INSIGHTS INTO THE SPATIO-TEMPORAL SPREAD OF *Xylella fastidiosa* IN SOUTH-EASTERN ITALY

Martínez-Minaya J[2], Conesa D[2], López-Quílez A[2], Saponari M[3], Vicent A[1]

[1] Instituto Valenciano de Investigaciones Agrarias (IVIA)
[2] Departament d'Estadística i Investigació Operativa, Universitat de València
[3] Istituto per la Protezione Sostenibile delle Piante, UOS Bari, CNR

Quick Decline Syndrome of Olive (OQDS)

Kick-off meeting XF-ACTORS (16 Nov 2016)

Objectives

- To estimate the probability of *Xf* occurrence in south-eastern Italy based on climatic variables and spatial factors

Objectives

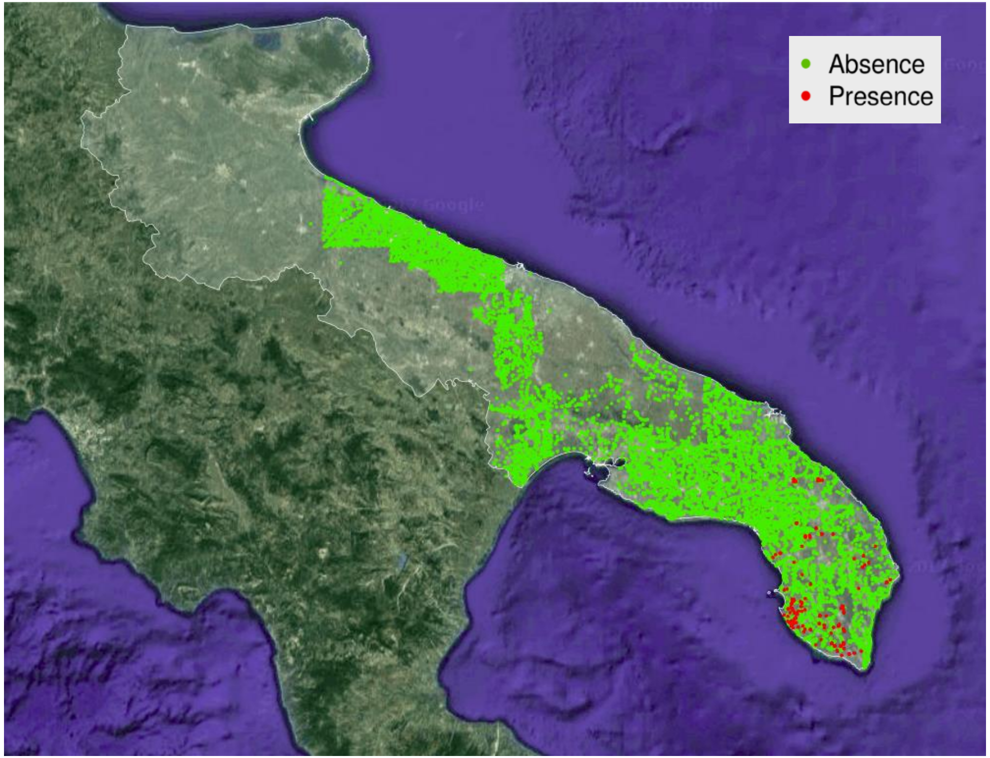
- To estimate the probability of *Xf* occurrence in south-eastern Italy based on climatic variables and spatial factors

- To better understand the role of climate and spatial dependency in *Xf* spread

Variables

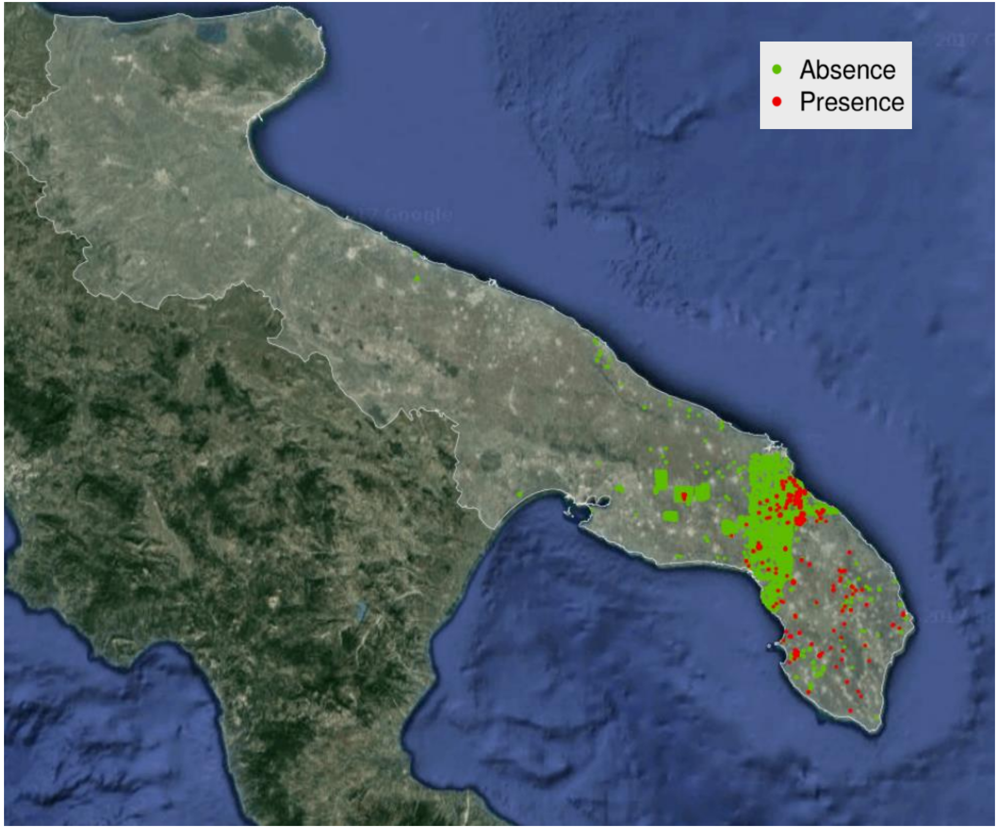
- Response variable
  - Presence/absence of *Xylella fastidiosa* (*Xf*)

