

EXTENT OF OCCURRENCE ESTIMATION FOR INVASIVE PLANTS

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Innpar2D Workshop
10th December 2019

Azorean islands, Terceira and São Miguel



Azorean islands



Figure: Geographical location of the Autonomous Region of the Azores.



NASA Terra satellite.

Extent of Occurrence for Invasive Plants in Portugal



5/28 invasive species in the database



Erigeron Karvinskianus



Pittosporum Undulatum



Agave Americana



Acacia Melanoxylon



Hedychium Gardnerianum



Figure: Terceira and São Miguel islands.

Extent of Occurrence for Invasive Plants in Portugal



Figure: 740 geographical locations for invasive plants in Terceira and São Miguel.

Extent of Occurrence for Invasive Plants in Portugal

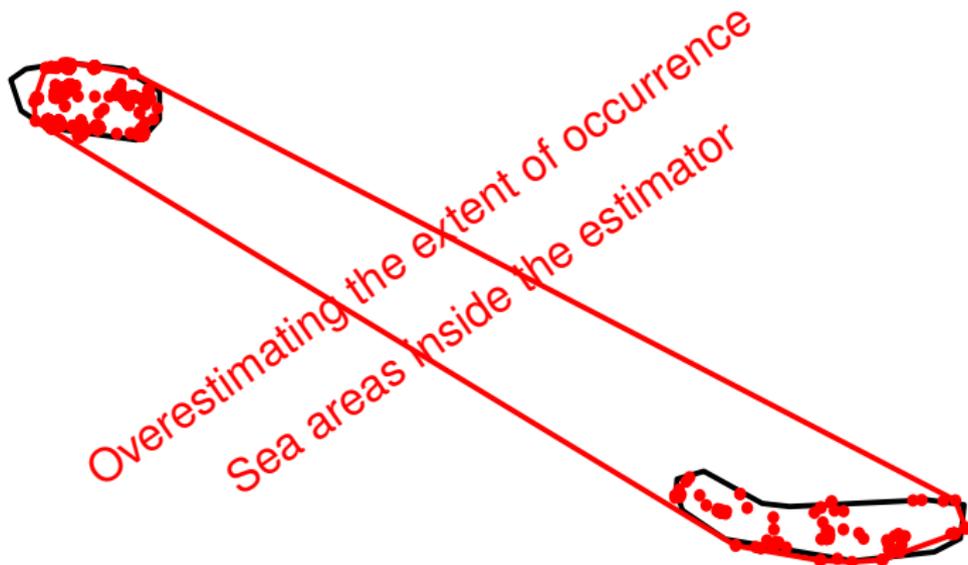


Figure: Convex hull of geographical locations.

