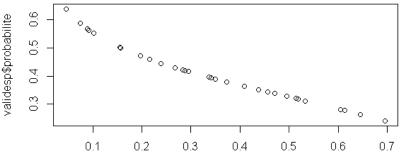


Confirmed id ~ software confidence



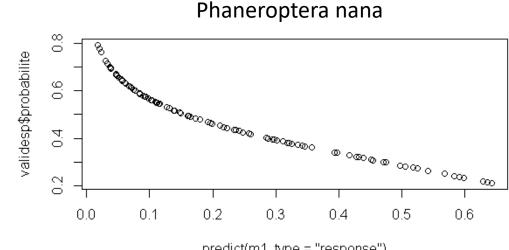
Barré et al. (in prep)

Platycleis albopunctata



predict(m1, type = "response")

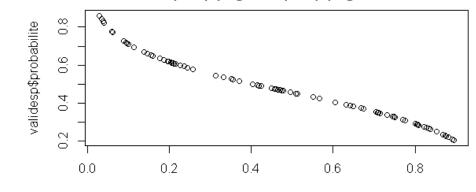
- Correlate error risk / confidence score
 - identify
 selection
 thresholds



predict(m1, type = "response")

Ephippiger ephippiger

Confirmed id ~ software confidence





Barré et al. (in prep)

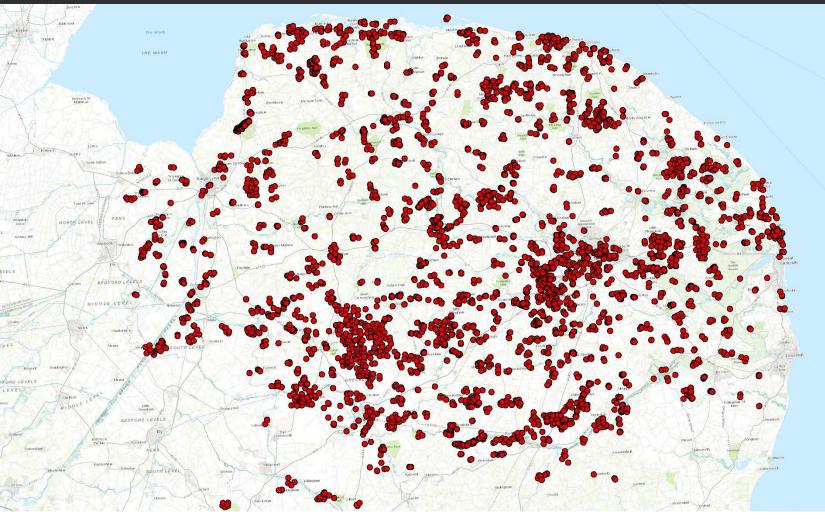
predict(m1, type = "response")

Varying thresholds^s

- Hedgerow effect (Barré et al. In prep)
- \Rightarrow Estimates vary little!
- ⇒ Inferences are robust against id errors!