2013-2014: Response variable: *Xf* presence/absence



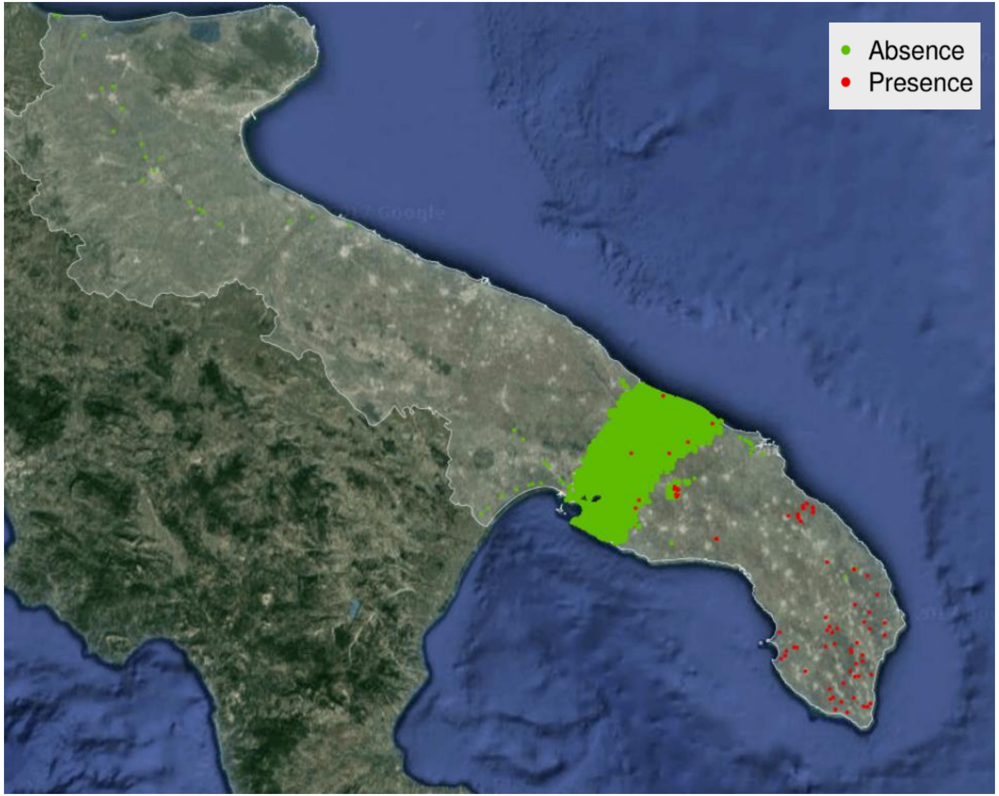
Data source:

2015: Response variable: *Xf* presence/absence



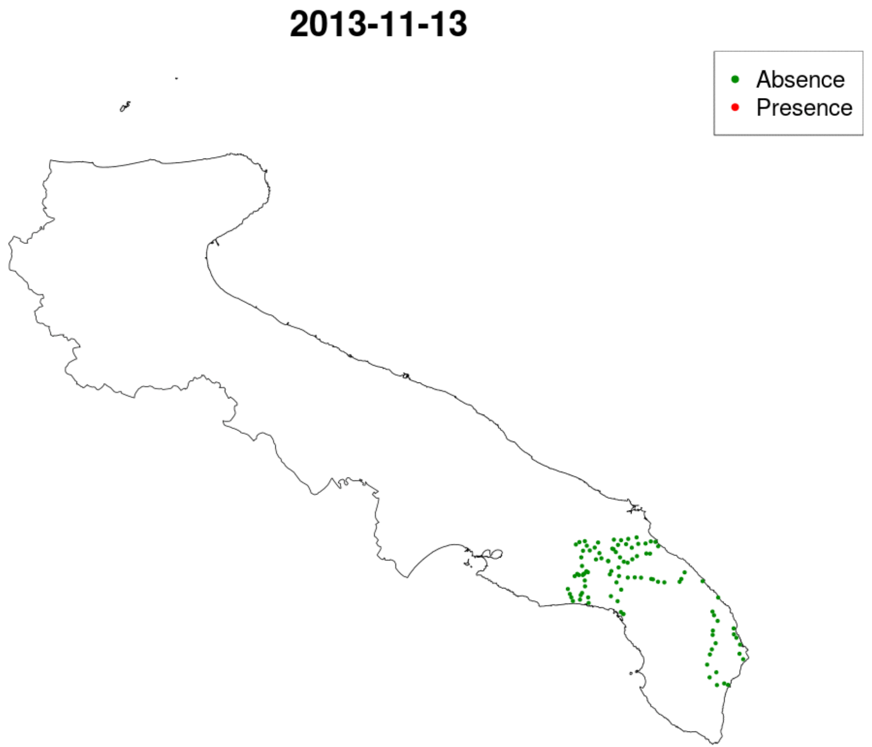
Data source:

2016: Response variable: *Xf* presence/absence



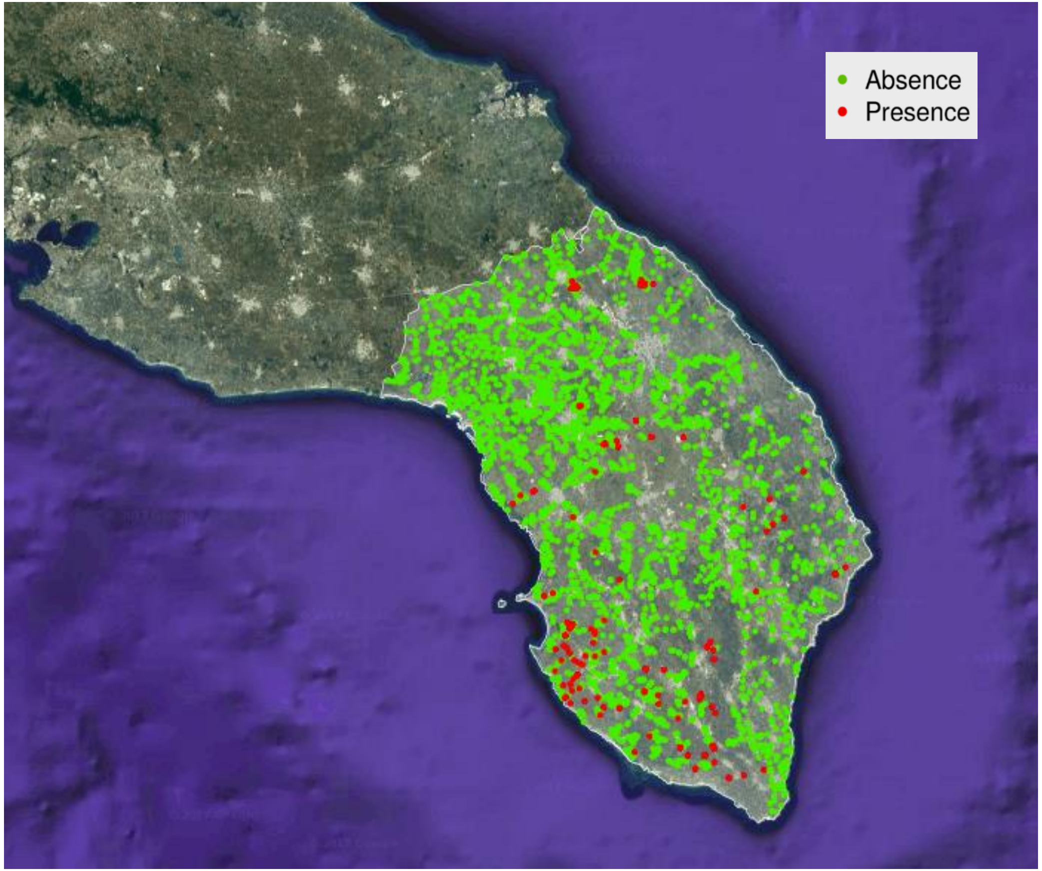
Data source:

Response variable: *Xf* presence/absence



Data source:

2013-2014: Response variable: *Xf* presence/absence



Data source:

Variables

- Response variable
  - Presence/absence of *Xylella fastidiosa*
- Covariates

Climate data: 1950-2000 (resolution 5′ (arc min))

WorldClim - Global Climate Data

Free climate data for ecological modeling and GIS

Download | Contact form | About us

Home

Bioclim

BIOCLIM

Bioclimatic variables are derived from the monthly temperature and rainfall values in order to generate more biologically meaningful variables. These are often used in ecological niche modeling (e.g., BIOCLIM, GARP). The bioclimatic variables represent annual trends (e.g., mean annual temperature, annual precipitation) seasonality (e.g., annual range in temperature and precipitation) and extreme or limiting environmental factors (e.g., temperature of the coldest and warmest month, and precipitation of the wet and dry quarters). A quarter is a period of three months (1/4 of the year).

They are coded as follows:

BIO1 = Annual Mean Temperature
BIO2 = Mean Diurnal Range (Mean of monthly (max temp - min temp))
BIO3 = Isothermality (BIO2/BIO7) (* 100)
BIO4 = Temperature Seasonality (standard deviation *100)
BIO5 = Max Temperature of Warmest Month
BIO6 = Min Temperature of Coldest Month
BIO7 = Temperature Annual Range (BIO5-BIO6)
BIO8 = Mean Temperature of Wettest Quarter
BIO9 = Mean Temperature of Driest Quarter
BIO10 = Mean Temperature of Warmest Quarter
BIO11 = Mean Temperature of Coldest Quarter
BIO12 = Annual Precipitation
BIO13 = Precipitation of Wettest Month
BIO14 = Precipitation of Driest Month
BIO15 = Precipitation Seasonality (Coefficient of Variation)
BIO16 = Precipitation of Wettest Quarter
BIO17 = Precipitation of Driest Quarter
BIO18 = Precipitation of Warmest Quarter
BIO19 = Precipitation of Coldest Quarter

INTERNATIONAL JOURNAL OF CLIMATOLOGY
Int. J. Climatol. **25**: 1965–1978 (2005)
Published online in Wiley InterScience (www.interscience.wiley.com). DOI: 10.1002/joc.1276

VERY HIGH RESOLUTION INTERPOLATED CLIMATE SURFACES FOR GLOBAL LAND AREAS

ROBERT J. HIJMANS,[a,*] SUSAN E. CAMERON,[a,b] JUAN L. PARRA,[a] PETER G. JONES[c] and ANDY JARVIS[c,d]
[a] *Museum of Vertebrate Zoology, University of California, 3101 Valley Life Sciences Building, Berkeley, CA, USA*
[b] *Department of Environmental Science and Policy, University of California, Davis, CA, USA; and Rainforest Cooperative Research Centre, University of Queensland, Australia*
[c] *International Center for Tropical Agriculture, Cali, Colombia*
[d] *International Plant Genetic Resources Institute, Cali, Colombia*

