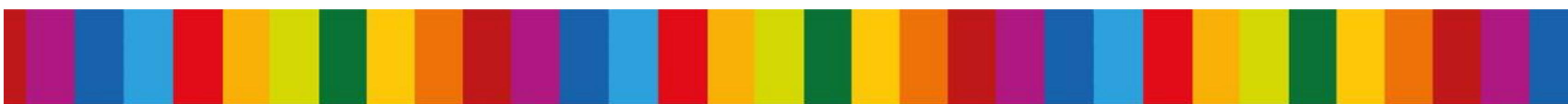


 @flograttarola

 ecoevo.social/@flograttarola

Modelos integrados de distribución de especies (ISDMs) para evaluar la dinámica en el rango de distribución geográfica de carnívoros Neotropicales

El caso del Yaguarundí (*Herpailurus yagouaroundi*) en América Latina



Florencia Grattarola | Czech University of Life Sciences in Prague



MOBI Lab

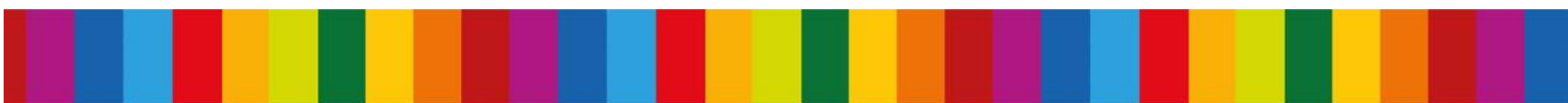
 Faculty of
Environmental Sciences

 @flograttarola

 ecoevo.social/@flograttarola

¿Cómo modelar los cambios en el área de distribución geográfica de las especies con datos insuficientes?

El caso del Yaguarundí (*Herpailurus yagouaroundi*) en América Latina





Received: 19 September 2022 | Revised: 14 March 2023 | Accepted: 31 March 2023

DOI: 10.1111/jbi.14622

RESEARCH ARTICLE

Integrating presence-only and presence-absence data to model changes in species geographic ranges: An example in the Neotropics

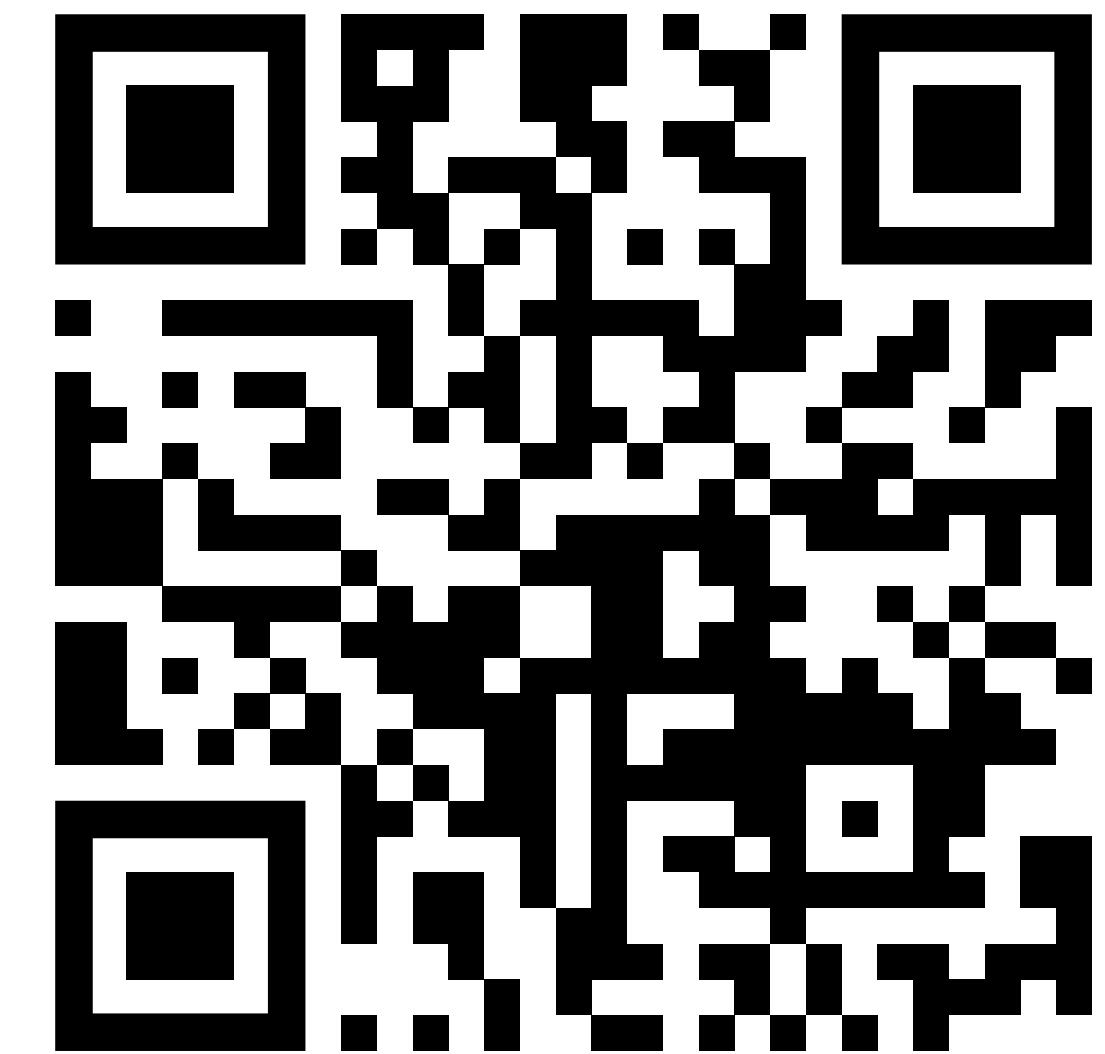
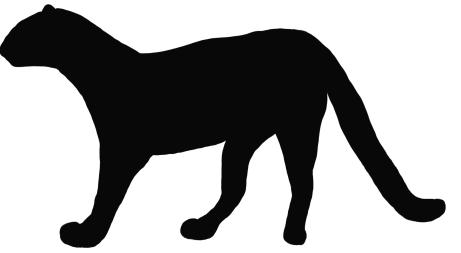
Florencia Grattarola¹  | Diana E. Bowler^{2,3,4} | Petr Keil¹



