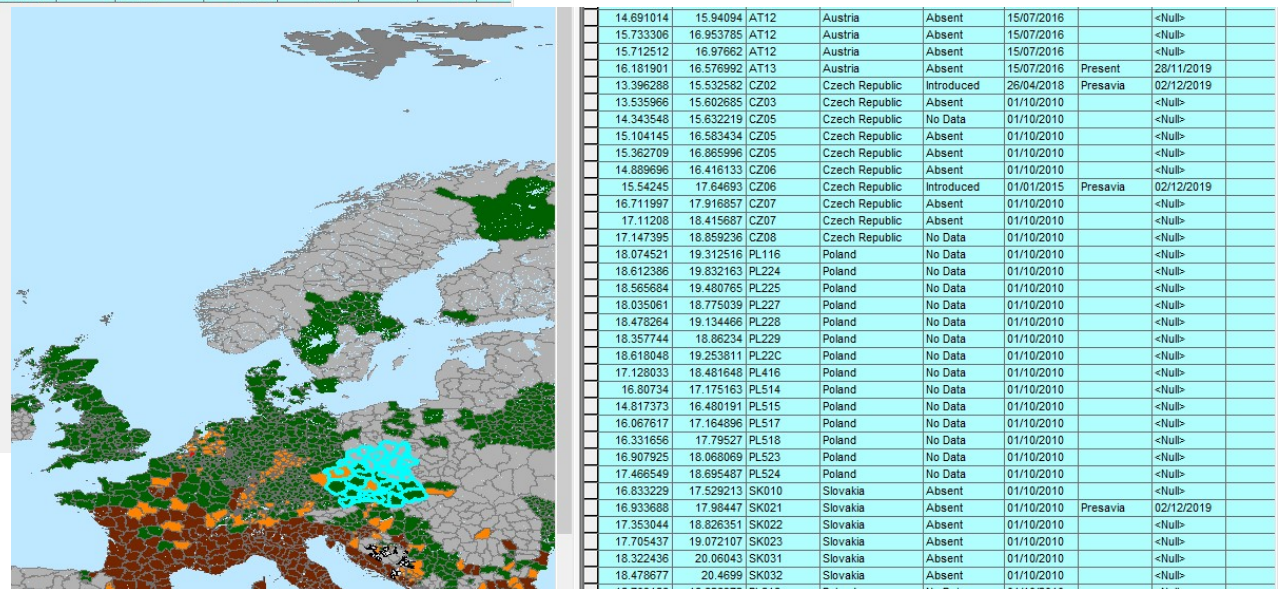
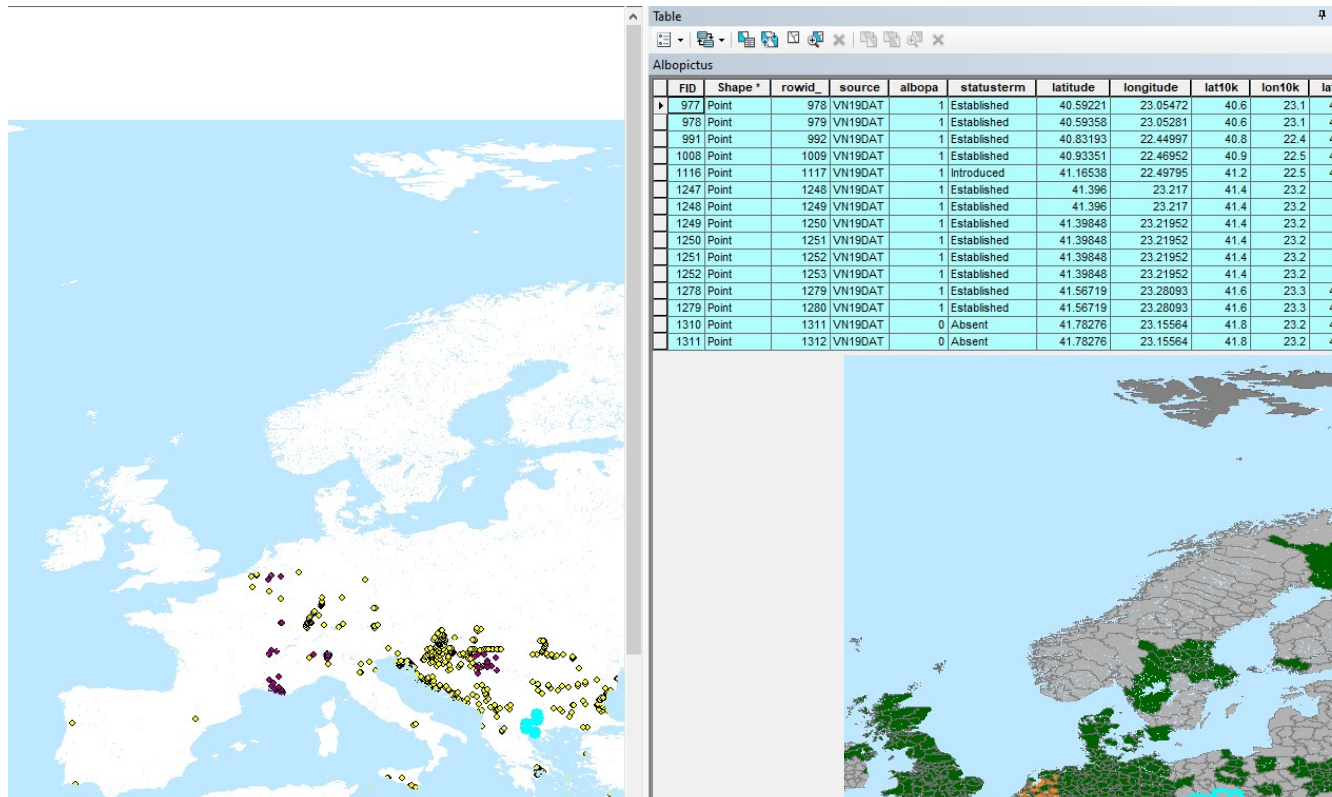


(WHAT) DATA FOR MAPS

BASICS OF TURNING DATA INTO MAPS

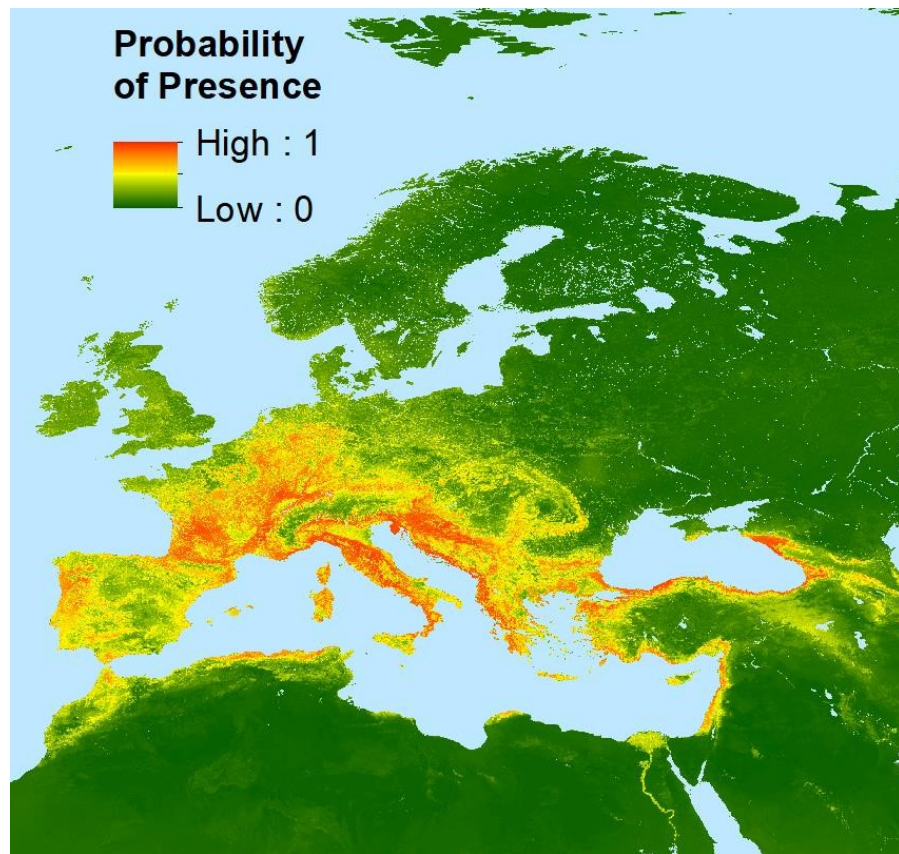
Simple maps are just spreadsheets with pictures attached to each row:

Points and countries



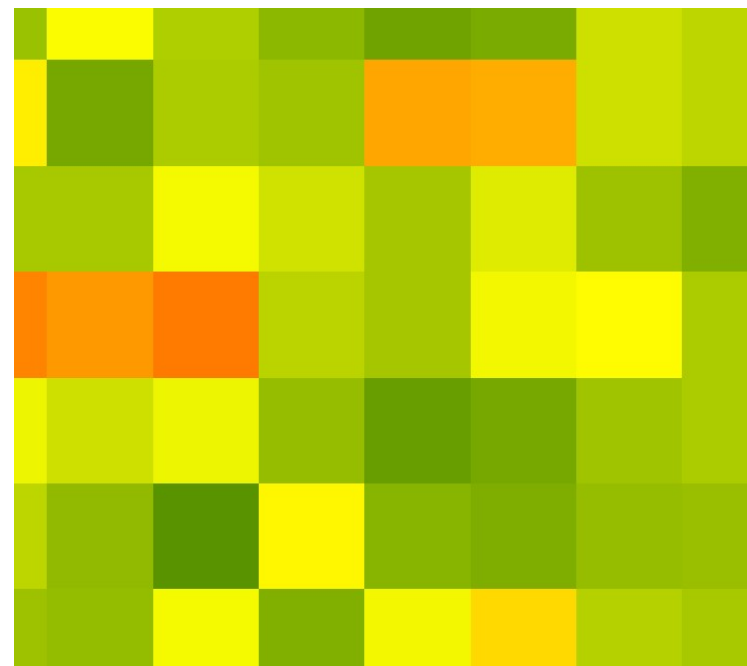
So vector data needs to be well structured to be mappable

BASICS OF TURNING DATA INTO MAPS



Particular colour assigned to particular values

‘Raster’ maps are in principal similar except a single value per pixel. And no readily accessible table



BASICS OF TURNING DATA INTO MAPS

Geo referencing is a requirement

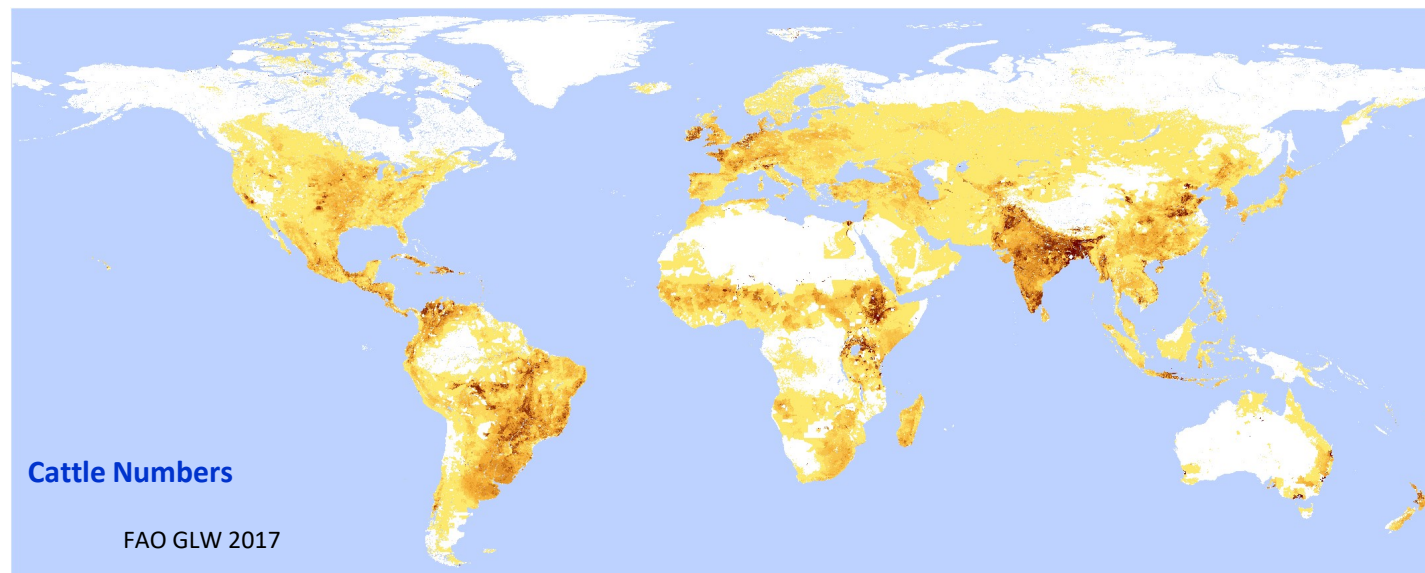
Maps need 'standard' data from everywhere because they are effectively comparing values for different places

Standardised sample number

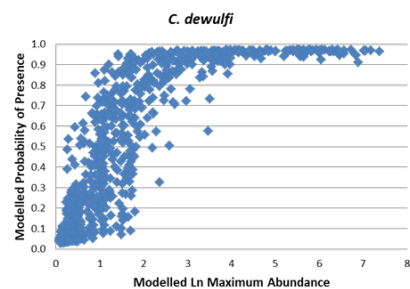
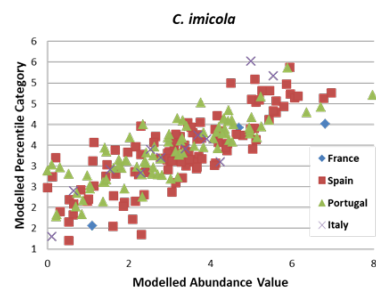
Zero is a (necessary) value

WHAT VECTOR MEASURES ARE NEEDED

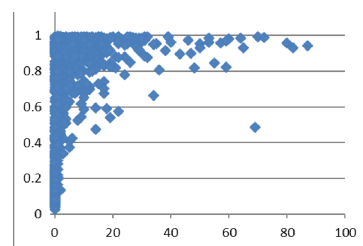
Presence absence or abundance?