Köppen-Geiger classification

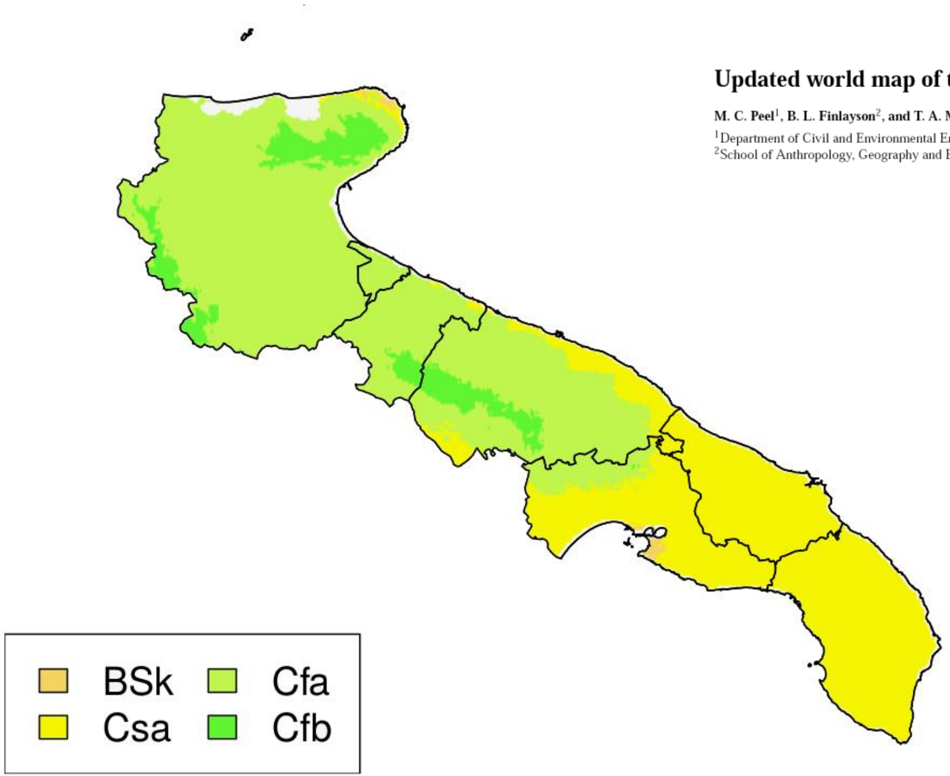
Hydrol. Earth Syst. Sci., 11, 1633–1644, 2007
www.hydrol-earth-syst-sci.net/11/1633/2007/

Hydrology and Earth System Sciences

Updated world map of the Köppen-Geiger climate classification

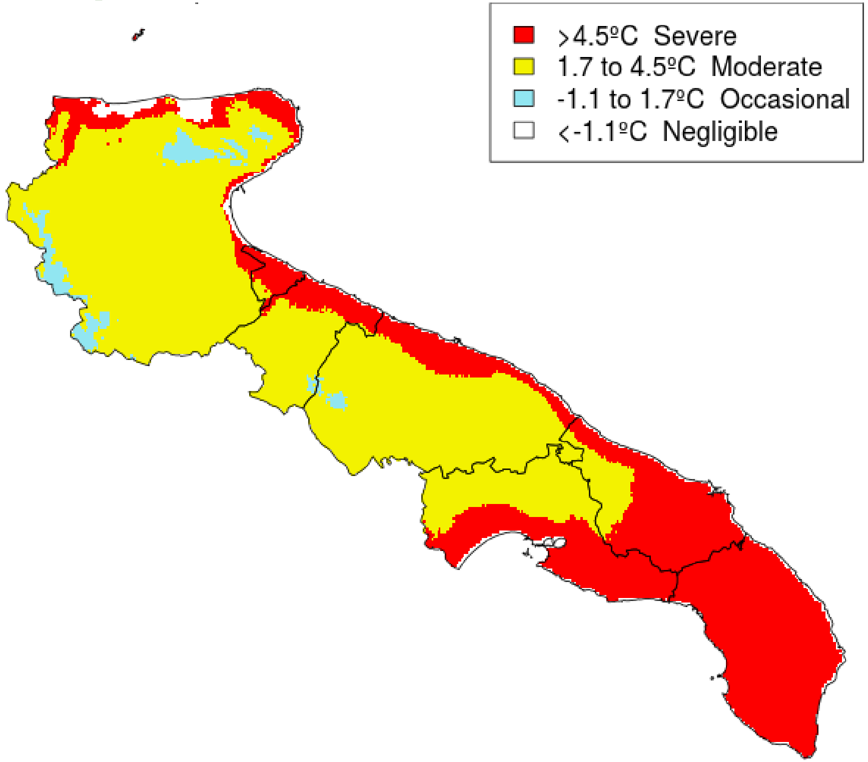
M. C. Peel[1], B. L. Finlayson[2], and T. A. McMahon[1]

[1]Department of Civil and Environmental Engineering, The University of Melbourne, Victoria, Australia
[2]School of Anthropology, Geography and Environmental Studies, The University of Melbourne, Victoria, Australia



Winter minimum temperature thresholds (ºC)

(as per A.H. Purcell)