Extent of Occurrence for Invasive Plants in Portugal

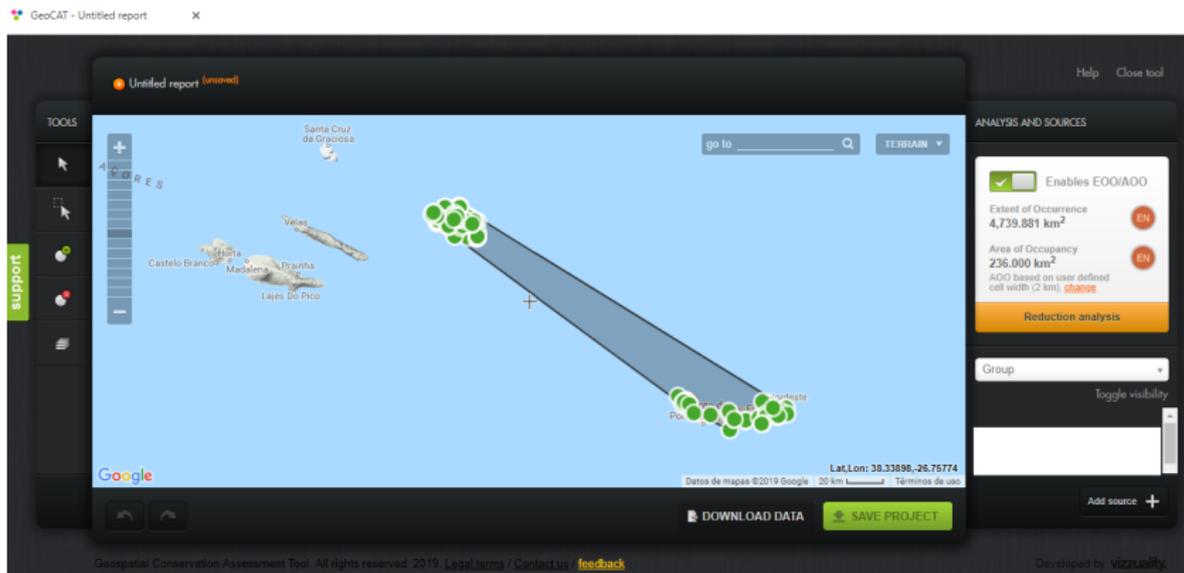


Figure: Geographical locations of invasive plants in Terceira and São Miguel islands.



GBIF.org (27th May 2019) GBIF Occurrence Download <https://doi.org/10.15468/dl.jto00d>.



International Union for Conservation of Nature



<http://geocat.kew.org/>

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The convex hull of a sample is the intersection of all halfspaces that contain it.

Figure: Convex hull of sample points.

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Figure: Convex hull of sample points.

Extent of Occurrence for Invasive Plants in Portugal

The r -convex hull of sample points for $r > 0$ can be calculated as the intersection of the complementaries of balls with radius bigger or equal than $r > 0$ containing the sample.

Figure: r -convex hull with $r = 0.3$.

Extent of Occurrence for Invasive Plants in Portugal

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Figure: r -convex hull with $r = 0.3$.

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Figure: r -convex hull with $r = 5$.



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Rodríguez-Casal, A. and Saavedra-Nieves, P. (2016). A fully data-driven method for estimating the shape of a point cloud. *ESAIM: Probability and Statistics*, 332-348.

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Figure: r -convex hull with $r = 5$



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Is it possible to estimate the shape index r from data?

Figure: r -convex hull with $r = 5$ (red) and convex hull (darkgreen).



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Is it possible to estimate the shape index r from data?



Figure: r -convex hull with $r = 0.03$.



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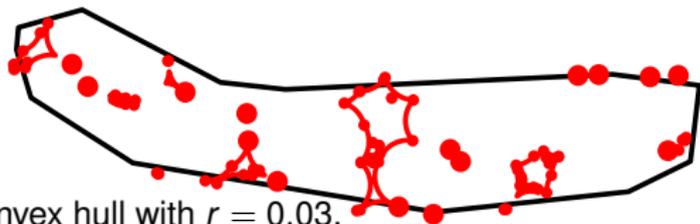
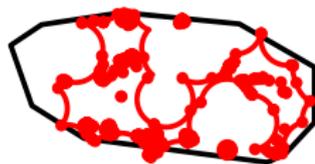


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 - ▶ Interpretation and influence of the shape index $r > 0$.
- A new automatic method to estimate the optimal value of r .
 - ▶ Theoretical results.
- Analysis of the resulting support estimator.
 - ▶ Convergence rates.
- Real data analysis.
 - ▶ Estimating the extent of occurrence for invasive plants.

Support estimation

Main task: Reconstructing the **support** S for an absolutely continuous probability measure from a random sample of points, $\mathcal{X}_n = \{X_1, \dots, X_n\}$.

Our goal: Proposing a new support estimator for reconstructing S that is r -convex and usually unknown.

How?

Step 1. Estimating the optimal value of the unknown parameter r , \hat{r} , from \mathcal{X}_n .

Step 2. Analyzing the \hat{r} -convex hull of \mathcal{X}_n as an estimator for S .

Support estimation

Our scenario: We will assume that S is r -convex which is a more flexible and general geometric condition than convexity*.

Definition: A set $A \subset \mathbb{R}^d$ is said to be r -convex, for $r > 0$, if

$$A = C_r(A),$$

where

$$C_r(A) = \bigcap_{\{B_r(x): B_r(x) \cap A = \emptyset\}} (B_r(x))^c$$

is the r -convex hull of A and $B_\epsilon(x)$, the open ball of radius $\epsilon > 0$ centered at x .