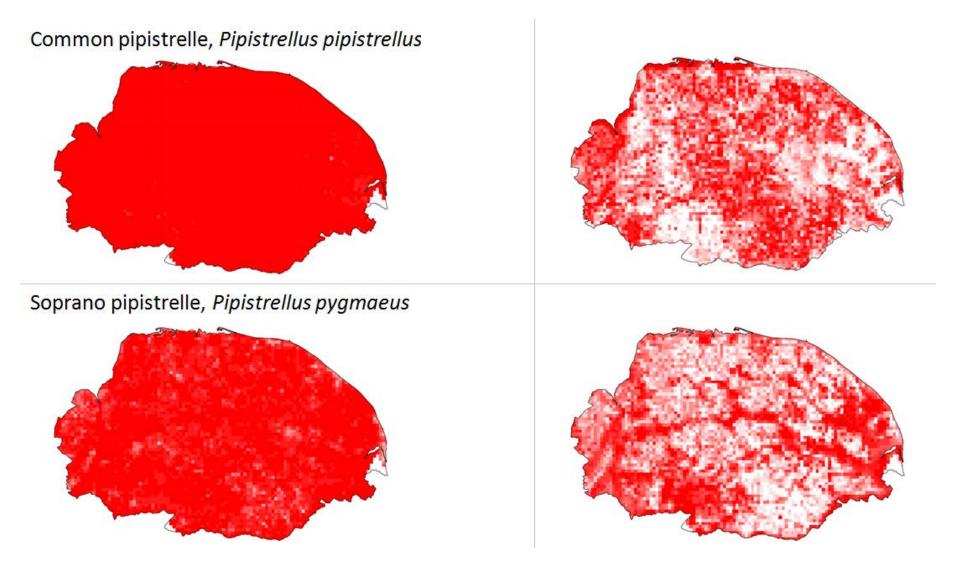
s	Species	Environmental variables	Error risk tolerance		
			0.5	0.1	
	Barbastellus barbastella	Open vs. edge habitat	-2.91±0.23 ***	-2.94±0.24 ***	
	Eptesicus serotinus	Open vs. edge habitat	-0.60±0.40	-0.52±0.42	
	Myotis nattereri	Open vs. edge habitat	-1.20±0.25 ***	-1.08±0.33 ***	
	Myotis ssp.	Open vs. edge habitat	-1.64±0.20 ***	-1.87±0.27 ***	
	Nyctalus leislerii	Open vs. edge habitat	-0.41±0.29	0.92±0.66	
	Nyctalus noctula	Open vs. edge habitat	1.27±0.28 ***	1.27±0.50 *	
	Pipistrellus kuhlii	Open vs. edge habitat	-2.08±0.26 ***	-2.17±0.27 ***	
	Pipistrellus nathusii	Open vs. edge habitat	0.68±0.32 *	/	
	Pipistrellus pipistrellus	Open vs. edge habitat	-2.93±0.19 ***	-2.93±0.19 ***	
	Plecotus ssp.	Open vs. edge habitat	-0.89±0.19 ***	-0.81±0.20 ***	
	Rhinolophus ferrumequinum	Open vs. edge habitat	0.23±0.99	0.23±0.99	
	Rhinolophus hipposideros	Open vs. edge habitat	-3.01±0.72 ***	-2.98±0.73 ***	

Survey coverage



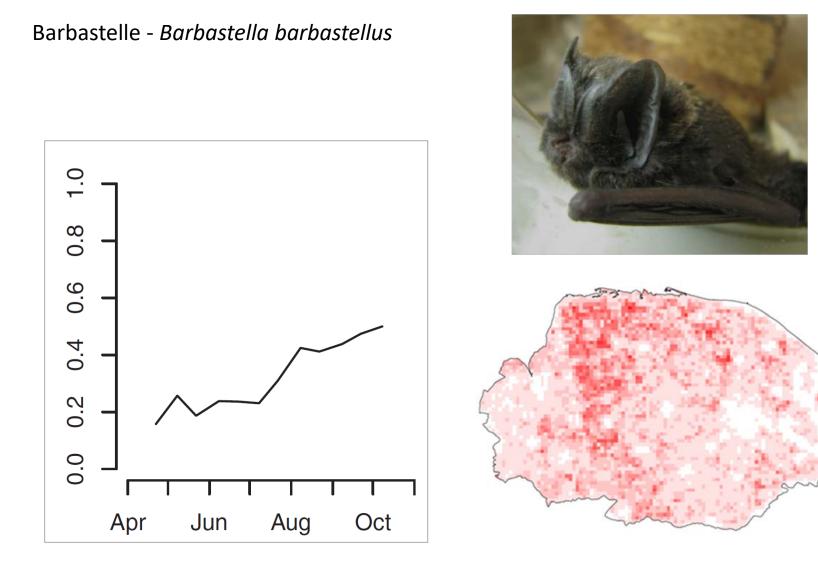
- 1,445 1-km squares surveyed (27% of Norfolk) 2013-2016
- 6,246 complete nights of recording
- > 1.4 million bat recordings

Predicted occurrence (left) and activity (right)



Newson, Evans & Gillings. Biological Conservation (2015)