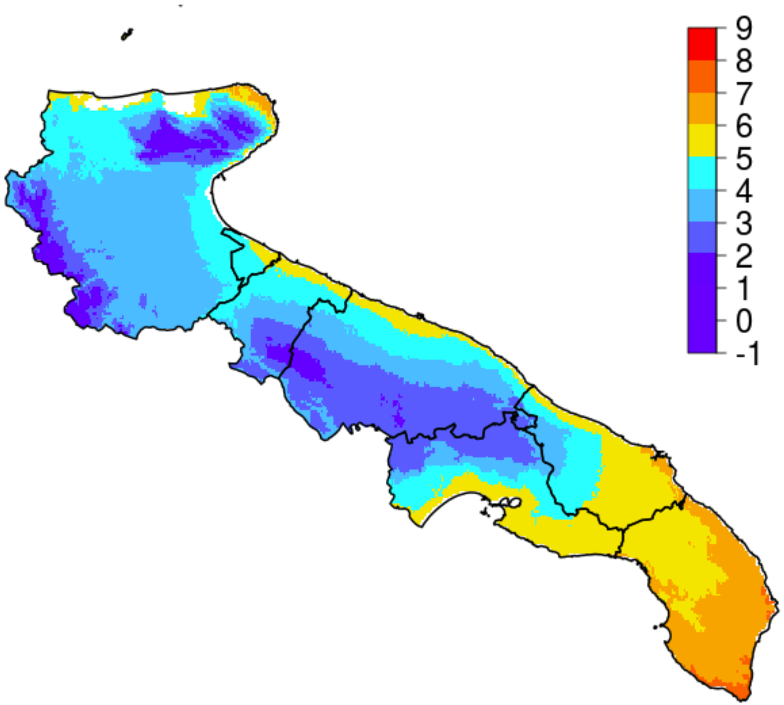


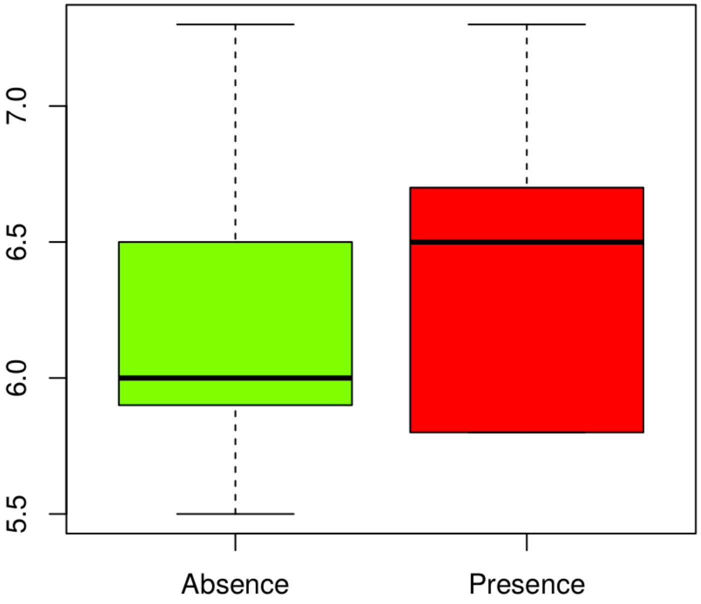
Variables

- Response variable
  - Presence/absence of *Xylella fastidiosa*

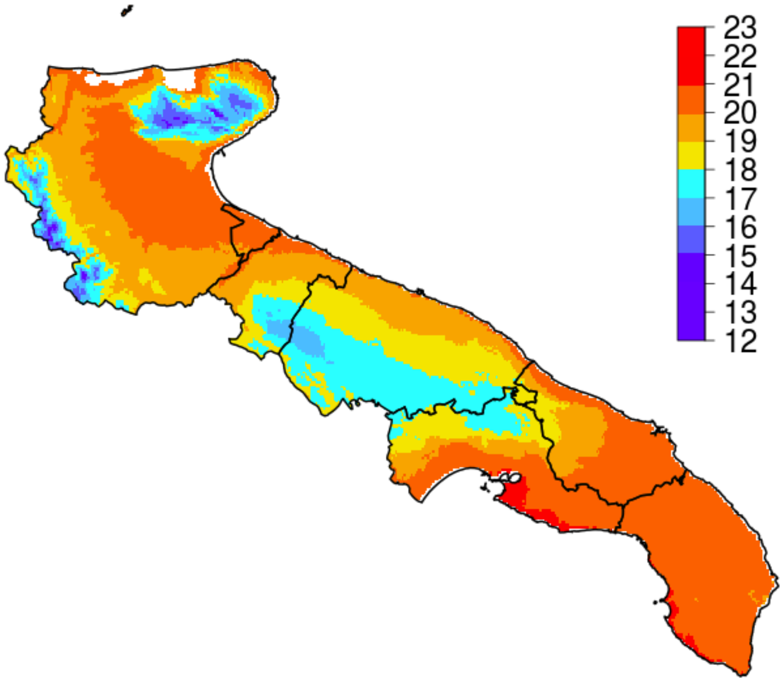
- Covariates
  - Minimun winter temperature (ºC)
  - Mean temperature (ºC) April-October (214 days)
  - Accumulated degree days April-October (T_{base}=15ºC)

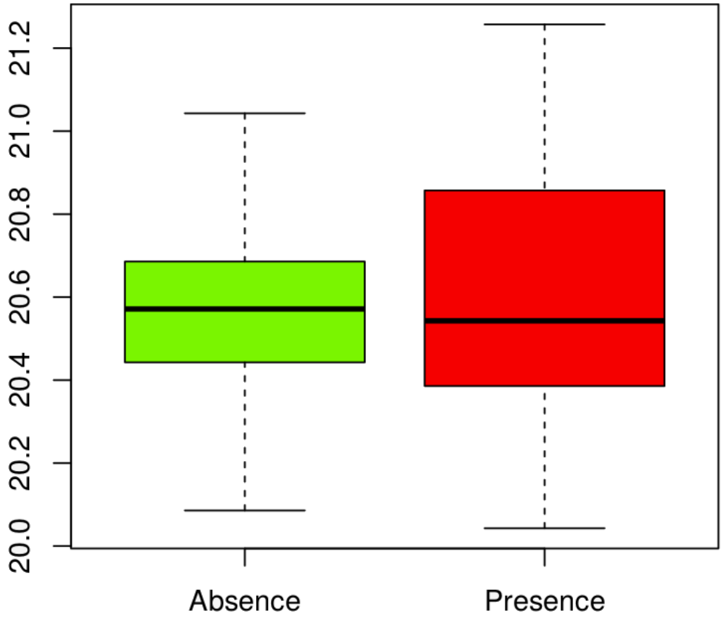
2013-2014: Covariates.Minimum winter temperature (ºC)