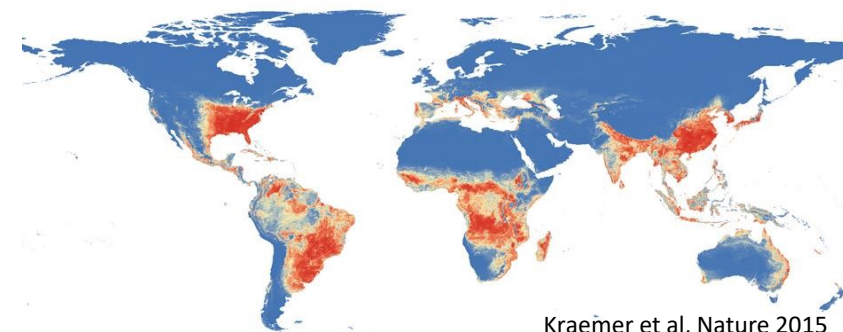
European Midges



Tick



Tiger Mosquito probability



Wint et al, ECDC Technical Opinion, Dec 2018

Aedes Invasive Mosquitoes

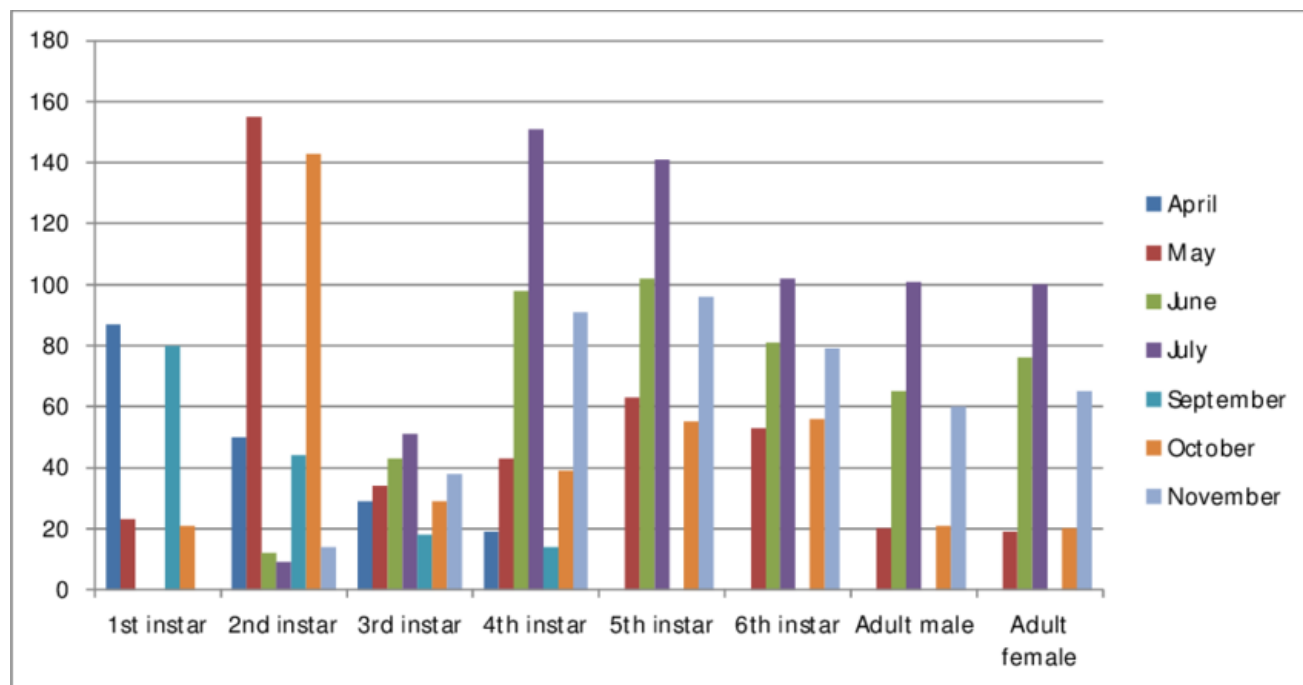
EUROPEAN COOPERATION
IN SCIENCE & TECHNOLOGY

WHAT VECTOR DATA ARE NEEDED

What targets: eggs, larvae, adults,

What traps used - what is sample unit?

When should the samples be taken?



WHAT VECTOR DATA ARE NEEDED ABUNDANCE

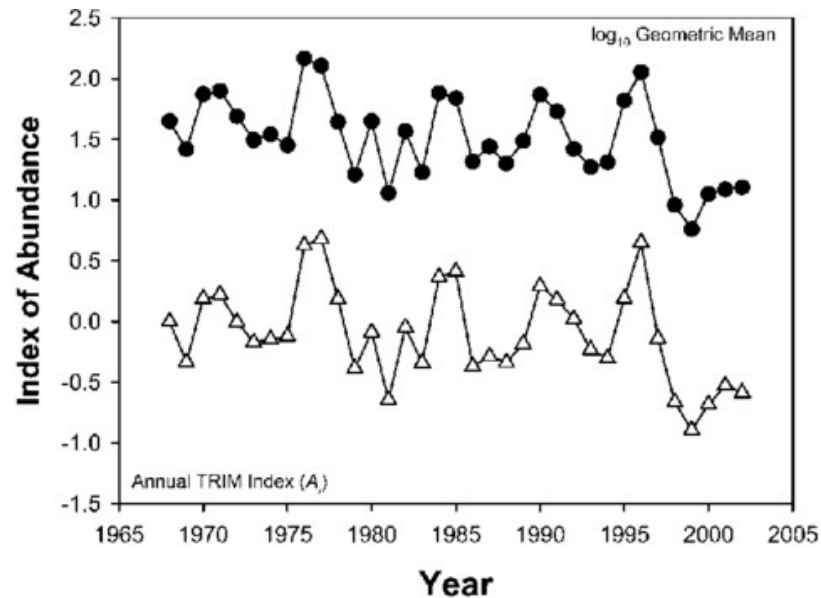
when: annual, monthly, weekly, once

Once – Presence, early warning,
not absence

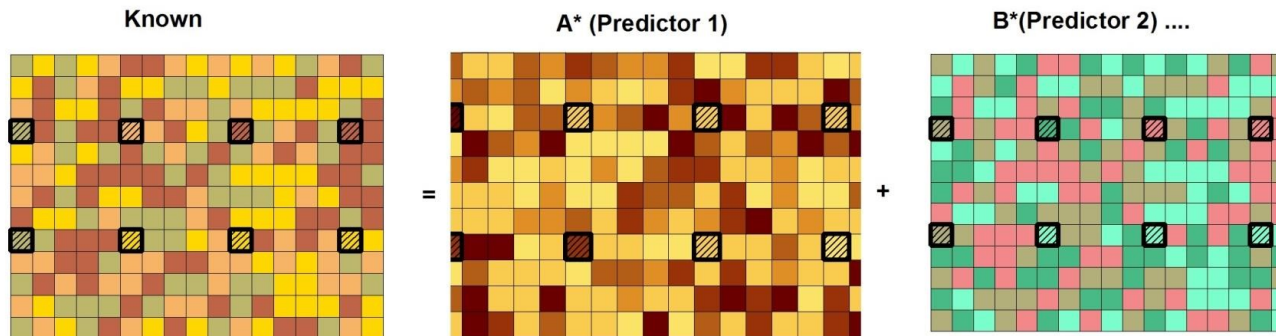
Weekly or monthly seasonal activity
annual comparisons

Maximum value or dates starts and end

Smoothed a second possibility



WHERE IS DATA NEEDED FROM



1) Convert all data maps to images with same pixel size (resolution). Then extract values for each data type at fixed sample points (hatched squares). NB one of these must be the 'known' values.

3) Providing the equation is statistically significant (i.e. reliable), apply the right hand side of the equation to all the pixels in the images, not just the ones sampled.

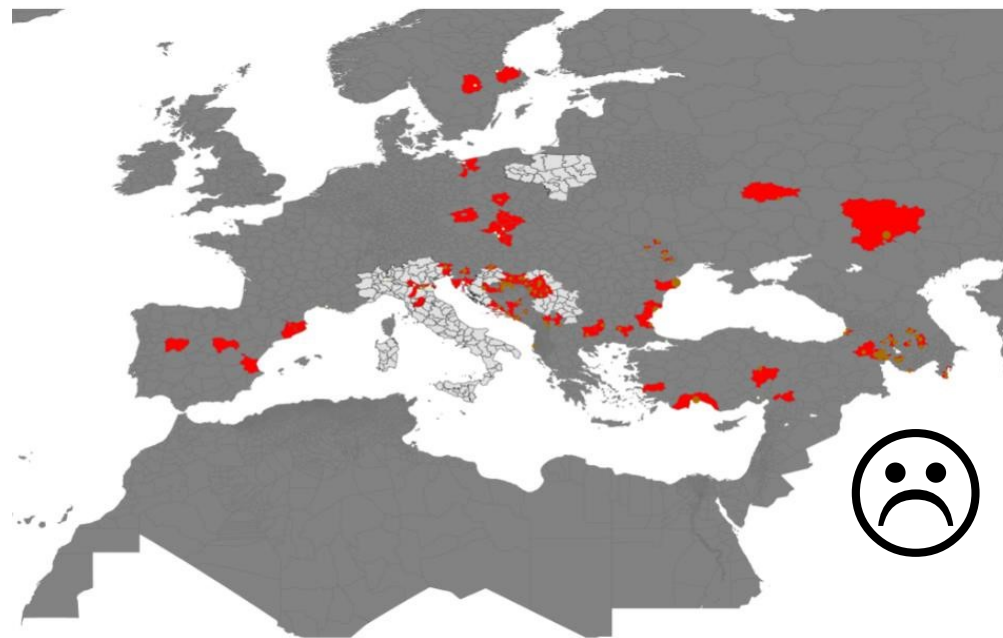
2) Calculate a 'regression equation' of the form:
 $\text{Known} = \text{Constant} + A^*(\text{Predictor1}) + B^*(\text{Predictor2}) \dots$
 NB There can be several predictor variables in the equations.

4) Repeat the process for each of a series of analysis zones (e.g. ecozones)

**Most models rely on some sort of extrapolation:
 This means that its important to decide not only what data but which
 locations are sampled**