Journal of
Biogeography



WILEY



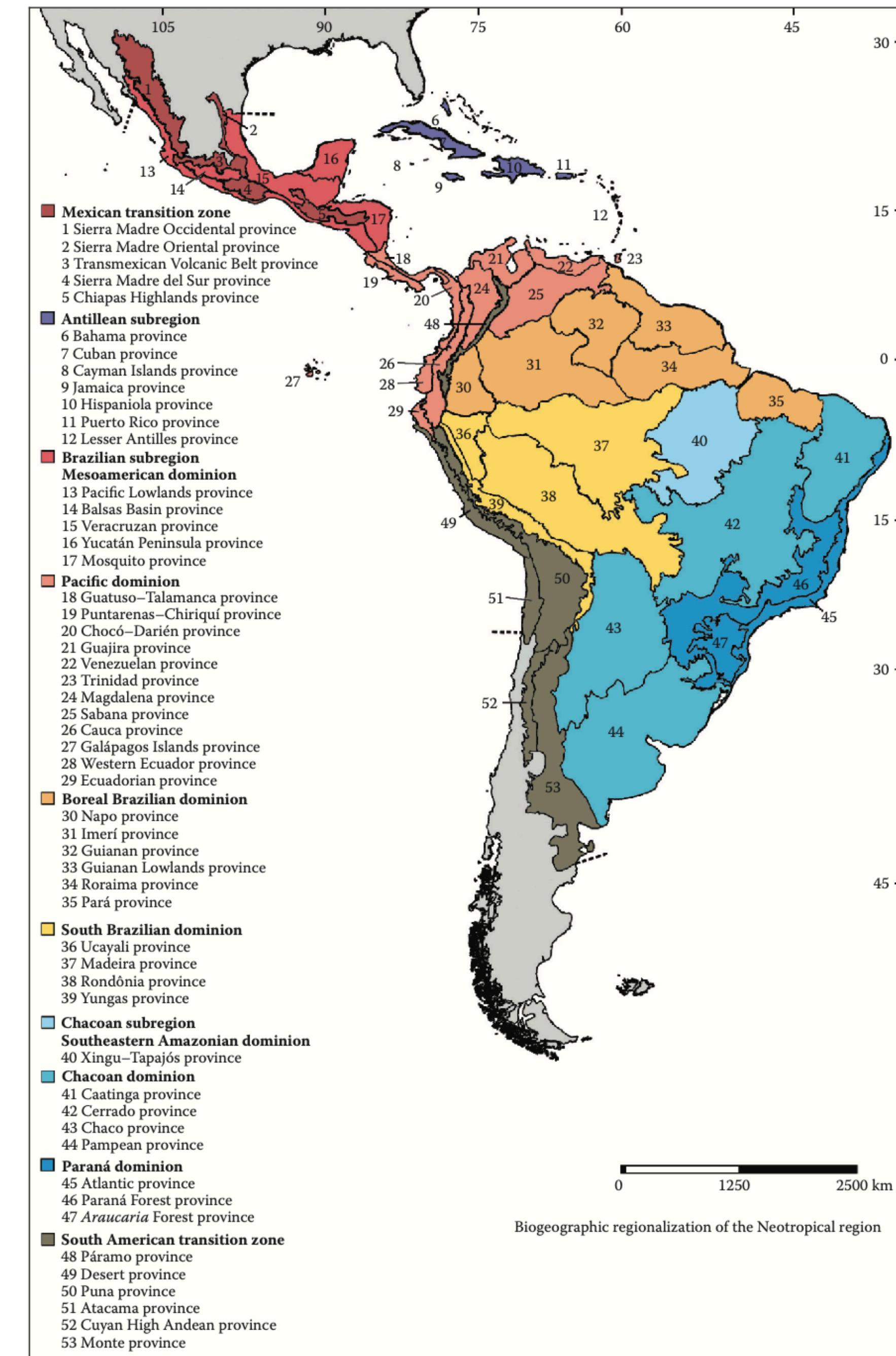
Artículo Open Access

<https://doi.org/10.1111/jbi.14622>

Región Neotropical

Megadiversa

- Uno de los hotspots de biodiversidad más importantes del mundo.
- Una de las zonas que ha experimentado la conversión más generalizada del hábitat natural.