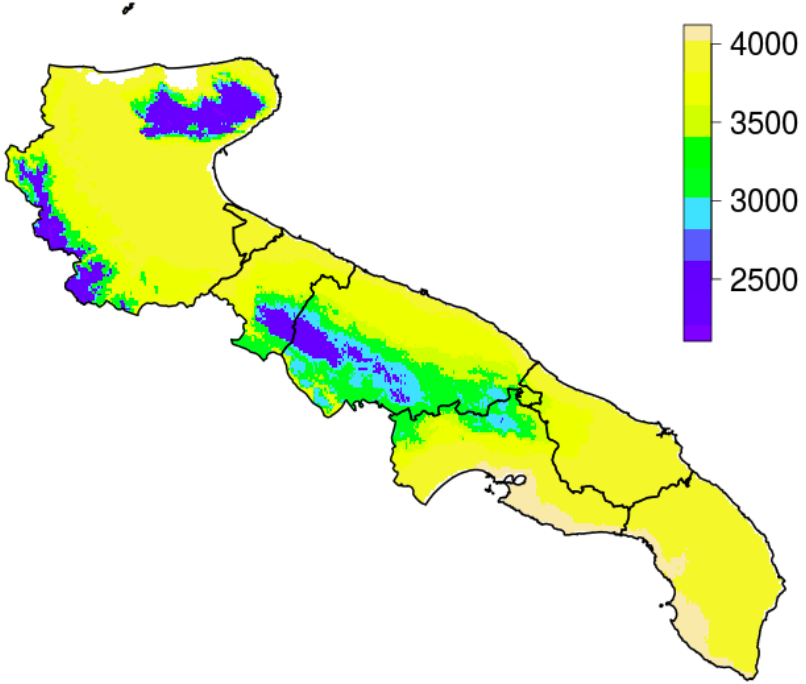


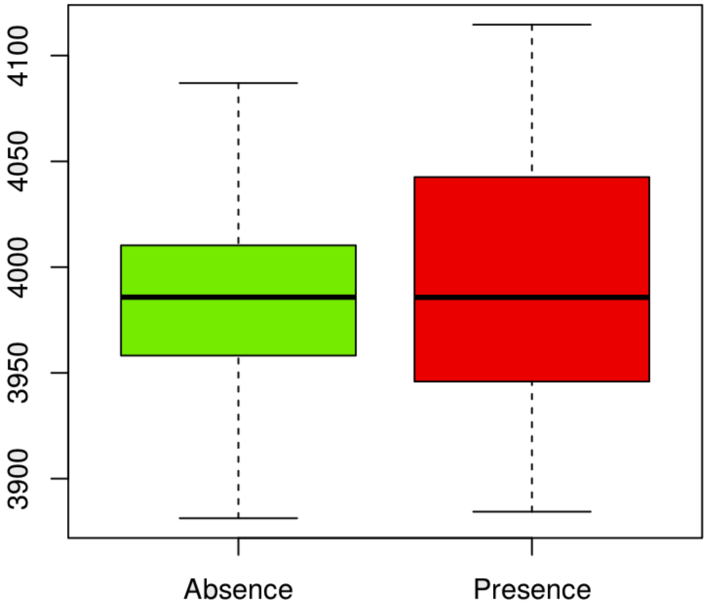
2013-2014: Covariates. Mean temperature (ºC) April-October (214 days)





2013-2014: Covariates. Accumulated degree days April-October (T_{base}=15ºC)





Bayesian inference

Prior distribution

Likelihood (data)

Posterior distribution

$$\pi(\theta|data) = \frac{\pi(\theta) \cdot \pi(data|\theta)}{\pi(data)}$$

- ADVANTAGES
  - Include prior information
  - Fit complex models
  - Posterior distribution of the parameters
    - Interpretation: confidence interval *vs.* credible interval
- DISADVANTAGES
  - To find an expression for the posterior distribution
    - Simulation

Bayesian inference

Prior distribution

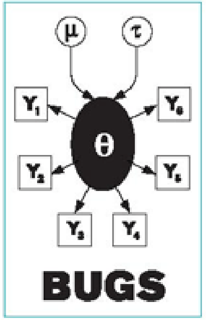
Likelihood (data)

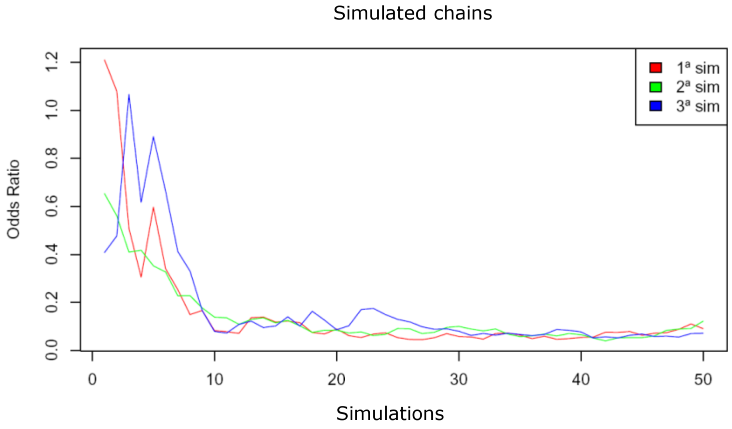
Posterior distribution

$$\pi(\theta|data) = \frac{\pi(\theta) \cdot \pi(data|\theta)}{\pi(data)}$$

Markov Chain Monte Carlo Methods (MCMC)

Bayesian inference Using Gibbs Sampling





Bayesian inference

Prior distribution

Likelihood (data)

Posterior distribution

$$\pi(\theta|data) = \frac{\pi(\theta) \cdot \pi(data|\theta)}{\pi(data)}$$

Fast and flexible modelling with R-INLA

Implementing Approximate Bayesian Inference using Integrated Nested Laplace Approximation: a manual for the `inla` program

Sara Martino and Håvard Rue
Department of Mathematical Sciences
NTNU, Norway

Compiled on September 1, 2009

Models

Likelihood

$$\begin{aligned} Y_i &\sim \text{Bernoulli}(\pi_i), \\ \text{logit}(\pi_i) &= \boldsymbol{X}_i\boldsymbol{\beta} + \boldsymbol{W}_i, \end{aligned}$$

Latent Gaussian field

$$\beta_0, \ldots, \beta_M \sim \text{N}(0; 10^{-4}), \boldsymbol{W} \sim \text{N}(0; \boldsymbol{Q}(r, \sigma_{\boldsymbol{W}})),$$

Hyperparameters

$$\log(r) \sim \text{N}(\mu_r; 0.1), \ \log(\sigma_{\boldsymbol{W}}) \sim \text{N}(\mu_{\sigma_{\boldsymbol{W}}}; 0.1).$$

$\boldsymbol{W}$ is the spatial effect with **Matérn covariance function**, r is referred to the range of the spatial effect and $\sigma_{\boldsymbol{W}}$ to the standard deviation of the spatial effect. μ_r has been chosen as the logarithm of the twenty percent of the total diameter of the region and $\mu_{\sigma_{\boldsymbol{W}}}$ as the logarithm of 1.