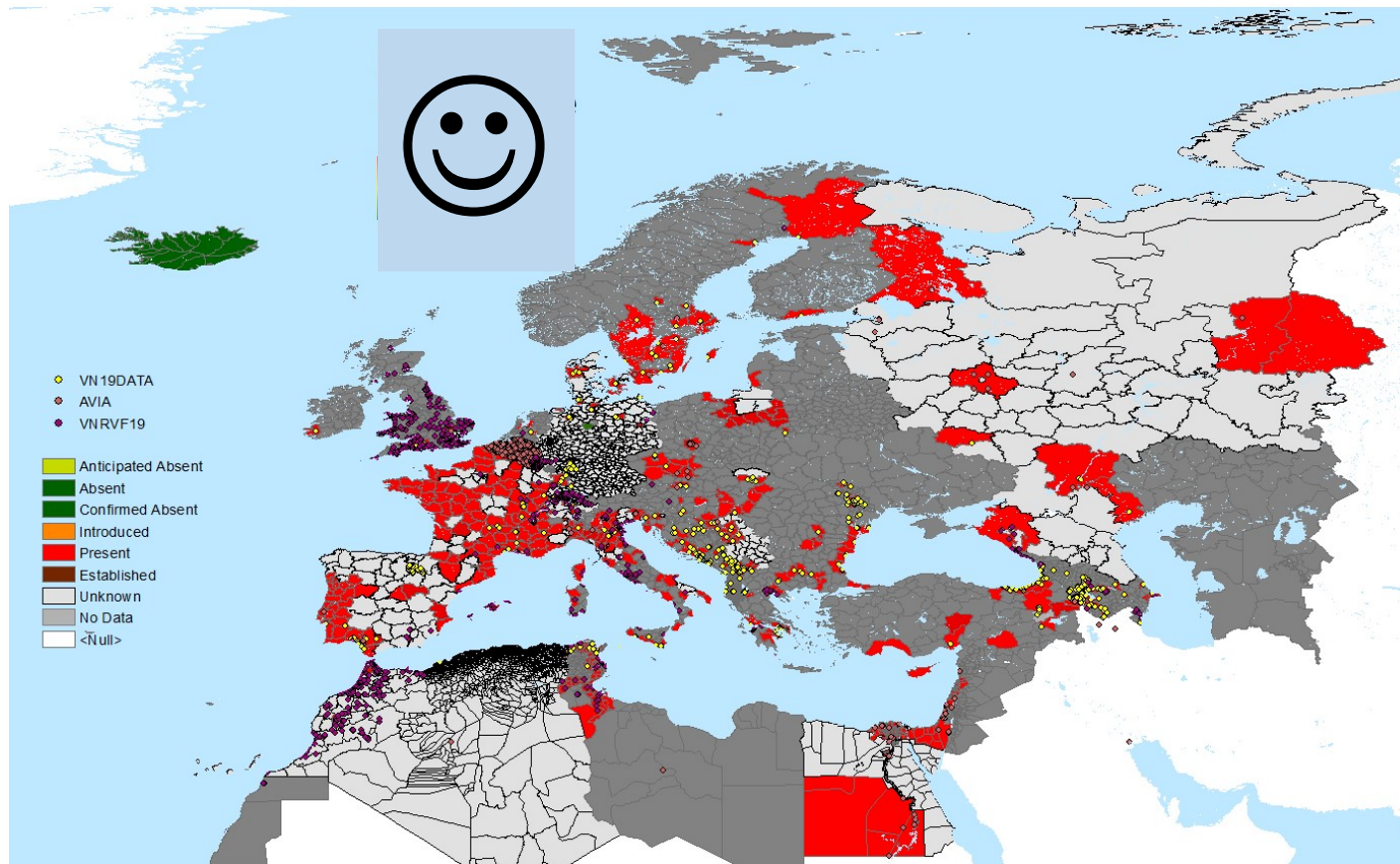
WHAT DATA ARE NEEDED

CLUSTERING, SCALE



Points sparse, many gaps

WHAT DATA ARE NEEDED CLUSTERING, SCALE



Pipiens

BUT

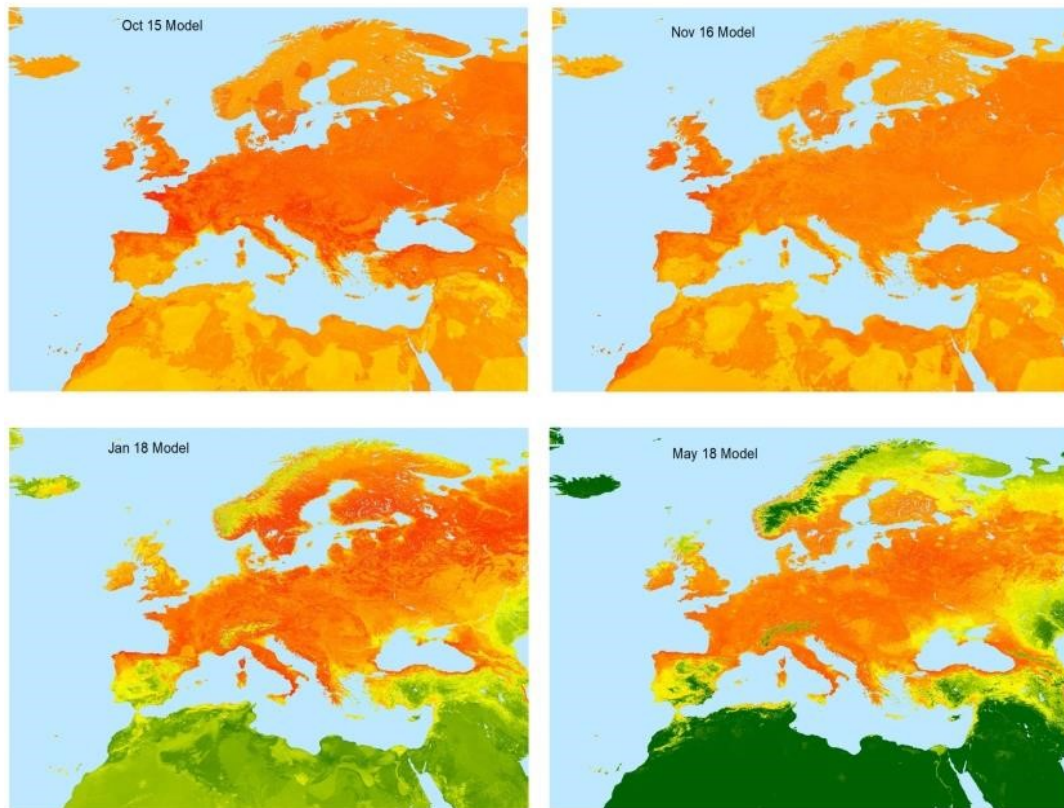
VERY clustered in some places

If these are (reliable) abundance data then good

What about absence

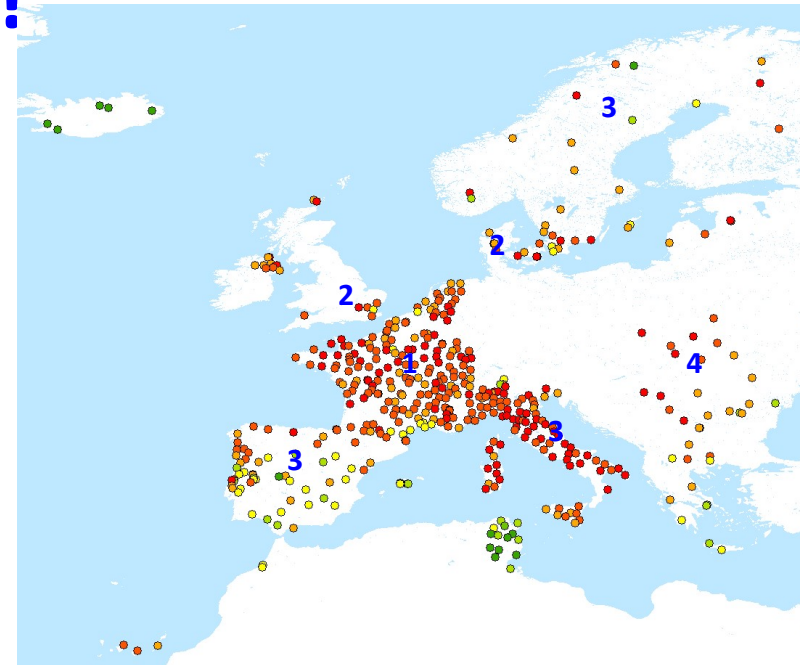
EXTRAPOLATION?

Evolution of changing midge models



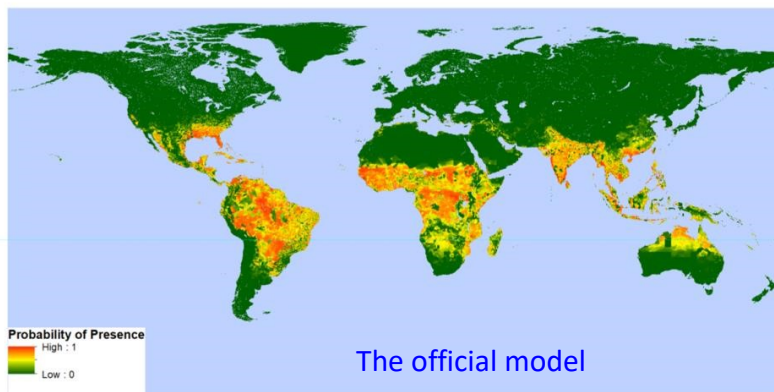
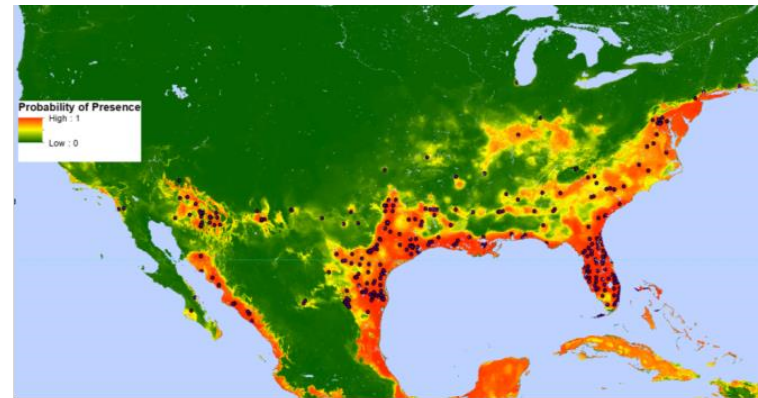
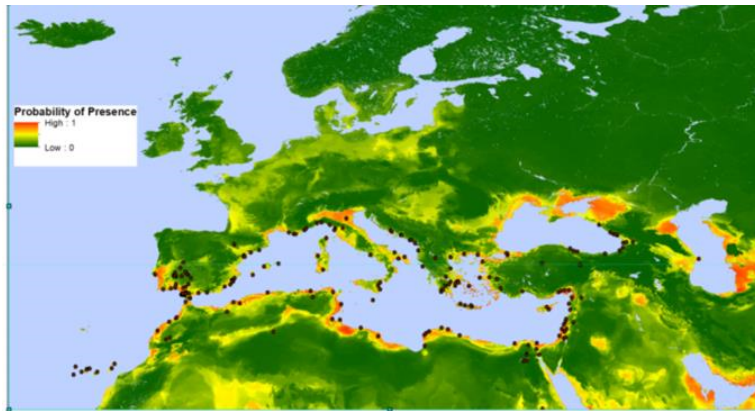
obsoletus

VectorNet

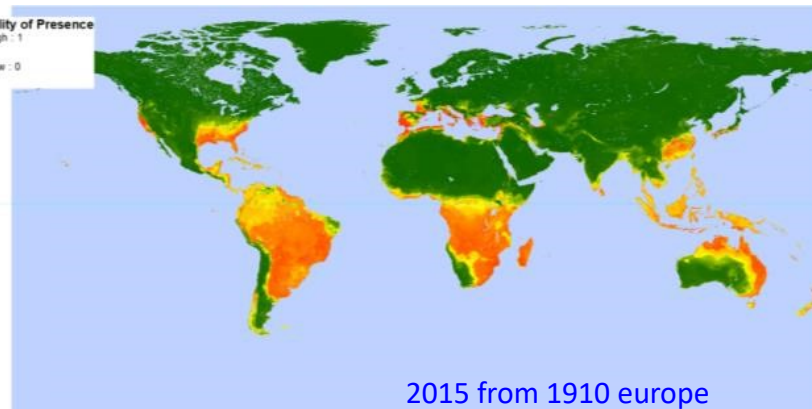


HAVING SAID THAT!

Europe from US DATA, with 1910 EU on top



The official model



2015 from 1910 europe

RECORD STRUCTURE

This means that for modelling, the data you collect needs to have a minimum number of components:

Record number

Coordinates, preferably decimal latitude and longitude. If other reference systems (e.g. UTM) then clear statements to say so

(Location name, admin unit, country)

Date of collection (DD/MM/YYYY)

Trap type, number of traps

Species

Number caught, of each stage (including zero).

Contact/reference

ARCHIVE RECORDS

If they are to be compatible with VectorNet, many of these data values should have specific codes – trap types/collection method, and a large number of other metadata are required:

FOR current PA ECDC Vector Maps

Mandatory:

- Species
- Mode
- Status
- Collection method
- Start date
- End date
- Expert
- Coordinates or Admin Units
- Identification method
- Life Stage

Optional:

- Publication
- Life Stage
- Sex
- Abundance
- Sample effort
- Study name (not on web form)
- Study identification (not on web form)
- Coordinate precision
- StudyContext
- TaxonomicRange
- TrapIdentifier and type (depending on the collection method)

Format should be something that can be converted to Excel: dbf, csv, tab delimited, or of course xls.

CASE STUDIES

How do these data look -

Cleaning/interpreting a dataset.

Preparing the clean dataset for modelling

Data used VectorNet:

Data sources

survey

published literature

unpublished records

A REAL DATASET

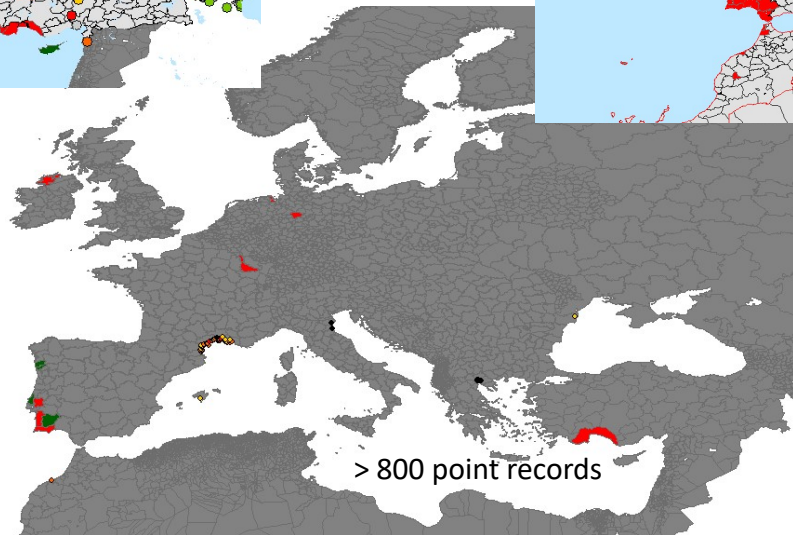
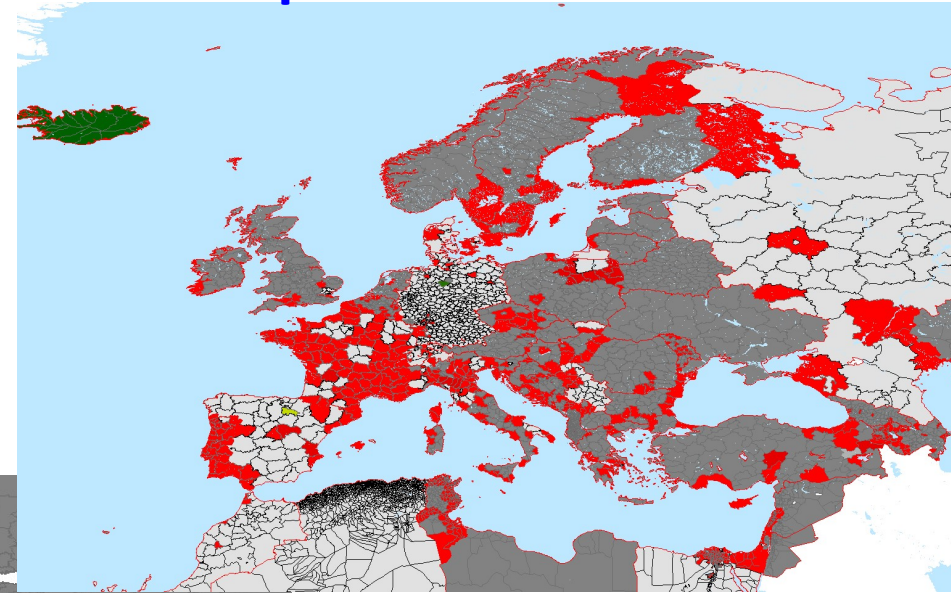
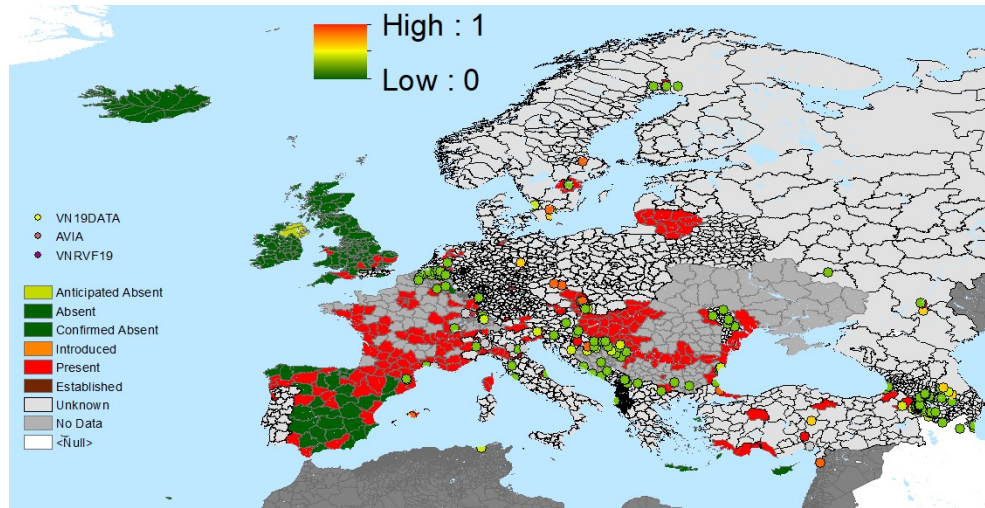
	Country	admin	lat	long	prec	status	meth	start	end	numb	stage	sex	ident	trno	comments
1	Slovenia		46.680361	#####	Exact locati	Present	Larval sam	12/6/2013	12/6/2013	1	larvae		morphological		CONTAINER POS n= NA TOT n= NA
2	Slovenia		46.157176	#####	Exact locati	Present	Larval sam	26/6/2013	26/6/2013	1	Adults	male	morphological		CONTAINER POS n= NA TOT n= NA
3	Slovenia		46.157176	#####	Exact locati	Present	Larval sam	26/6/2013	26/6/2013	2	Adults	female	morphological		CONTAINER POS n= NA TOT n= NA
4	Slovenia		46.157176	#####	Exact locati	Present	Larval sam	26/6/2013	26/6/2013	16	larvae		morphological		CONTAINER POS n= NA TOT n= NA
5	Slovenia		45.681509	#####	Exact locati	Present	Larval sam	28/9/2015	28/9/2015	6	Adults	female	morpholog	80	CONTAINER POS n= 10 TOT n= 80
6	Austria	Niederösterreich-Süd			Region	Present	Ovitrap	1/7/2017	30/10/2017	21	Eggs		Malditof		
7	Austria	West- und Südsteiermark			Region	Present	Ovitrap	1/8/2017	30/10/2017	114	Eggs		Malditof		
8	Austria	Südburgenland			Region	Present	Ovitrap	1/8/2017	30/10/2017	12	Eggs		Malditof		
9	Austria	Nordburgenland			Region	Present	Ovitrap	1/8/2017	30/10/2017	16	Eggs		Malditof		
10	Austria	Linz-Wels	48°17.001'N	14°16.663	Exact locati	Present	Other	10/7/1905	10/7/1905	7	Adults	female	PCR		light trap and Gravid trap; 1 trap-night
11	Austria	Graz	47°04.995'N	15°27.865	Exact locati	Present	Other	10/7/1905	10/7/1905	17	Adults	female	PCR		light trap and Gravid trap; 2 trap-nights
12	Germany	Bitburg-Prum	6.164760	49.987799	Exact locati	Present	Larval sam	2/8/2018	2/8/2018	8	Larvae		morpholog	1	
13	Germany	Rhein-Hunsrück	7.511174	49.981248	Exact locati	Present	Larval sam	13/8/2018	13/8/2018	2	Larvae		morpholog	1	
14	Germany	Bernkastel-W	7.132197	49.818163	Exact locati	Present	Larval sam	13/8/2018	13/8/2018	31	Larvae		morpholog	1	
15	Germany	Bernkastel-W	6.743988	49.910280	Exact locati	Present	Larval sam	13/8/2018	13/8/2018	6	Larvae		morpholog	1	
16	Luxembourg	Luxembourg	49.962348	6.168536	Exact locati	Present	Human bai	5/7/2018	5/7/2018	3	Adults	Female	morpholog	1	
17	Luxembourg	Luxembourg	49.962024	6.167952	Exact locati	Present	Larval sam	1/8/2018	1/8/2018	27	Larvae		morphological		
18	Luxembourg	Luxembourg	49.962066	6.167973	Exact locati	Present	Larval sam	1/8/2018	1/8/2018	1	Larvae		morpholog	1	
19	Luxembourg	Luxembourg	49.962257	6.168106	Exact locati	Present	Larval sam	1/8/2018	1/8/2018	12	Larvae		morpholog	1	
20	Luxembourg	Luxembourg	49.961676	6.167431	Exact locati	Present	Larval sam	1/8/2018	1/8/2018	36	Larvae		morpholog	1	
21	Luxembourg	Luxembourg	49.962733	6.168749	Exact locati	Present	Larval sam	1/8/2018	1/8/2018	10	Larvae		morpholog	1	
22	Luxembourg	Luxembourg	49.957706	6.189971	Exact locati	Present	Larval sam	1/8/2018	1/8/2018	22	Larvae		morpholog	1	
23	Luxembourg	Luxembourg	49.926524	6.217778	Exact locati	Present	Larval sam	1/8/2018	1/8/2018	2	Larvae		morpholog	1	
24	Luxembourg	Luxembourg	49.982247	6.123373	Exact locati	Present	Larval sam	2/8/2018	2/8/2018	1	Larvae		morpholog	1	
25	Luxembourg	Luxembourg	49.952061	6.017269	Exact locati	Present	Larval sam	14/8/2018	14/8/2018	10	Larvae		morpholog	1	
26	Luxembourg	Luxembourg	49.882011	6.258663	Exact locati	Present	Larval sam	15/8/2018	15/8/2018	2	Larvae		morpholog	1	
27	Luxembourg	Luxembourg	49.815946	6.417555	Exact locati	Present	Larval sam	15/8/2018	15/8/2018	7	Larvae		morpholog	1	
28	Luxembourg	Luxembourg	49.790678	6.302217	Exact locati	Present	Larval sam	15/8/2018	15/8/2018	4	Larvae		morpholog	1	
29	Luxembourg	Luxembourg	49.873726	6.156638	Exact locati	Present	Larval sam	15/8/2018	15/8/2018	18	Larvae		morpholog	1	
30	Luxembourg	Luxembourg	49.707217	6.427252	Exact locati	Present	Larval sam	15/8/2018	15/8/2018	1	Larvae		morpholog	1	
31	Luxembourg	Luxembourg	49.849343	6.093564	Exact locati	Present	Larval sam	16/8/2018	16/8/2018	2	Larvae		morpholog	1	
32	Luxembourg	Luxembourg	49.706832	6.370539	Exact locati	Present	Larval sam	4/10/2018	4/10/2018	0	Larvae		morpholog	1	
33	Luxembourg	Luxembourg	49.679666	6.251942	Exact locati	Present	Larval sam	5/10/2018	5/10/2018	12	Larvae		morpholog	1	
34	France	Meurthe-et-M	48.461592	6.847366	Exact locati	Present	Larval sam	08/16/2018	08/16/2018	8	Larvae		morpholog	1	
35	France	Moselle	49.448238	6.359291	Exact locati	Present	Larval sam	4/10/2018	4/10/2018	4	Larvae		morpholog	1	
36															

A REAL DATASET: SOME ISSUES

	Country	admin	lat	long	prec	status	meth	start	end	numb	stage	sex	ident	trno	comments
1	Slovenia		46.680361	#####	Exact locati	Present	Larval sam	12/6/2013	12/6/2013	1	larvae		morphological		CONTAINER POS n= NA TOT n= NA
3	Slovenia		46.157176	#####	Exact locati	Present	Larval sam	26/6/2013	26/6/2013	1	Adults	male	morphological	9	CONTAINER POS n= NA TOT n= NA
4	Slovenia		46.157176	#####	Exact locati	Present	Larval sam	26/6/2013	26/6/2013	2	Adults	female	morphological		CONTAINER POS n= NA TOT n= NA
5	Slovenia		46.157176	#####	Exact locati	Present	Larval sam	26/6/2013	26/6/2013	16	larvae		morphological		CONTAINER POS n= NA TOT n= NA
6	Slovenia		45.681509	#####	Exact locati	Present	Larval sam	28/9/2015	28/9/2015	6	Adults	female	morpholog	80	CONTAINER POS n= 10 TOT n= 80
7	Austria	Niederösterreich-Süd	2		Region	Present	Ovitrap	1/7/2017	30/10/2017	21	Eggs		Malditof		
8	Austria	West- und Südsteiermark			Region	Present	Ovitrap	1/8/2017	30/10/2017	114	Eggs	7	Malditof		
9	Austria	Südburgenland			Region	Present	Ovitrap	1/8/2017	30/10/2017	12	Eggs		Malditof		
10	Austria	Nordburgenland	3		Region	Present	Ovitrap	1/8/2017	30/10/2017	16	Eggs		Malditof		
11	Austria	Linz-Wels	48°17.001'N	14°16.663	Exact locati	Present	Other	10/7/1905	10/7/1905	7	Adults	female	PCR		light trap and Gravid trap; 1 trap-night
12	Austria	Graz	47°04.995'N	15°27.865	Exact locati	Present	Other	10/7/1905	10/7/1905	17	Adults	female	PCR		light trap and Gravid trap; 2 trap-nights
13	Germany	Bitburg-Prüm	6.164760	49.987799	Exact locati	Present	Larval sam	2/8/2018	2/8/2018	8	Larvae		morpholog	1	
14	Germany	Rhein-Hunsrück	7.511174	49.981248	Exact locati	Present	Larval sam	13/8/2018	13/8/2018	2	Larvae		morpholog	1	
15	Germany	Bernkastel-W	7.132197	49.818163	Exact locati	Present	Larval sam	13/8/2018	13/8/2018	31	Larvae		morpholog	1	
16	Germany	Bernkastel-W	6.743988	49.910280	Exact locati	Present	Larval sam	13/8/2018	13/8/2018	6	Larvae		morpholog	1	
17	Luxembourg	Luxembourg	49.962348	6.168536	Exact locati	Present	Human bai	5/7/2018	5/7/2018	3	Adults	Female	morpholog	1	
18	Luxembourg	Luxembourg	49.962024	6.1649.987799	locati	Present	Larval sam	1/8/2018	1/8/2018	27	Larvae		morphological		
19	Luxembourg	Luxembourg	49.962066	6.1649.981248	locati	Present	Larval sam	1/8/2018	1/8/2018	1	Larvae		morpholog	1	
20	Luxembourg	Luxembourg	49.962257	6.1649.818163	locati	Present	Larval sam	1/8/2018	1/8/2018	12	Larvae		morpholog	1	
21	Luxembourg	Luxembourg	49.961676	6.1649.910280	locati	Present	Larval sam	1/8/2018	1/8/2018	36	Larvae		morpholog	1	
22	Luxembourg	Luxembourg	49.962733	6.168749	Exact locati	Present	Larval sam	1/8/2018	1/8/2018	10	Larvae		morpholog	1	
23	Luxembourg	Luxembourg	49.957706	6.189971	Exact locati	Present	Larval sam	1/8/2018	1/8/2018	22	Larvae		morpholog	1	
24	Luxembourg	Luxembourg	49.926524	6.217778	Exact locati	Present	Larval sam	1/8/2018	1/8/2018	2	Larvae		morpholog	1	
25	Luxembourg	Luxembourg	49.982247	6.123373	Exact locati	Present	Larval sam	2/8/2018	2/8/2018	1	Larvae		morpholog	1	
26	Luxembourg	Luxembourg	49.952061	6.017269	Exact locati	Present	Larval sam	14/8/2018	14/8/2018	10	Larvae		morpholog	1	
27	Luxembourg	Luxembourg	49.882011	6.258663	Exact locati	Present	Larval sam	15/8/2018	15/8/2018	2	Larvae		morpholog	1	
28	Luxembourg	Luxembourg	49.815946	6.417555	Exact locati	Present	Larval sam	15/8/2018	15/8/2018	7	Larvae		morpholog	1	
29	Luxembourg	Luxembourg	49.790678	6.302217	Exact locati	Present	Larval sam	15/8/2018	15/8/2018	4	Larvae		morpholog	1	
30	Luxembourg	Luxembourg	49.873726	6.156638	Exact locati	Present	Larval sam	15/8/2018	15/8/2018	18	Larvae		morpholog	1	
31	Luxembourg	Luxembourg	49.707217	6.427252	Exact locati	Present	Larval sam	15/8/2018	15/8/2018	1	Larvae		morpholog	1	
32	Luxembourg	Luxembourg	49.849343	6.093564	Exact locati	Present	Larval sam	16/8/2018	16/8/2018	2	Larvae		morpholog	1	
33	Luxembourg	Luxembourg	49.706832	6.370539	Exact locati	Present	Larval sam	4/10/2018	4/10/2018	0	Larvae		morpholog	1	
34	Luxembourg	Luxembourg	49.679666	6.251942	Exact locati	Present	Larval sam	5/10/2018	5/10/2018	12	Larvae		morpholog	1	
35	France	Meurthe-et-M	48.461592	6.847366	Exact locati	Present	Larval sam	08/16/2018	08/16/2018	8	Larvae		morpholog	1	
36	France	Moselle	49.448238	6.359291	Exact locati	Present	Larval sam	4/10/2018	4/10/2018	4	Larvae		morpholog	1	