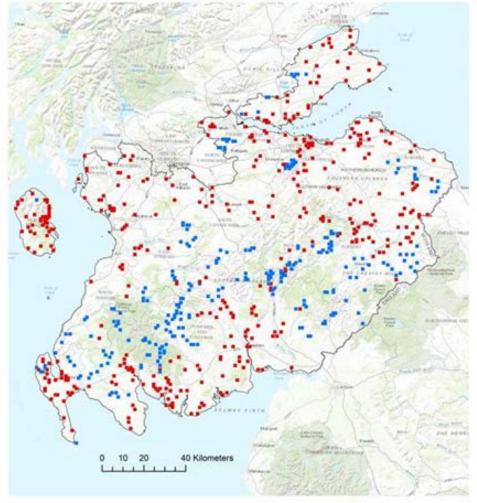
Insight into seasonal movements



Newson, Evans & Gillings. Biological Conservation (2015)

Survey coverage

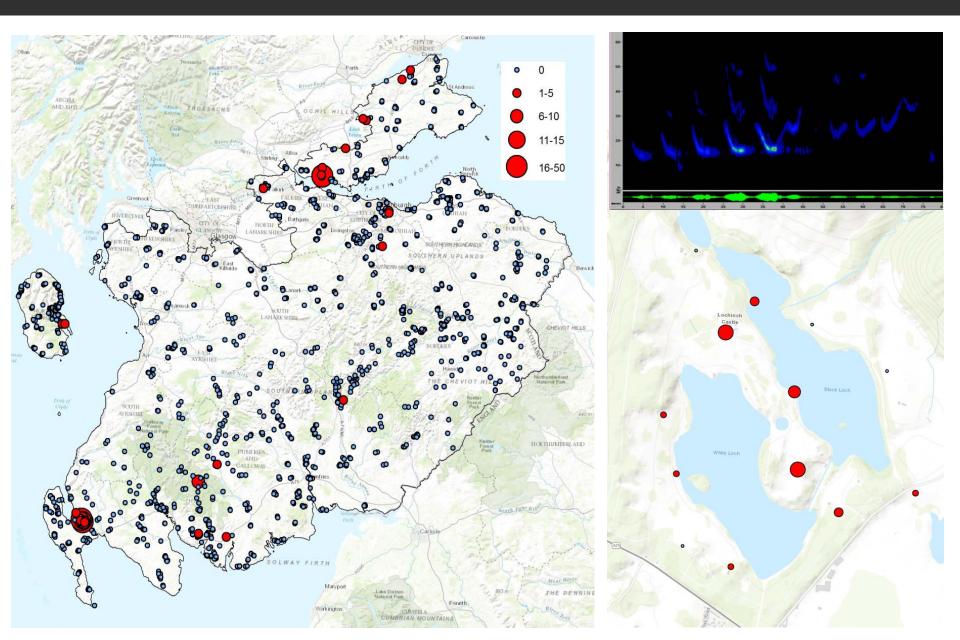
Red = Volunteers Blue = BTO fieldworkers



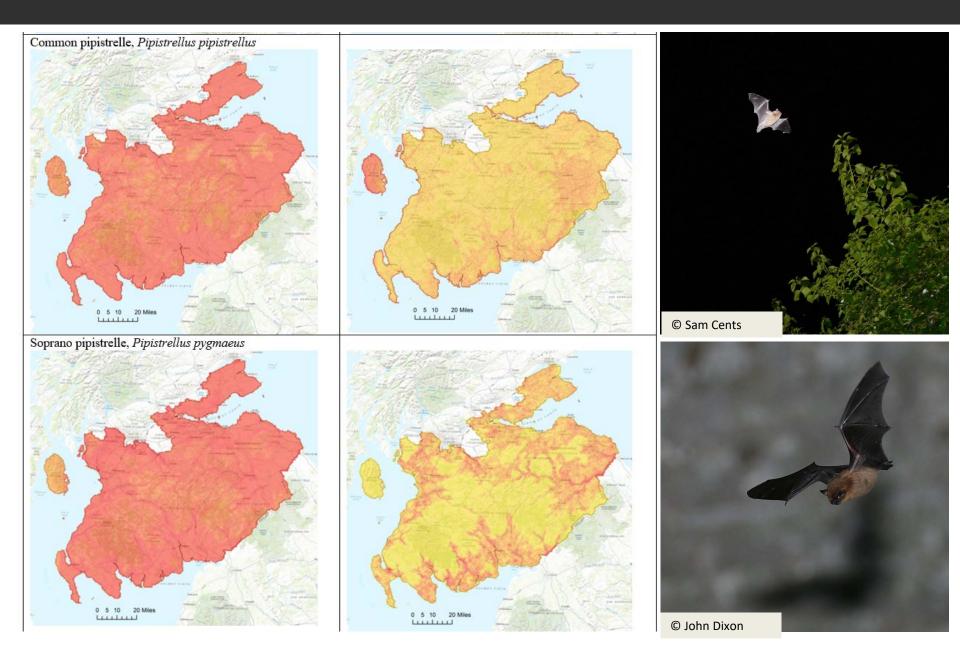


- 715 1-km's
- 1,537 nights of recording
- 399,242 bat recordings
- 275 volunteers 375 squares
- Two BTO fieldworkers -339 squares