Models fitted for the 2013-2014 data

Models	WAIC	LCPO
y ~ intercept + tmin + w	1097.2540	0.1318
y ~ intercept + tmin	1717.5911	0.2042
y ~ intercept + tmin + ADD + tmean	1721.6515	0.2047
y ~ intercept + tmin + tmean	1722.8706	0.2049
y ~ intercept + tmin + ADD	1723.1563	0.2049
y ~ intercept + ADD + tmean	1750.2143	0.2081
y ~ intercept + tmean	1749.5566	0.2080
y ~ intercept + ADD	1750.0056	0.2081
y ~ intercept	1751.5407	0.2083

Models fitted for the 2013-2014 data

Models	WAIC	LCPO
y ~ intercept + tmin + w	**1097.2540**	**0.1318**
y ~ intercept + tmin	**1717.5911**	**0.2042**
y ~ intercept + tmin + ADD + tmean	1721.6515	0.2047
y ~ intercept + tmin + tmean	1722.8706	0.2049
y ~ intercept + tmin + ADD	1723.1563	0.2049
y ~ intercept + ADD + tmean	1750.2143	0.2081
y ~ intercept + tmean	1749.5566	0.208
y ~ intercept + ADD	1750.0056	0.2081
y ~ intercept	1751.5407	0.2083

Posterior distributions of the parameters for the best model (mean and 95% credibility interval)

Model	$\beta_0 + \beta_1$ tmin $+ W$
Intercept	-16.788 (-31.709, 0.881)
tmin	1.318 (-1.549, 3.575)
r	4.649 (2.693, 6.920)
σ_W	4.304 (3.034, 5.509)

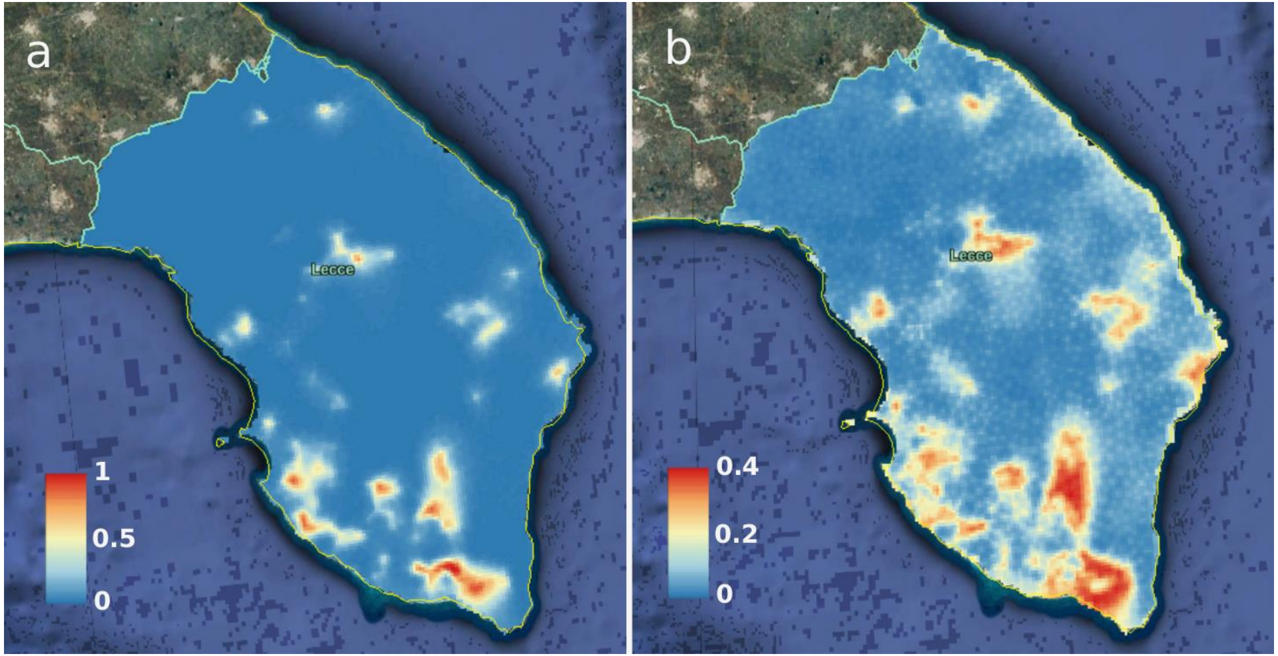
Posterior distribution: maps

Prediction

(Mean probability 0-1)

Uncertainty

(Standard deviation)

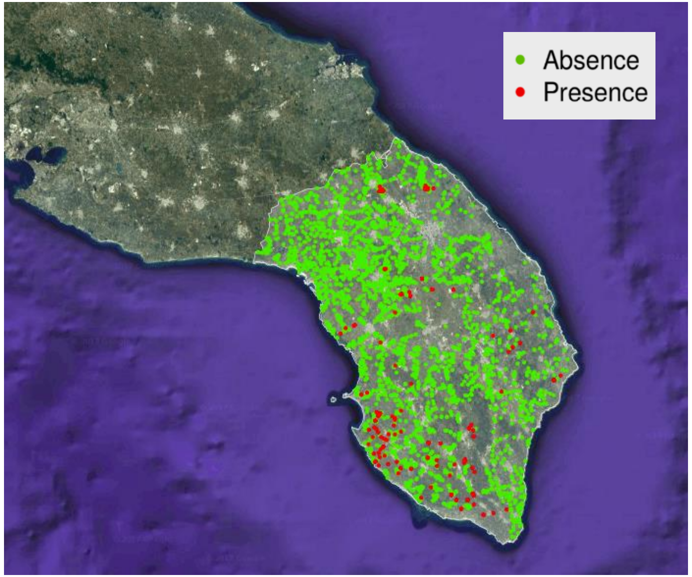


Evaluation of the model fitted to 2013-2014 data *vs.* 2015-2016 data

Model fitting (2013-2014)