*If A is convex and closed then it is also r -convex for all $r > 0$ (see [Walther, 1999](#)).



Walther, G. (1999). On a generalization of Blaschke's rolling theorem and the smoothing of surfaces. *Mathematical Methods in the Applied Sciences*, 22, 301-316.

Support estimation

How could we interpret the parameter r ?

Figure: A ball of radius r rolls freely in $\overline{A^c}$.

* If A is r -convex then A ball of radius r rolls freely in $\overline{A^c}$ (see Cuevas et al., 2012).



Cuevas, A., Fraiman, R. and Pateiro-López, B. (2012). On statistical properties of sets fulfilling rolling-type conditions. *Advances in Applied Probability*, 44, 311–329.

A new method for selecting r

Our goal: We will estimate $r_0 = \sup\{r > 0 : C_r(S) = S\}$ under (f_L) :

(f_L) \mathcal{X}_n is generated from a density f that is bounded from below and Lipschitz continuous restricted to its bounded support S .

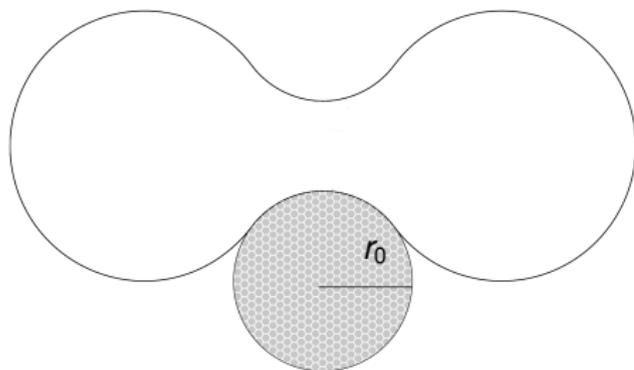


Figure: The value r_0 could be seen as a shape parameter.

r_0 is the optimal value to be estimated:

- If S is r -convex then it is r^* -convex for all $0 < r^* \leq r$. So, $C_{r^*}(S) \subset C_r(S) = S$.

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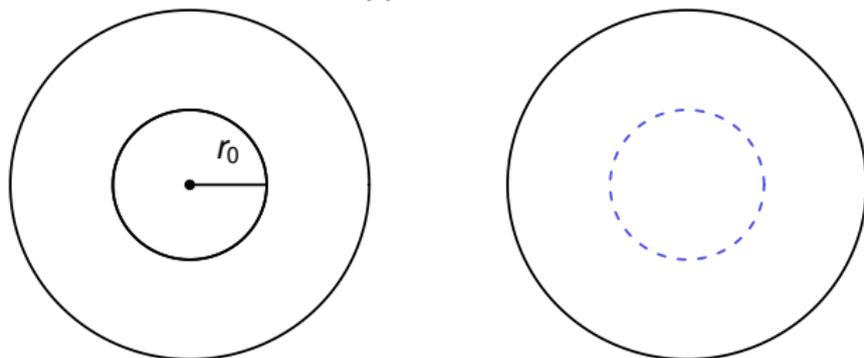


Figure: $C_r(S)$ (right) is considerably bigger than the circular ring S (left) if $r > r_0$.

r_0 is the optimal value to be estimated:

- If S is r -convex then it is r^* -convex for all $0 < r^* \leq r$. So, $C_{r^*}(S) \subset C_r(S) = S$.
- If $r > r_0$ then $C_r(S)$ and S could be very different

A new method for selecting r

Is always $r_0 = \sup\{r > 0 : C_r(S) = S\}$ a maximum? It is a maximum under (R'_λ) .