Nathusius' pipistrelle (0.05% of recordings)



Predicted occurrence (left) and activity (right)



Detectors recording over the day and night

Dark bush-cricket

58

Sep 01

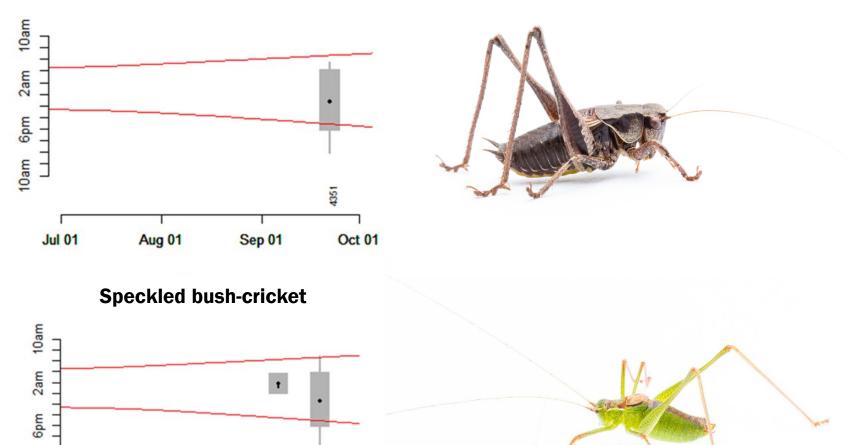
3251

Oct 01

10am

Jul 01

Aug 01



Newson et al. (2017). Methods in Ecology & Evolution

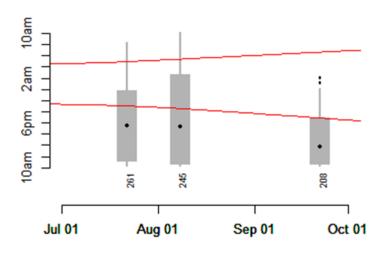
Detectors recording over the day and night

Jul 01 Aug 01 Sep 01 Oct 01

Short-winged Conehead



Roesel's bush-cricket

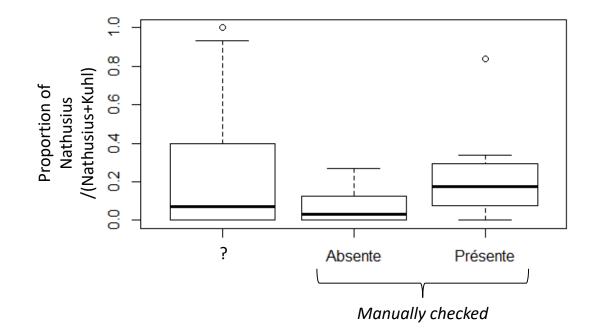




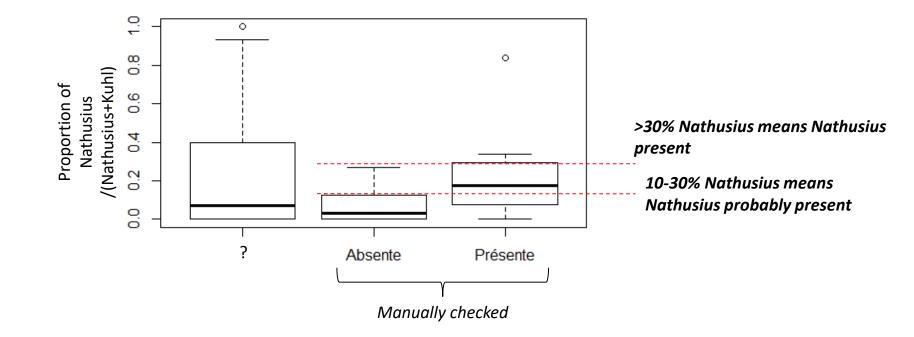
Newson et al. (2017). Methods in Ecology & Evolution