REAL DATASETS

Real datasets: what can you see that might cause a problem



TOPIC 2: DOING THE MODELLING

Intro to spatial modelling

What else is needed to produce models

Doing the modelling

How (not) to make maps useful

WHAT ARE THE ISSUES

Producing risk maps is often to a deadline for planning requirements set by people who just want answers and for whom risk is a black box component, NOT a research project

Issues are : Data acquisition, networks and sharing

Objectives: what is good enough

Data not just disease/vector risk

Using appropriate methods

Getting the results out: Customisation and translation

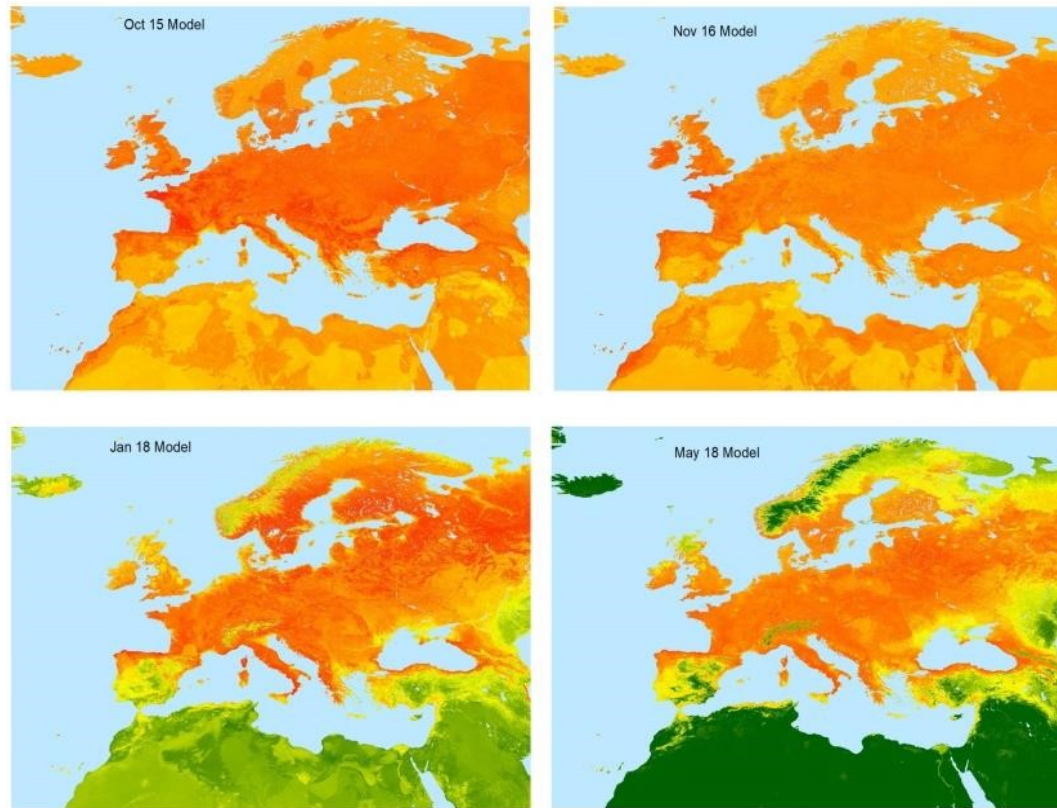


WHAT IS GOOD ENOUGH: IS SOMETHING BETTER THAN NOTHING?

Evolution of changing midge models

Do we provide a model for Oct 15, or refuse

Did we know how wrong it would be?



Species:

7 *Culicoides* spp.

chiopterus

dewulfi

kingi

lupicaris

imicola

newsteadii

obsoletus

pulicaris

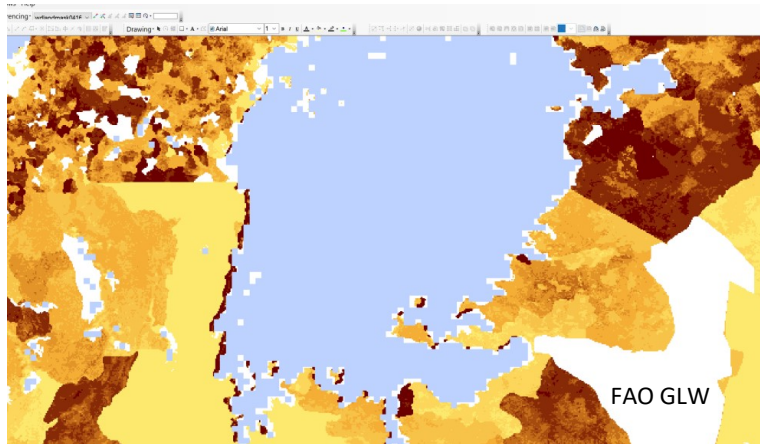
punctatus

scoticus

VectorNet

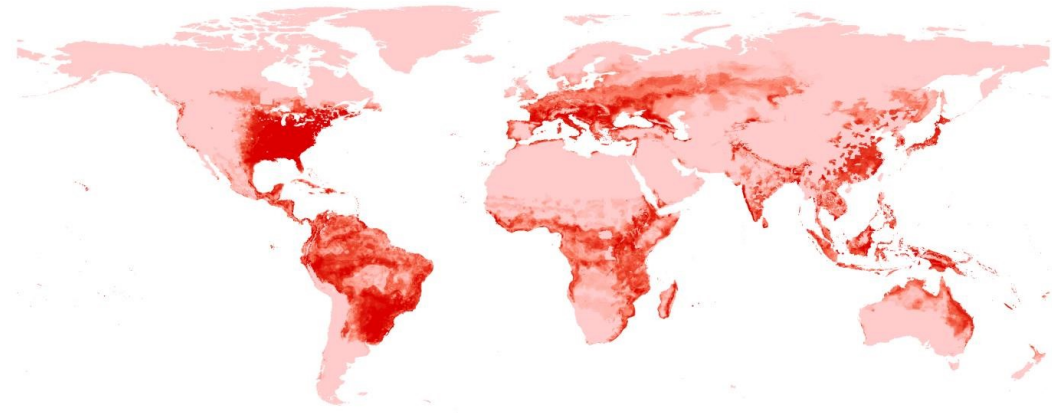
IS SOMETHING BETTER THAN NOTHING?

Global maps will have howlers: cattle



NB Cryptic tags
can be useful to
prove ownership!

Projection logic arguable, models misleading: Tiger Mosquito, Yellow Fever mosquito



AIM
Aedes Invasive Mosquitoes

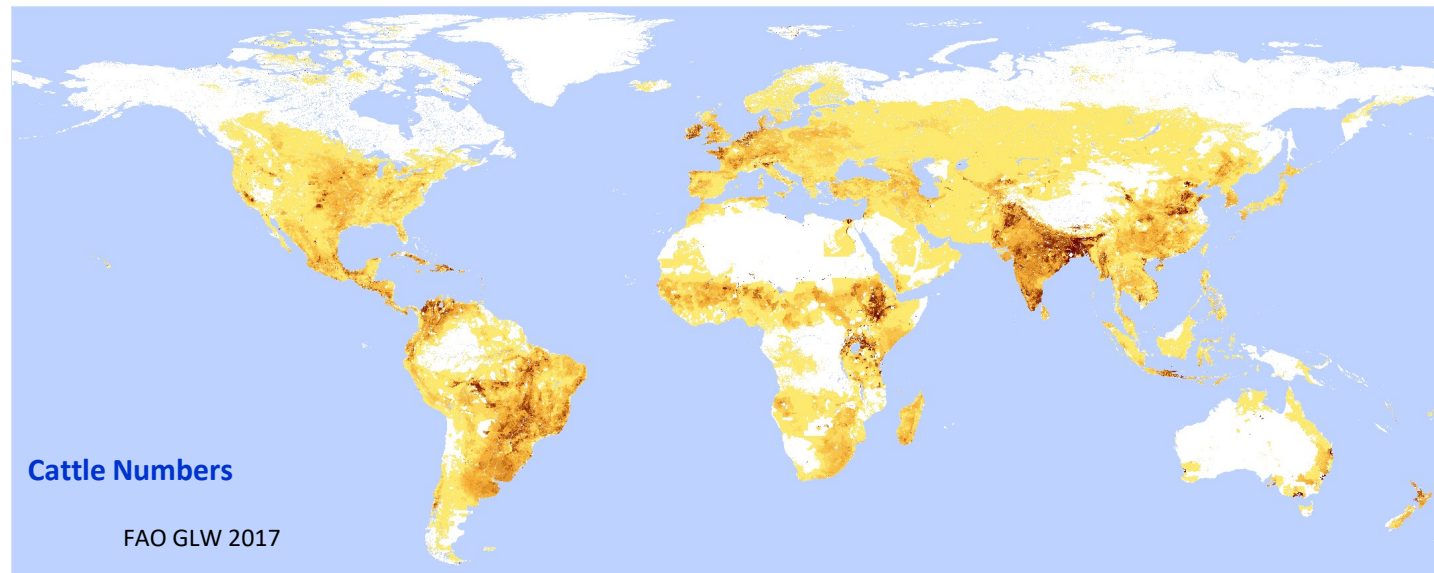
Funded by the Horizon 2020 Framework Programme
of the European Union

cost

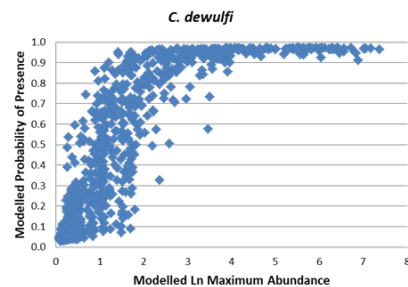
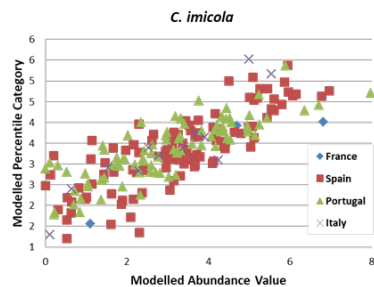
EUROPEAN COOPERATION
IN SCIENCE & TECHNOLOGY

IS SOMETHING BETTER THAN NOTHING?

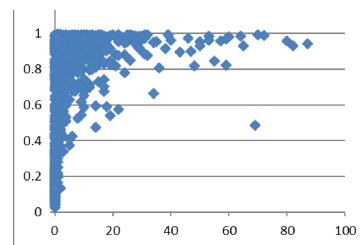
Presence absence or abundance?