224 presences 3981 absences

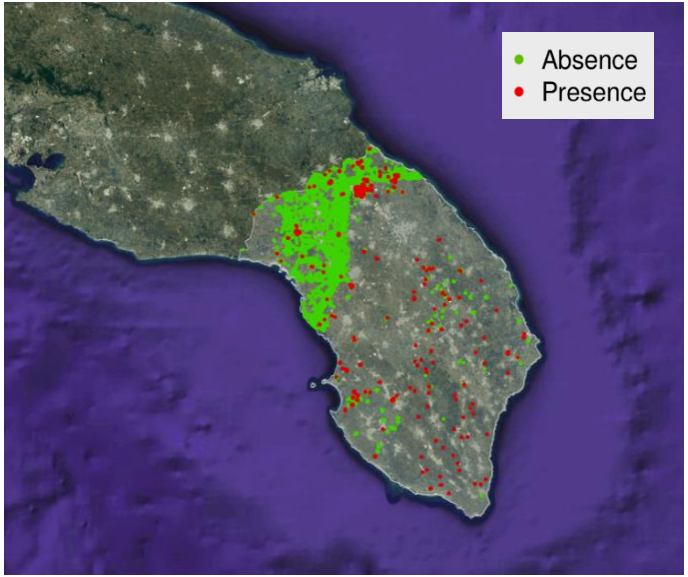
Prevalence = 5.32 %



Model evaluation (2015-2016)

4029 presences 35008 absences

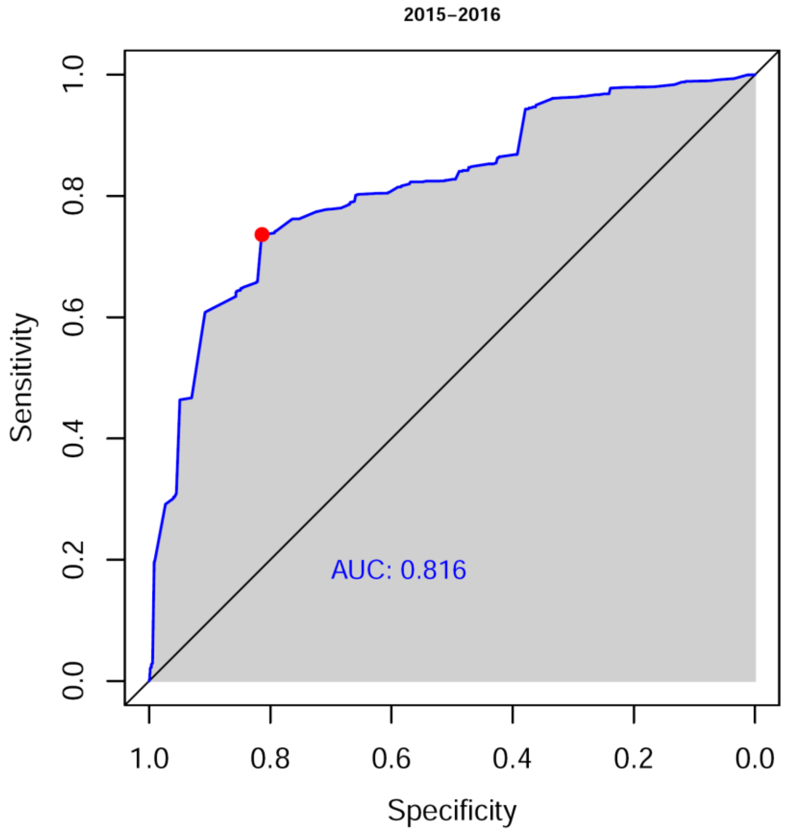
Prevalence = 10.32 %



Evaluation of the model fitted to 2013-2014 data *vs*. 2015-2016 data

True positive rate: 73%
True negative rate: 81%

False negative rate: 27%
False positive rate: 19%

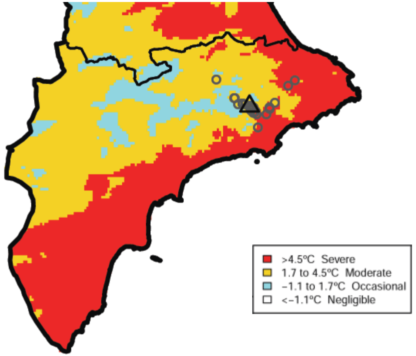


- CONCLUSIONS
  - The spatial effect had the strongest influence in *Xf* occurrence
  - Higher probability of *Xf* occurrence with increasing winter minimum temperature

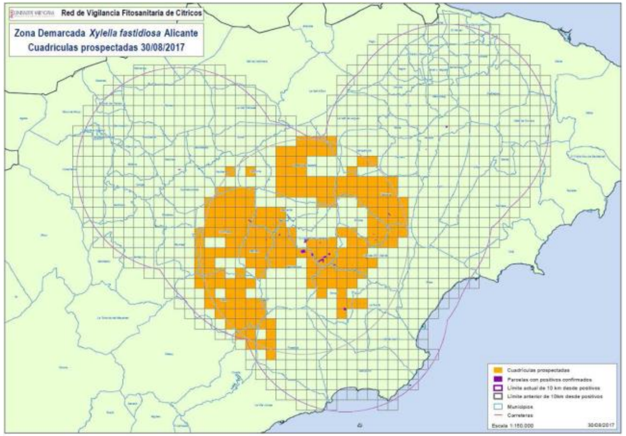
- CONCLUSIONS
  - The spatial effect had the strongest influence in *Xf* occurrence
  - Higher probability of *Xf* occurrence with increasing winter minimum temperature

- ONGOING WORK
  - New climatic databases (JRC-Agri4Cast, CMCC)
  - Include a temporal effect in the model
  - Other spatial models

June 2017, Detection of almond leaf scorch in Alicante, mainland Spain



GENERALITAT VALENCIANA
CONSELLERIA DE AGRICULTURA, MEDIO AMBIENTE, CAMBIO CLIMÁTICO Y DESARROLLO RURAL



THANKS FOR YOUR ATTENTION

PONTE
Pest Organisms Threatening Europe

XF ACTORS
Xylella Fastidiosa Active Containment Through a multidisciplinary-Oriented Research Strategy

European Commission