• Solution: looking at other « auto id » results on the same location

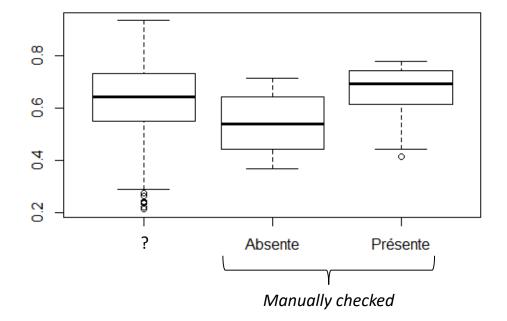
Solution: looking at other « auto id » results on the same location
 1) Rate of Nathusius' positive id among « Kuhl's + Nathusius' »



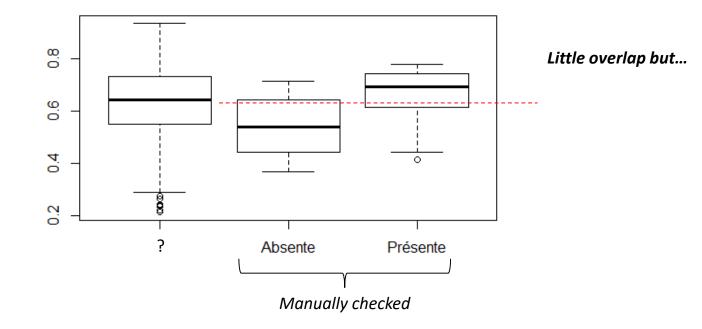
Solution: looking at other « auto id » results on the same location
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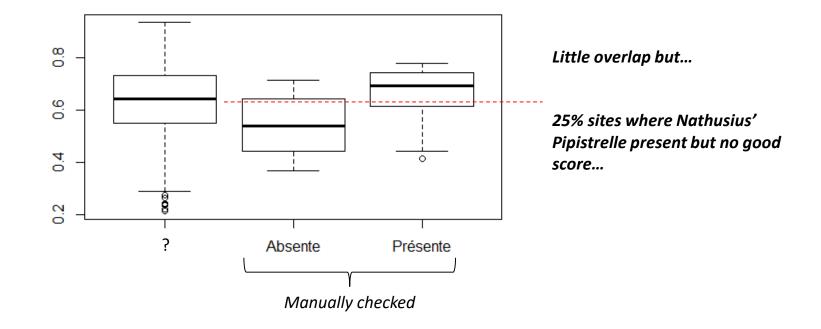
Solution: looking at other « auto id » results on the same location
 2) Maximum random forest score among Nathusius' positive id



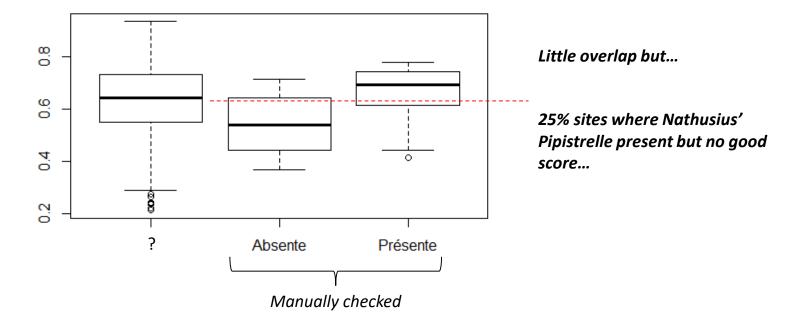
Solution: looking at other « auto id » results on the same location
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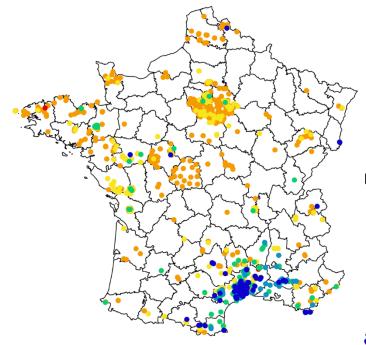


Solution: looking at other « auto id » results on the same location
2) Maximum random forest score among Nathusius' positive id