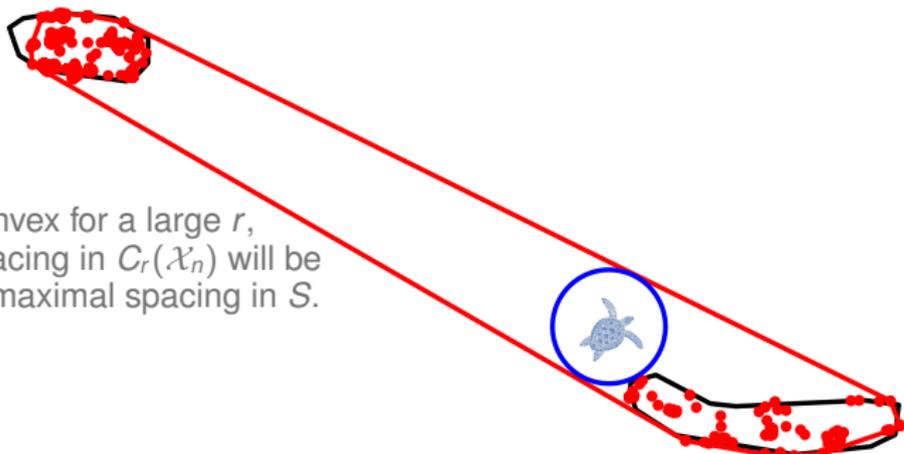
Figure: (R'_λ) A ball of radius $\lambda > 0$ rolls freely in S and a ball of radius $r > 0$ rolls in $\overline{S^c}$. If $r = \lambda$, the boundary is smooth and the curvature is bounded by $1/r$, see [Walther \(1997\)](#).



Walther, G. (1997). Granulometric smoothing. *Annals of Statistics*, 25, 2273–2299.

A new method for selecting r

How will we estimate the shape parameter r_0 ? Testing r -convexity for a given $r > 0$!



If S is not r -convex for a large r , the maximal spacing in $C_r(\mathcal{X}_n)$ will be larger than the maximal spacing in S .

Figure: Largest ball (blue) inside the convex hull of \mathcal{X}_n that does not intersect \mathcal{X}_n .

- Given $r > 0$, we have proposed a test:

$H_0 : S$ is r -convex versus $H_1 : S$ is not r -convex.

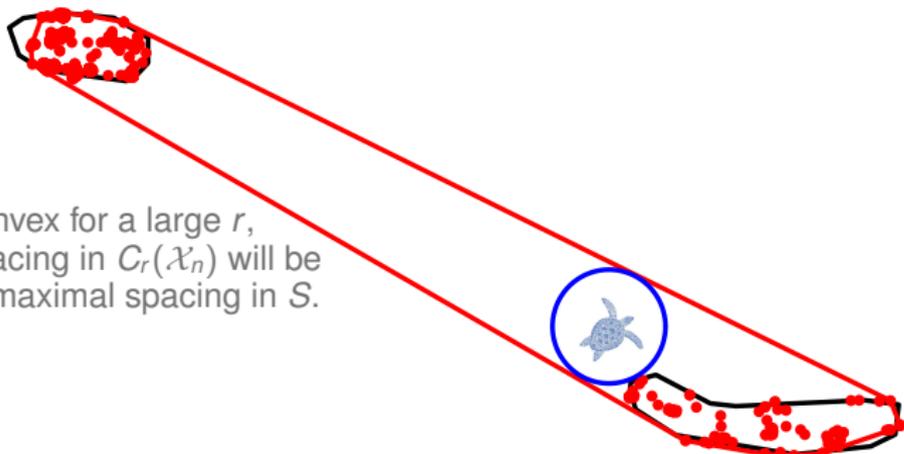
- This test rejects H_0 when it detects a large spacing in $C_r(\mathcal{X}_n)$.
- Under (f_L) and (R_λ^r) , the test rejects H_0 if r is too large.



Janson, S. (1987). Maximal Spacings in Several Dimensions. *Annals of Probability*, 1, 274–280.