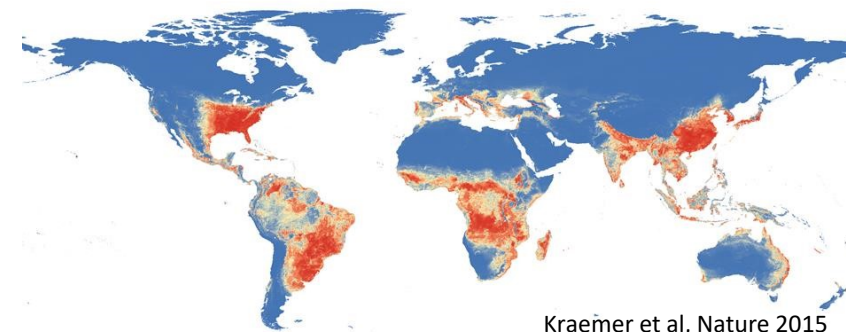
European Midges



Tick



Tiger Mosquito probability



Wint et al, ECDC Technical Opinion, Dec 2018

AIM COST Training School, Cyprus, January 2020



EUROPEAN COOPERATION
IN SCIENCE & TECHNOLOGY

RISK OF PATHOGEN/VECTOR NOT JUST ABOUT PATHOGEN/VECTOR

Need information about:
Disease, Host, Vector

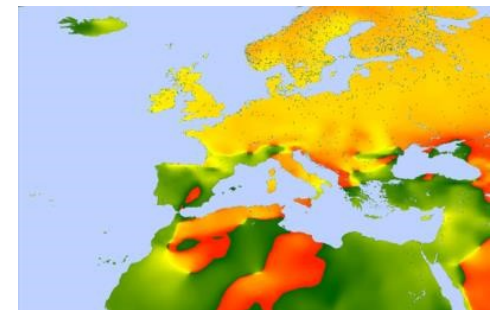
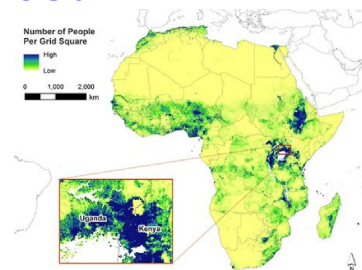
e.g. Dengue, ECF

Where there are the vectors AND
Where the vectors are infected AND
Where there are there are hosts (bovids, people)
(Suitability later)

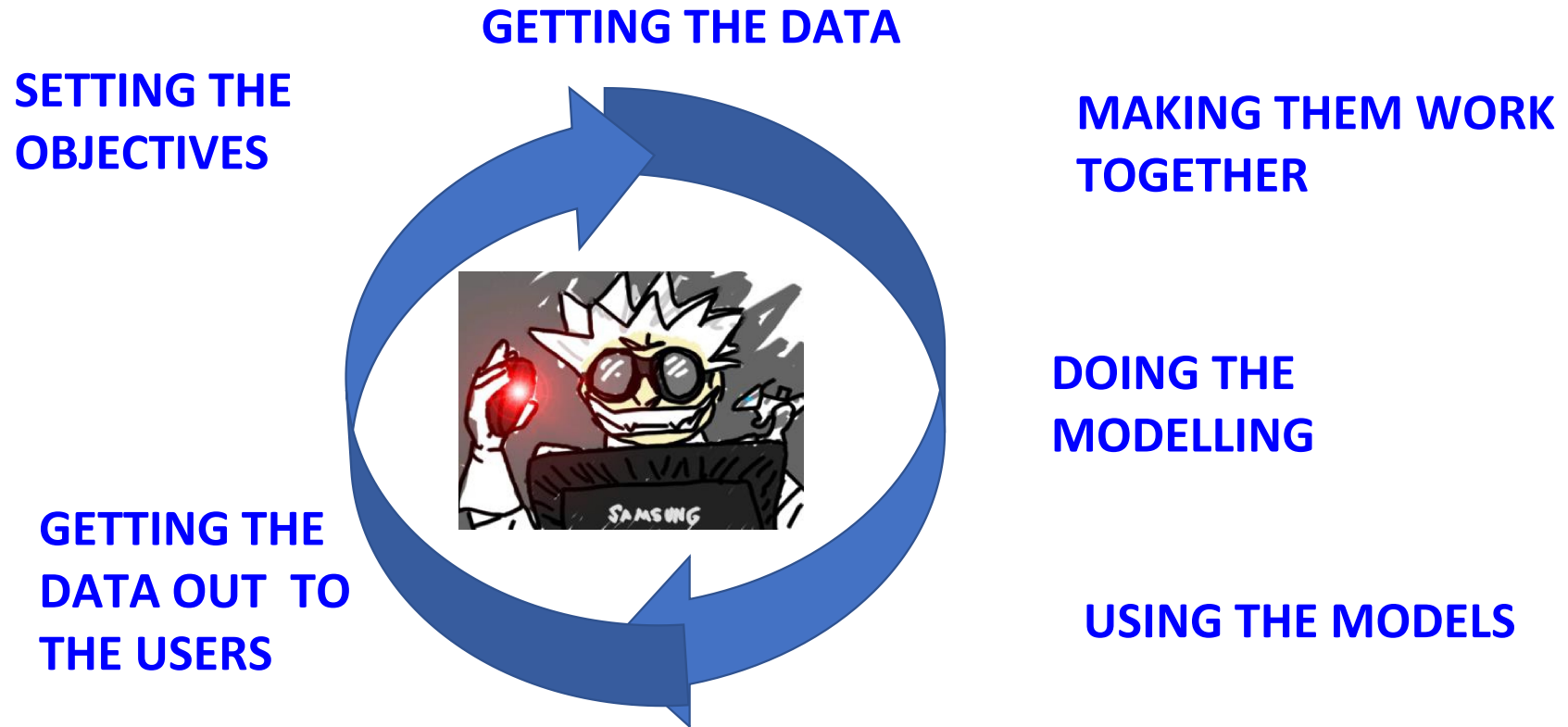


Covariates

Environmental, demographic, economic,.....
Customised



NOT JUST ABOUT MODELLING EITHER



MODELING OFTEN THE EASY BIT

THE STEPS NEEDED: FINDING THE DATA

DATA TYPES: THE TARGETS = DISEASE, HOST, VECTOR

Most difficult stage:

Often restricted data (wildlife, disease)

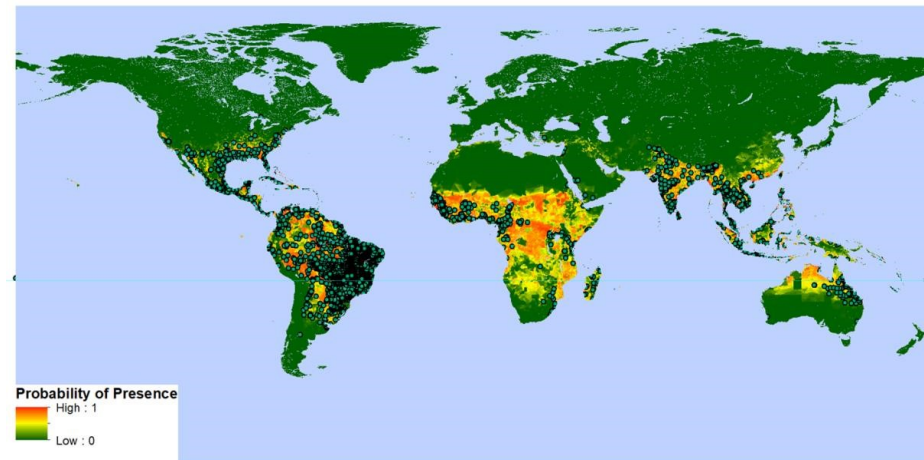
Inevitably patchy, or inconsistent

Often poor quality (zeros!)

**Large Scale models rely on LITERATURE and NETWORKS
and data SHARING**



VectorNet



THE STEPS NEEDED: FINDING THE DATA

SHARING THE DATA

What is needed to facilitate data collection

What data owners can do

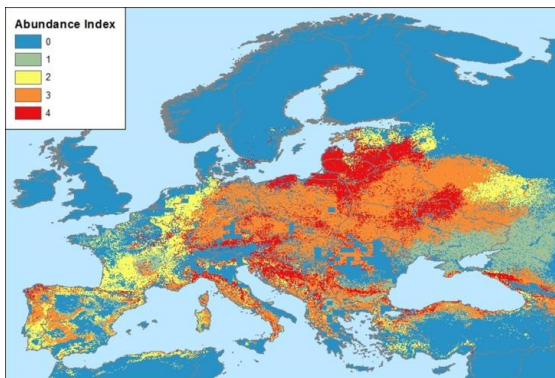
Networks

Data sharing

Anonymised

Summary aggregations

Transboundary



What data analysts can do

Share results & processed versions

Not one way flow! Culture change needed

Offer to adapt analysis for owners

Open data archives to owners

Explain outputs properly

**NEED PROTECTION
OF OWNERSHIP**



THE STEPS NEEDED: SHARING THE DATA

WHY SHARE YOUR DATA FOR MODELLING

PROS OF SHARING

Personal:

- It fulfills my contractual obligations

- I get access to other data/outputs in return

Public Health/Societal:

- My data can be used to do things I cant to create PH/academic outputs .

- It allows my data to be used at larger scales and have wider relevance

CONS OF SHARING

Personal:

- Someone else gets the benefit of my work before I do

- I don't get enough acknowledgement

- I don't get additional funding because I have shared my data

- I don't control the quality of what is done

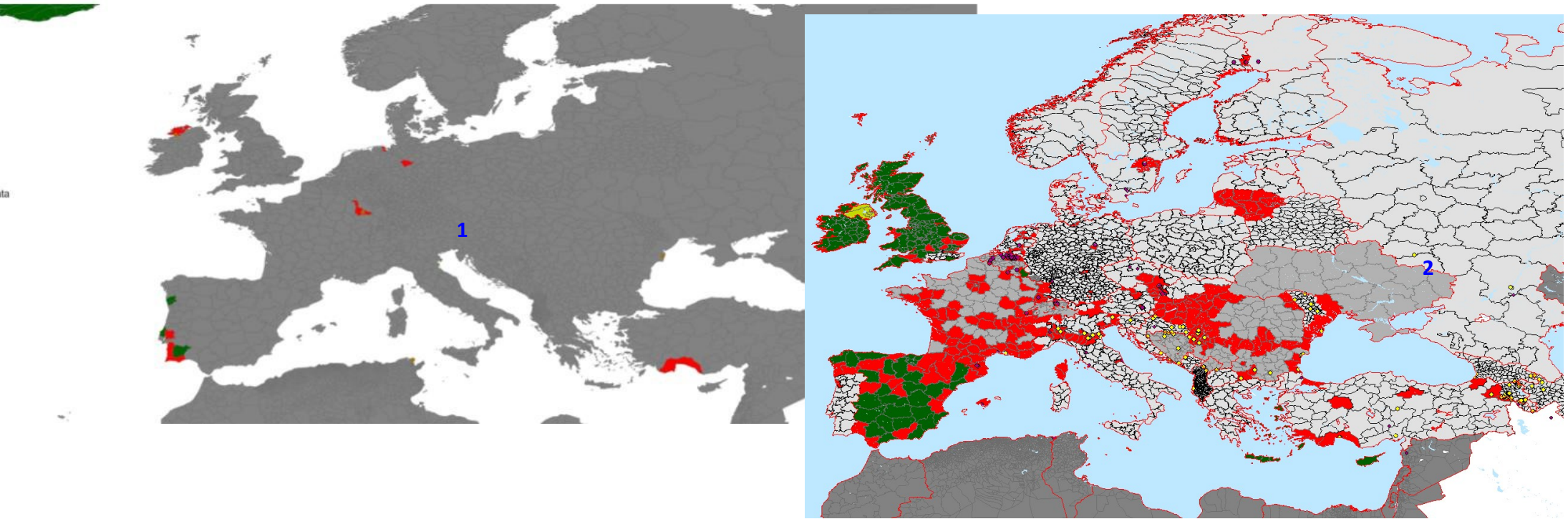
- Someone else is always hassling me to hurry up

Public Health/Societal:

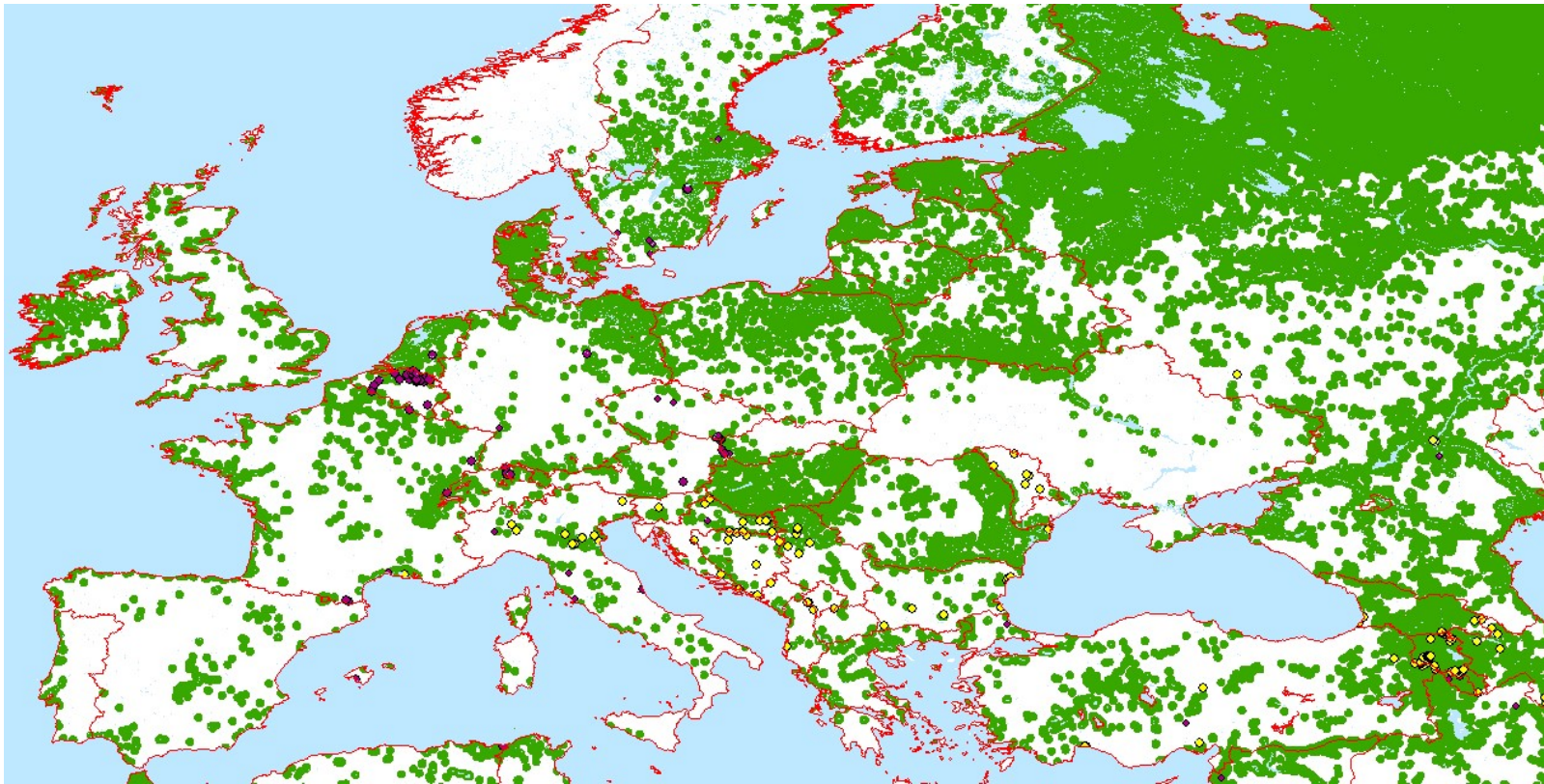
ENHANCING THE DATA

Sometimes it's a hopeless case, others we can 'cheat'

Can we define absences?