More complex modelling in progress: integrating features measured at several temporal scale (call sequence, minute, hour, night, etc) = **2**nd **layer of classification**

Pipistrelle soprane : présence-absence



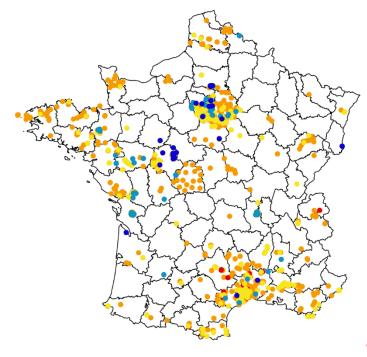
Nombreux faux positifs dans le Nord, mais la plupart peuvent être discriminés par un score faible

Légende

- Présence vérifiée manuellement
- Présence très probable (p>0.97)
- Présence probable (p>0.9)
- Présence à vérifier (0.55<p<0.8)
- Absence probable (non détectée ou p<0.55)
- Absence vérifiée manuellement



Noctule commune : présence-absence



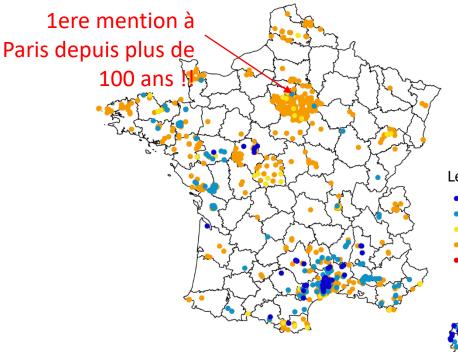
La plupart des faux positifs peuvent être discriminés par un score faible

Légende

- Présence vérifiée manuellement
- Présence très probable (p>0.75)
- Présence à vérifier (0.4<p<0.75)
- Absence probable (non détectée ou p<0.4)
- Absence vérifiée manuellement



Petit Rhinolophe : présence-absence

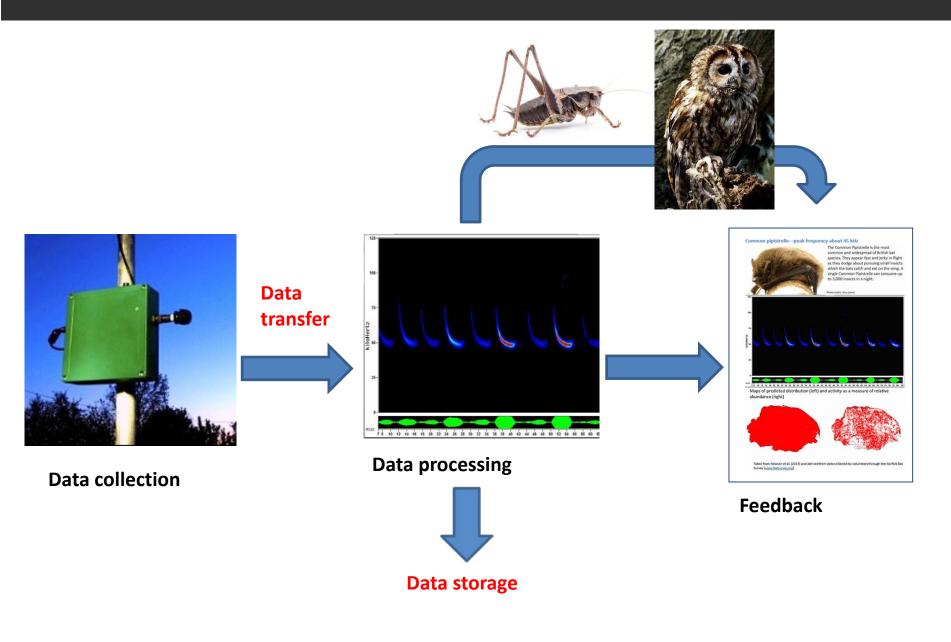


La plupart des faux positifs peuvent être discriminés par un score faible

Légende

- Présence vérifiée manuellement
- Présence très probable (p>0.5)
- Présence à vérifier (p<0.5)
- Absence probable (non détectée)
- Absence vérifiée manuellement

Data collection, analysis, feedback pipeline



Auto Id: for what purpose?

Main acoustically active groups (long range)