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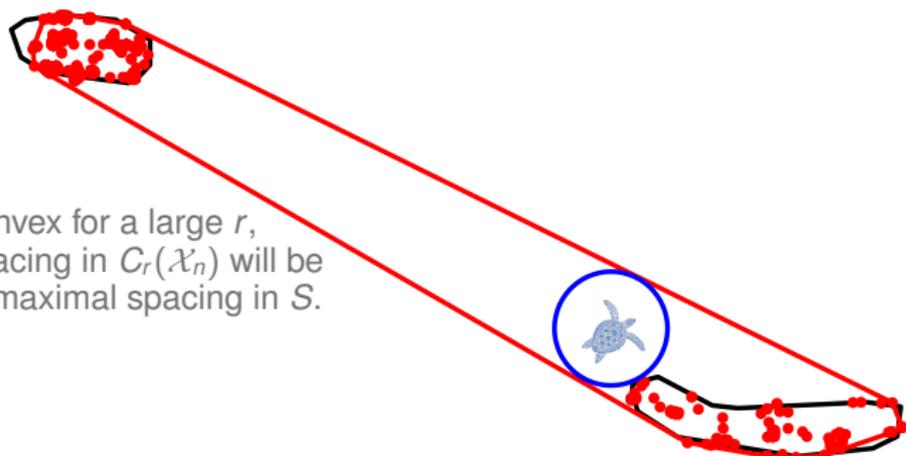
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Berrendero, J. R., Cuevas, A. and Pateiro-López, B. (2012). A multivariate uniformity test for the case of unknown support. *Statistics and Computing*, 22, 259-271.

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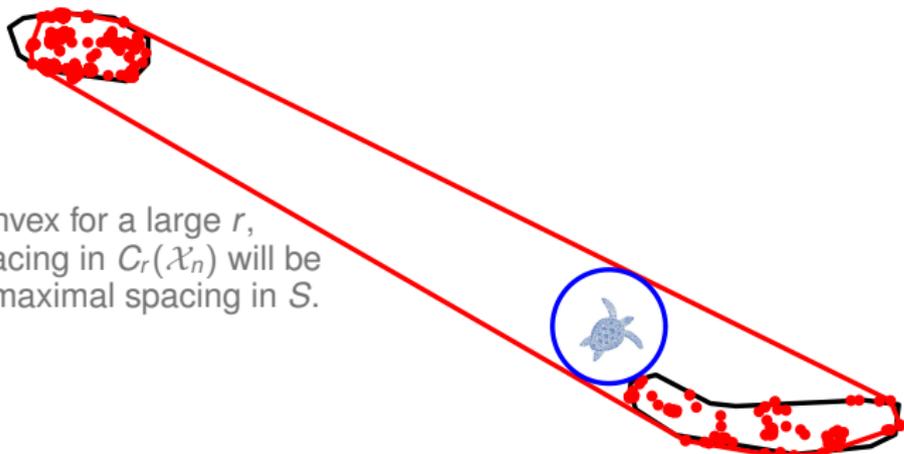
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Aaron, C., Cholaquidis, A. and Fraiman, R. (2017). A generalization of the maximal-spacings in several dimensions and a convexity test. *Extremes*, 20, 605-634.

A new method for selecting r

How will we estimate the shape parameter r_0 ? Testing r -convexity for a given $r > 0$!



If S is really r -convex, the maximal spacings in $C_r(\mathcal{X}_n)$ and S will be similar.



Figure: Largest ball (blue) inside the estimator $C_{0.3}(\mathcal{X}_n)$ that does not intersect \mathcal{X}_n .

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A new method for selecting r

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Figure: Largest ball (blue) inside the known support S that does not intersect \mathcal{X}_n .

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A new method for selecting r

Our estimator:

$\hat{r}_0 = \sup\{\gamma > 0 : \text{The null hypothesis } H_0 \text{ that } S \text{ is } \gamma\text{-convex is accepted}\}.$

Dependence on the significance level α of the test:

- It is not important from the theoretical point of view:
 - ▶ It is assumed that $\alpha = \alpha_n$ goes to zero as the sample size increases.
- In practice, \hat{r}_0 could be too small for a fixed sample:
 - ▶ The level of fragmentation of the estimator was bounded.

Consistency of the new method for selecting r

Theorem: Let α_n be a sequence converging to zero. Under (R_λ^r) , (f_L) and some additional assumptions,

$$\lim_{n \rightarrow \infty} \mathbb{P}(\hat{r}_0 \geq r_0) = 1.$$

Theorem: Let α_n be a sequence converging to zero such that $\log(\alpha_n)/n \rightarrow 0$. Under (R_λ^r) , (f_L) and some additional assumptions,

$$\hat{r}_0 \rightarrow r_0 \text{ in probability.}$$

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$\hat{r}_0 \rightarrow r_0$ in probability.