SUITABILITY



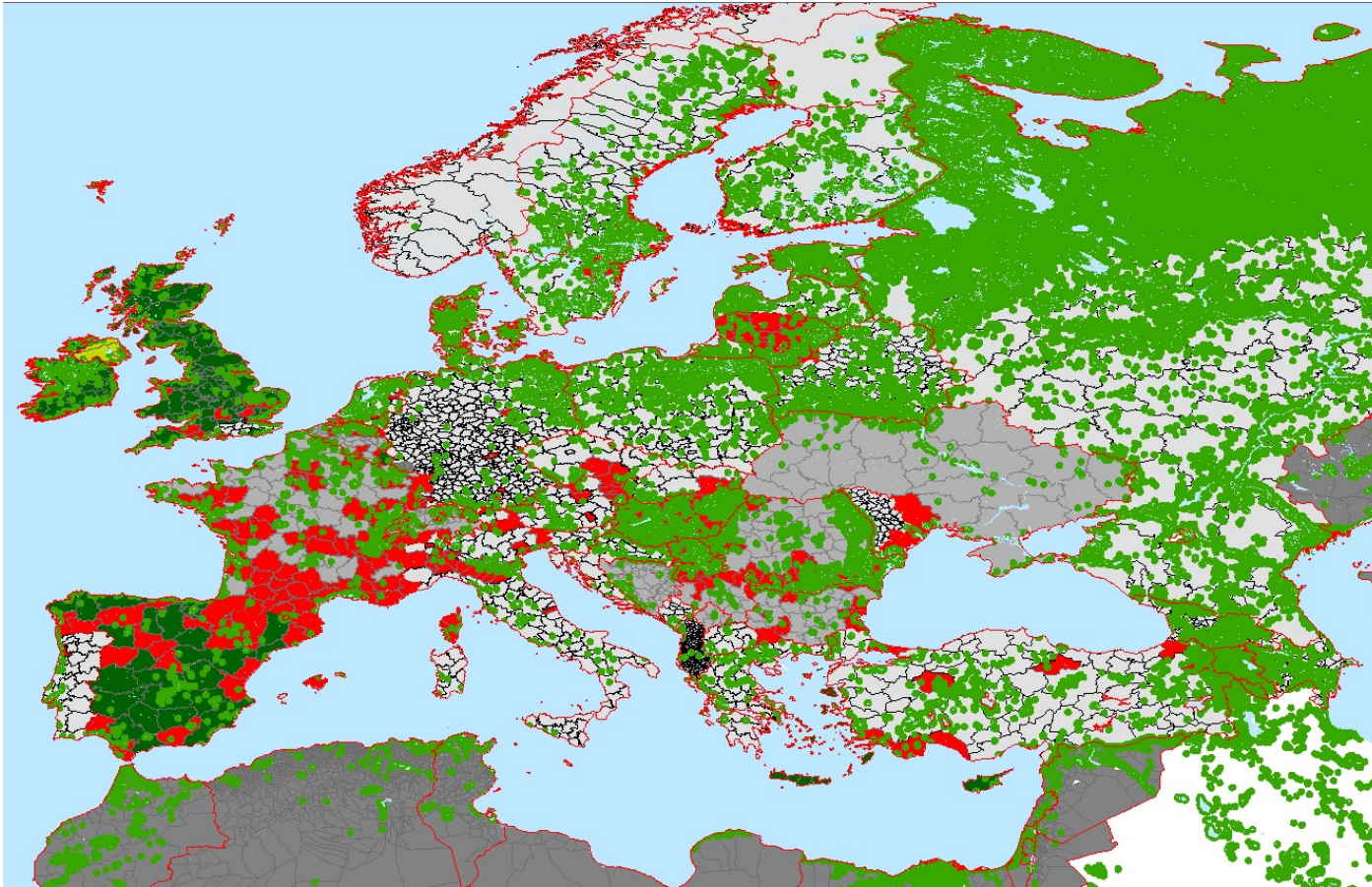
Suitability defined by land cover, environmental limits and dispersal capability

Unsuitable land identifiable

Absences can be assigned to unsuitable areas

Note (pleasing) correspondence between suitability and observations

USING SUITABILITY



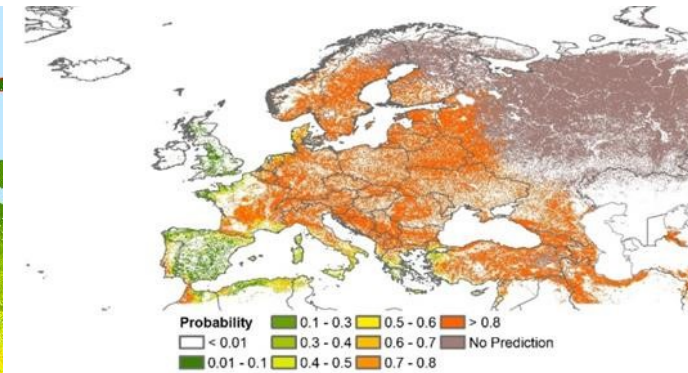
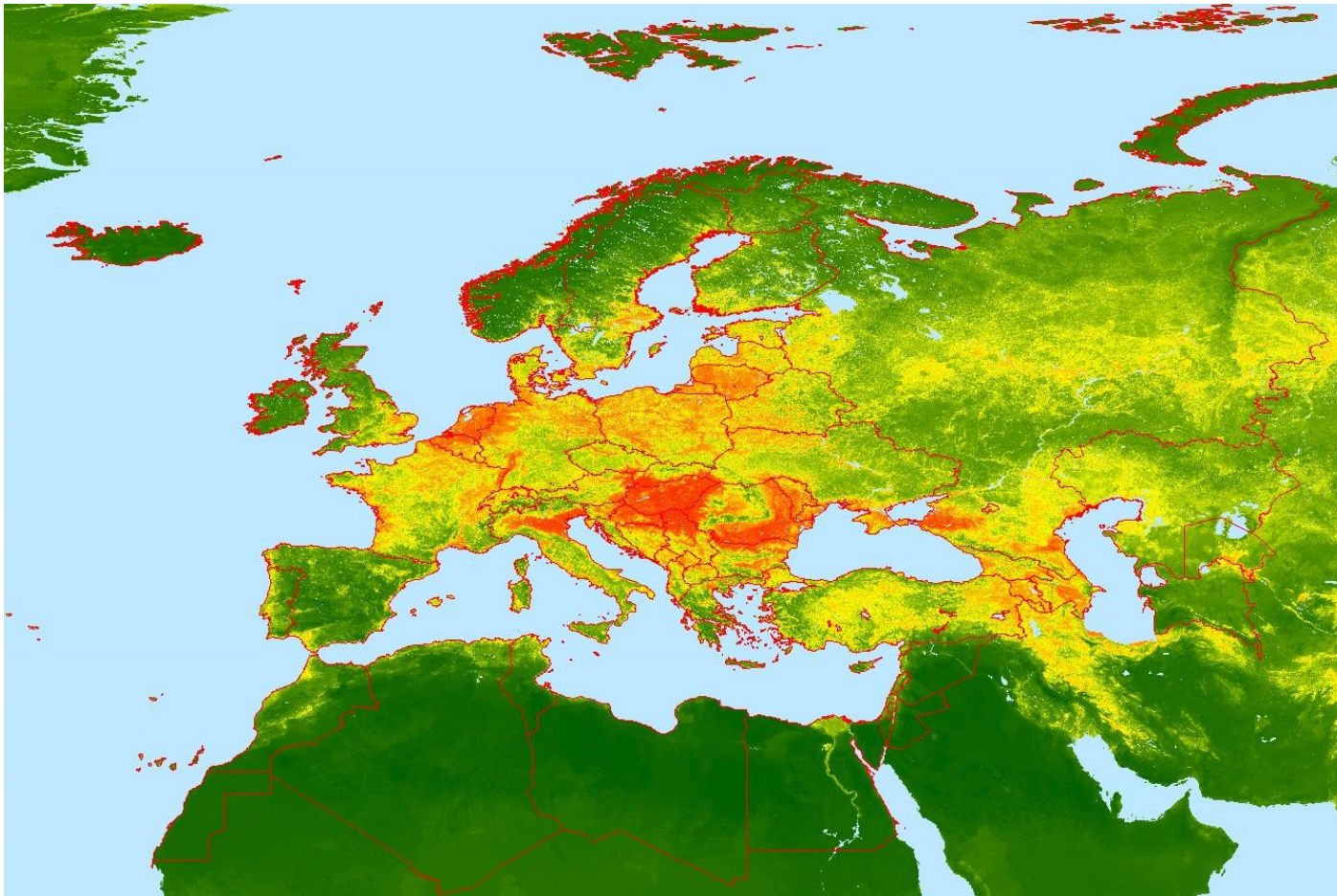
Absences can be assigned to unsuitable areas in unknown polygons,

in all absence polygons,

and in unsuitable parts of presence polygons

**SHOULD THEN BE BALANCED
WITH PRESENCES
NB number or density??**

USING SUITABILITY

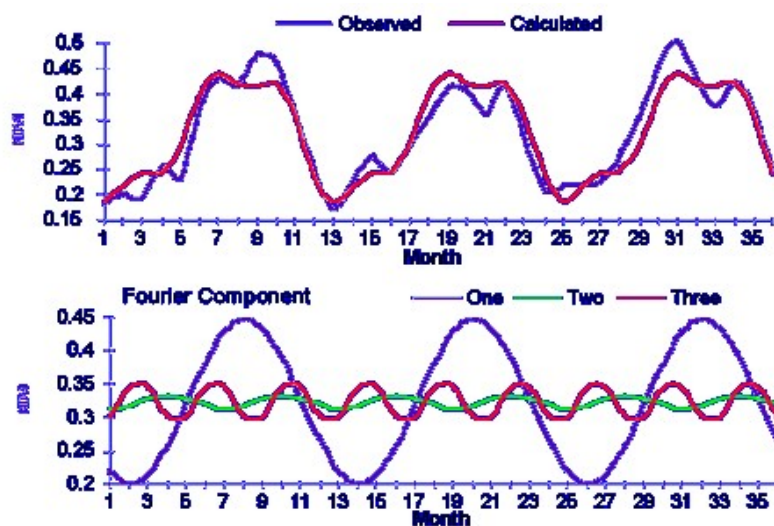


Big difference

THE STEPS NEEDED: FINDING THE DATA COVARIATES: DATA REDUCTION

Turn large datasets to meaningful (manageable) parameters

Temporal Fourier Processing Imagery (2000-2016)

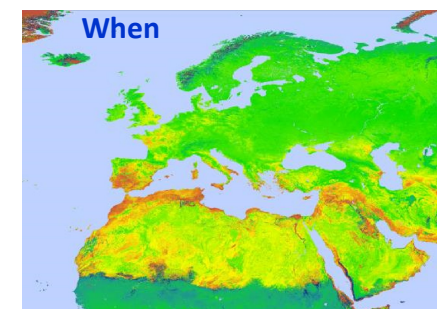
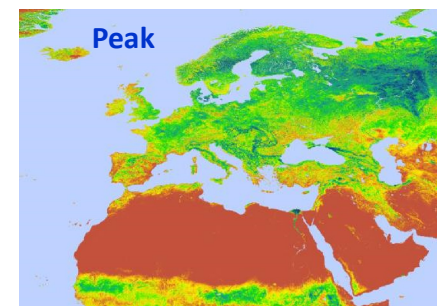
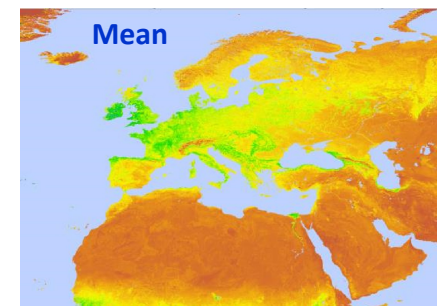


Decomposes irregular time series into regular components annual, bi annual, tri annual