*Could we consider $C_{\hat{r}_0}(\mathcal{X}_n)$ as an estimator for the support S ?

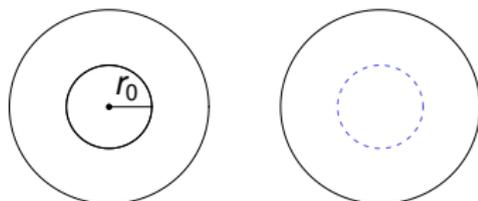


Figure: If $r > r_0$, $C_r(S)$ (right) can be considerably bigger than the circular ring S (left).

Consistency of the new support estimator

Theorem: Let α_n be a sequence converging to zero such that $\log(\alpha_n)/n \rightarrow 0$. Under (R_λ^r) , (f_L) and some additional assumptions, let be $\nu \in (0, 1)$ and $r_n = \nu \hat{r}_0$. Then,

$$d_H(\mathcal{S}, C_{r_n}(\mathcal{X}_n)) = O_P \left(\left(\frac{\log n}{n} \right)^{\frac{2}{d+1}} \right),$$

$$d_H(\partial \mathcal{S}, \partial C_{r_n}(\mathcal{X}_n)) = O_P \left(\left(\frac{\log n}{n} \right)^{\frac{2}{d+1}} \right),$$

$$\mu(\mathcal{S} \Delta C_{r_n}(\mathcal{X}_n)) = O_P \left(\left(\frac{\log n}{n} \right)^{\frac{2}{d+1}} \right).$$

* This estimator achieves the same convergence rates as the convex hull for convex sets, see [Dümbgen and Walther \(1996\)](#).



Dümbgen, L. and Walther, G. (1996). Rates of convergence for random approximations of convex sets. *Advances in Applied Probability*, 28, 384-393.



Rodríguez-Casal, A. and Saavedra-Nieves, P. (2014). A fully data-driven method for estimating the shape of a point cloud. *ESAIM: Probability and Statistics*, 20, 332-348.

Real data analysis

Estimation of the extent of occurrence from the 740 geographical locations:



5/28 invasive species in the database



Erigeron Karvinskianus



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Acacia Melanoxylon



Hedychium Gardnerianum



Figure: $\hat{\tau}_0$ —convex hull of \mathcal{X}_{740} . The significance level for the test was fixed equal to 0.01.

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Real data analysis

Estimation of the extent of occurrence in São Miguel island by year:



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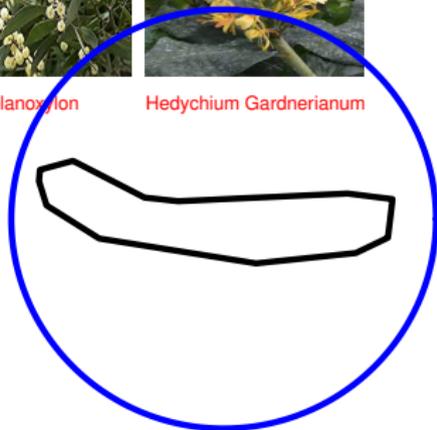


Figure: São Miguel island.

Real data analysis

Estimation of the extent of occurrence in São Miguel island by year:

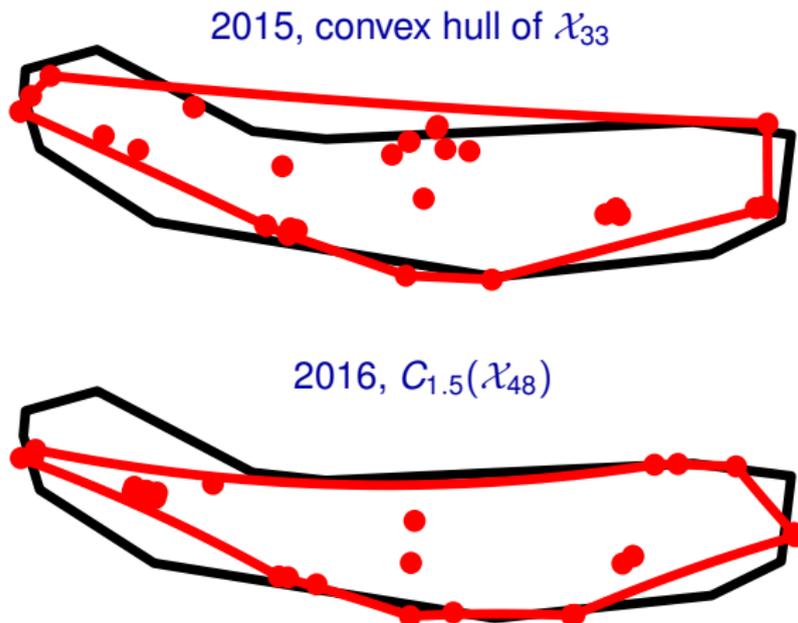


Figure: Estimations for the São Miguel island. The significance level for the test was fixed equal to 0.01.

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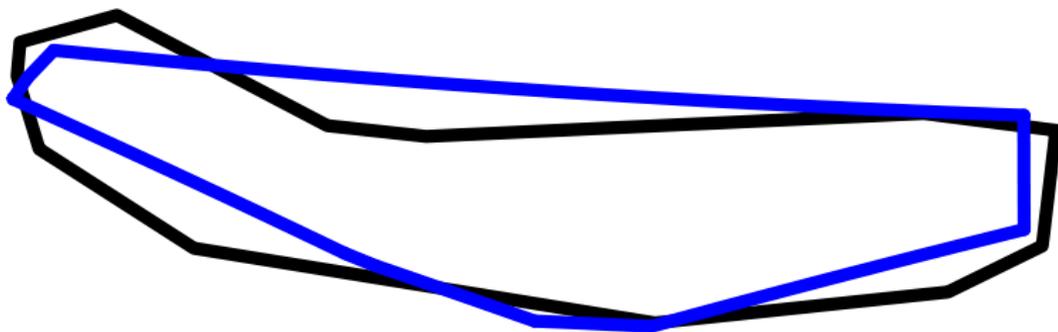


Figure: Evolution of invasive species in São Miguel island: 2015 (blue) and 2016 (gray).

Real data analysis

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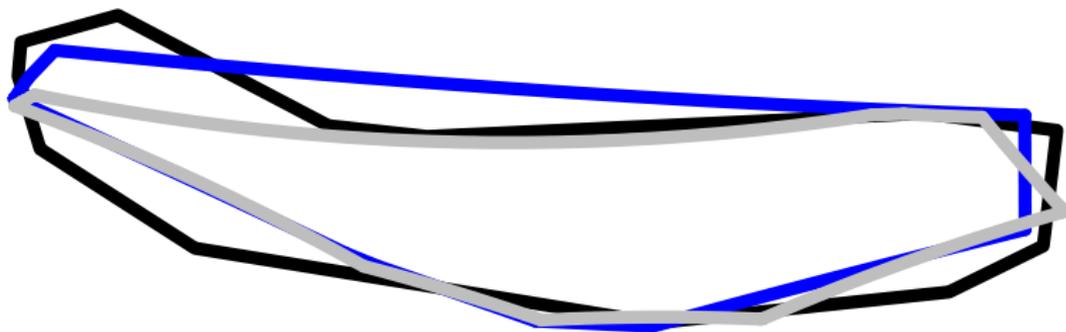


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YHANS

The image shows the word "YHANS" in a stylized, outlined font. Each letter is filled with a grid of small black dots. The letters are: 'Y' with a central vertical stem and two side arms; 'H' with two vertical stems and a connecting horizontal bar; 'A' with a central vertical stem, a horizontal bar, and a triangular top; 'N' with a vertical stem, a horizontal bar, and a diagonal stem; 'S' with a vertical stem, a horizontal bar, and a curved bottom; and 'S' with a vertical stem, a horizontal bar, and a curved bottom. The dots are arranged in a regular grid pattern within each letter's outline.

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