Amplitude = Importance of each component
Here: annual>biannual>triannual

Mean = levels

Phase = timing of seasonal peaks



Provides aspects of seasonality as well as smoothed levels

FINDING THE DATA

COVARIATES: NEW VARIABLES

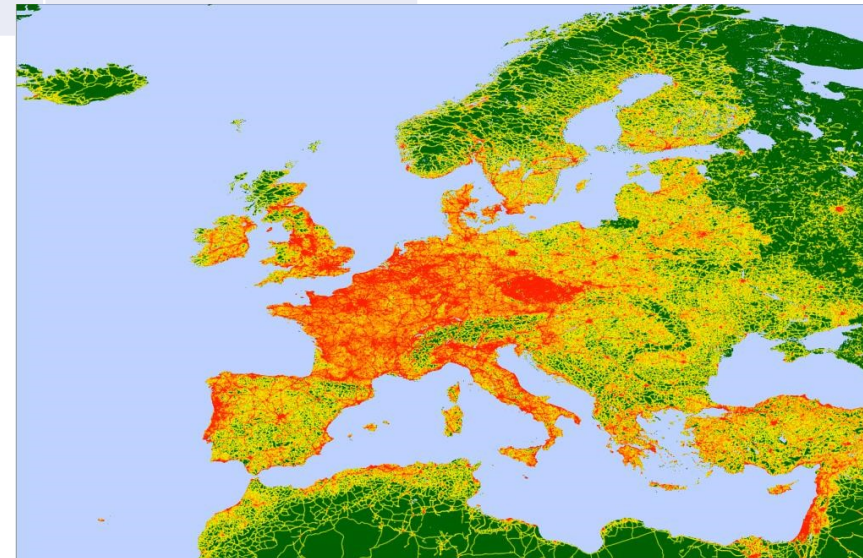
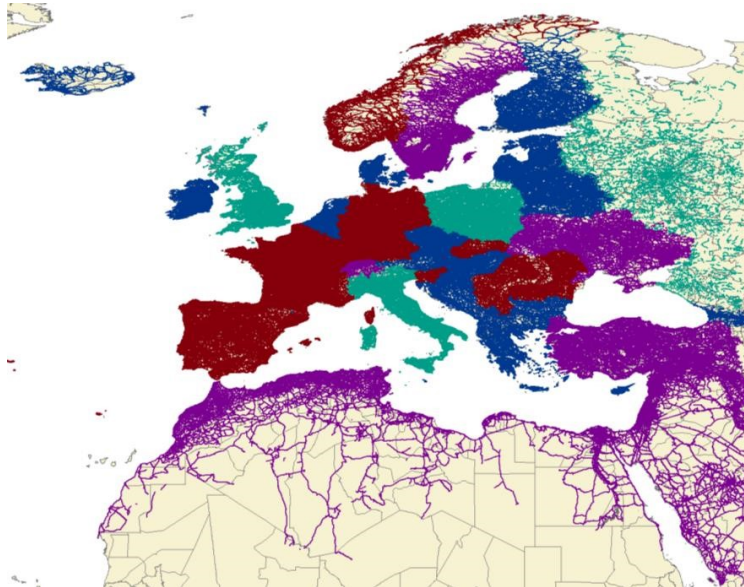
Accessibility:

Measured as road density.

Could also be distance to...

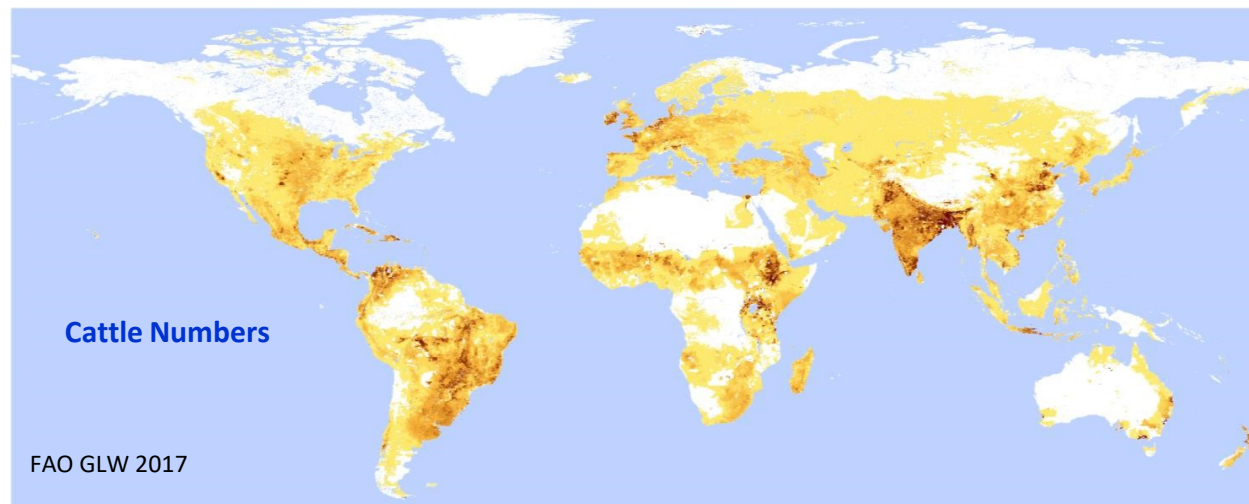
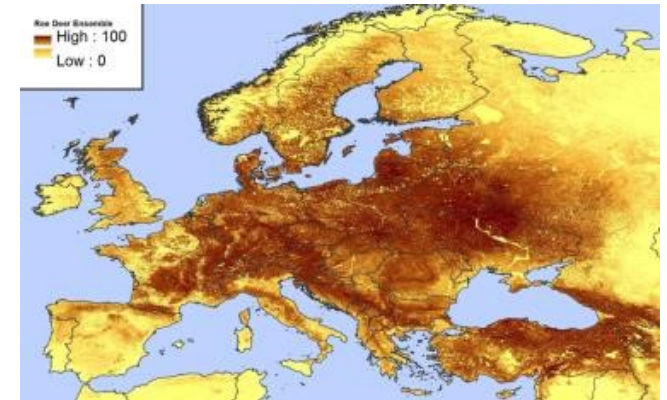
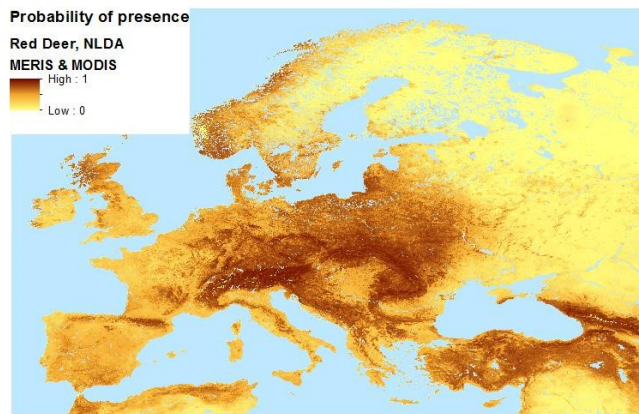
Global first surprisingly

Road Category	Filename	Approx No. Features, shape file size
All classified (motorway, trunk, primary, secondary, tertiary) with link roads	Eumenardsclassifiedwlinks	5.75M; 1.7GB
Major (Primary, trunk, Motorway) and link roads	Eumenahighmajorwlinknov17	1.95m; 450MB
Secondary and link roads	Eumenardssecondarywlinknov17	1.53m; 450MB
Tertiary and link roads	Eumenardstertiarywlinknov17	2.3m; 820MB
Unclassified	Eumenardsunclassifiednov17	2.5m; 1.4GB
Residential and 'living_streets' with link roads	Eumenardsresidlivingwlinknov17	13m; 2.6GB



THE STEPS NEEDED: FINDING THE DATA

May also need to model
drivers like hosts:
Deer for ticks
Cattle as denominator



THE STEPS NEEDED: FINDING THE DATA COVARIATE ARCHIVES

Don't re-invent the Wheel, you could get it wrong
Go to archives.... Standardised data



Google Earth Engine

DATA

Several
Global
Dataset
Firsts



DOING THE MODELLING

Modelling methods:

Process Based:

Rare (difficult) at global level

Stochastic:

Many methodologies

Spatial, Spatio Temporal

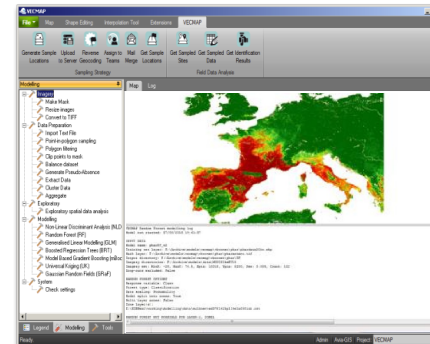
Networks, Machine Learning

If to be global (regional) standard,

People have more faith in the well established techniques



BOOSTED REGRESSION TREES
RANDOM FOREST
MAXENT,
BAYESIAN, and many others



DOING THE MODELLING

Input data is primary determinant of model quality :

GARBAGE IN GARBAGE OUT

Accuracy of data

Non standardised sampling

Mismatching data types

Clustering

Degree of extrapolation

Models mostly pattern matching not identification of drivers

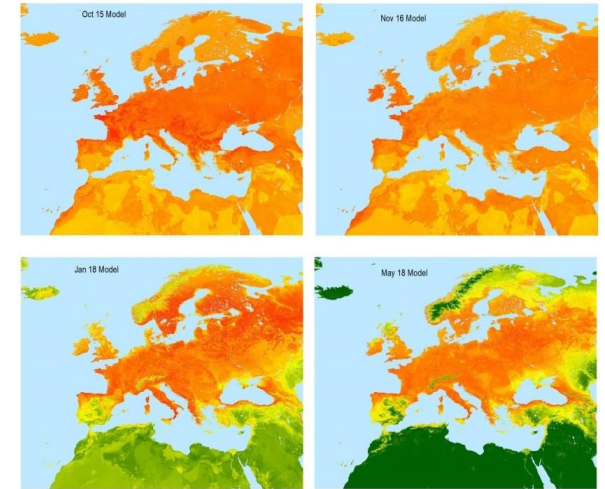
Exaggerated expectations:

85% accurate is good => 15% wrong

models often not accurate at the pixel level

MORE IMPORTANT TO GET DATA RIGHT: MANY METHODS WILL WORK

ALSO IMPORTANT TO MODEL USEFUL VARIABLES AND PRODUCE USEFUL OUTPUTS



DOING THE MODELLING

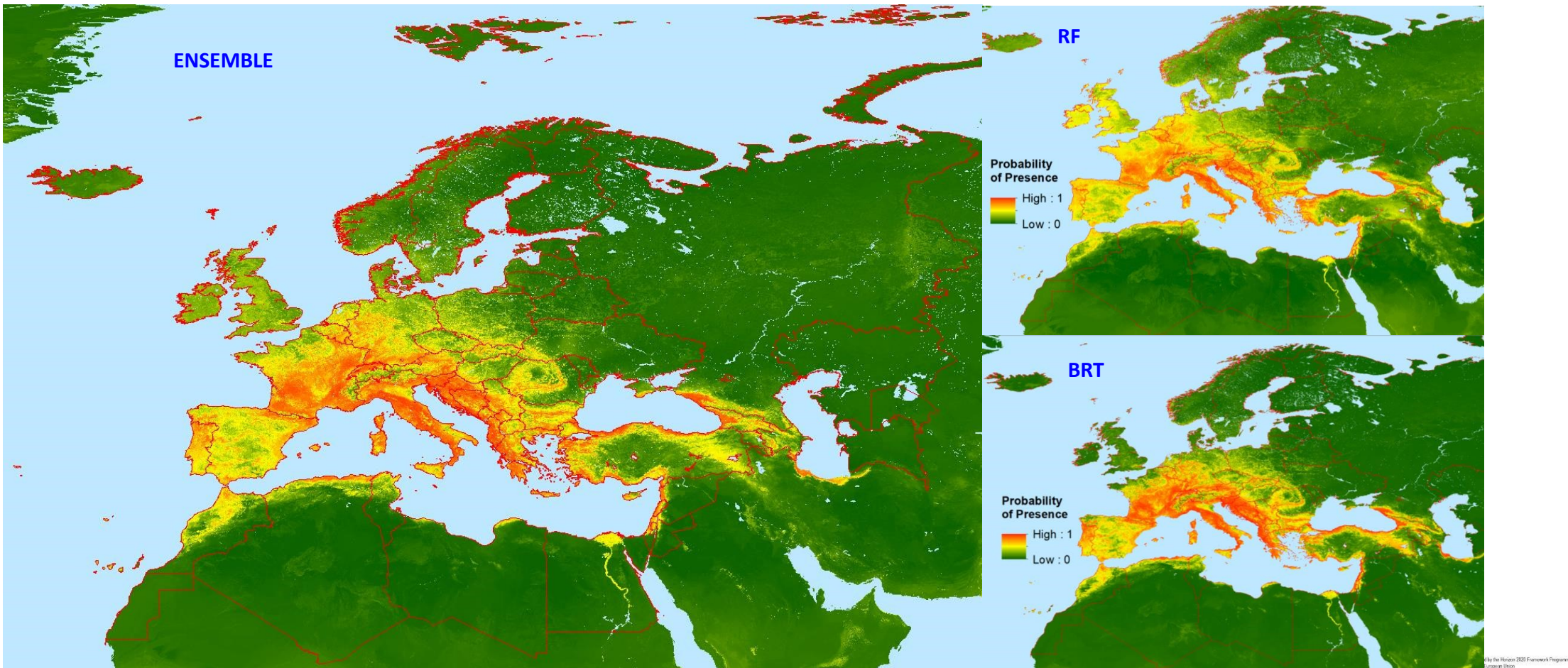
As have said earlier, most spatial modelling methods based on using sample to extrapolate.

Different methods have different quirks. BRT tends to overfit, RF tends to smooth, but does categories well. BAYESIAN is very computer intensive, MAXENT purports not to need Absences. GLMM Logistic bias for presence, NLDA for absence. HURDLE combines PA and abundance modelling etc etc.

So get different result with same input data (like GCM projections !)

=> => strong case for ensembling methods, as well as doing replicate models.

DOING THE MODELLING: ENSEMBLING



by the Horizon 2020 Framework Programme
European Union

DOING THE MODELLING: OUTPUTS

Decisions for Model output types

Depends on User, easy to get driven by “have tools will model”

Other things to consider:

Resolution (depends on extent)

country

admin

pixel

Update frequency

Snapshot

Projection

Levels of Uncertainty:

Ensembles, Replicates

Covariate errors

Modelling errors

Diminishing returns??