Región Neotropical

Falta de datos

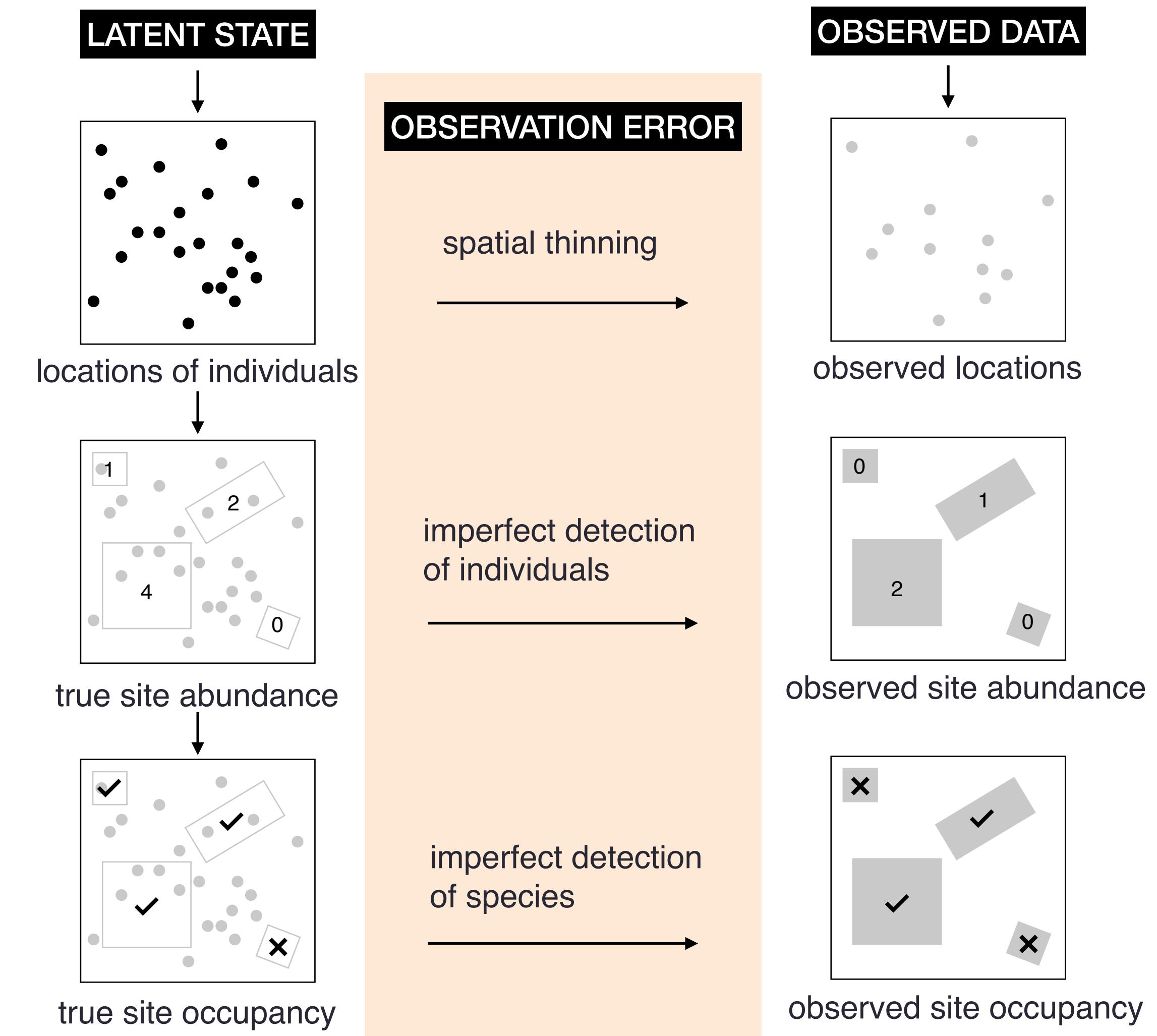
- La cantidad de datos abiertos sobre biodiversidad en la región ha aumentado notablemente en las últimas décadas.
- Sin embargo, los datos que cubren grandes áreas durante períodos largos de tiempo suelen ser escasos.



ISDMs

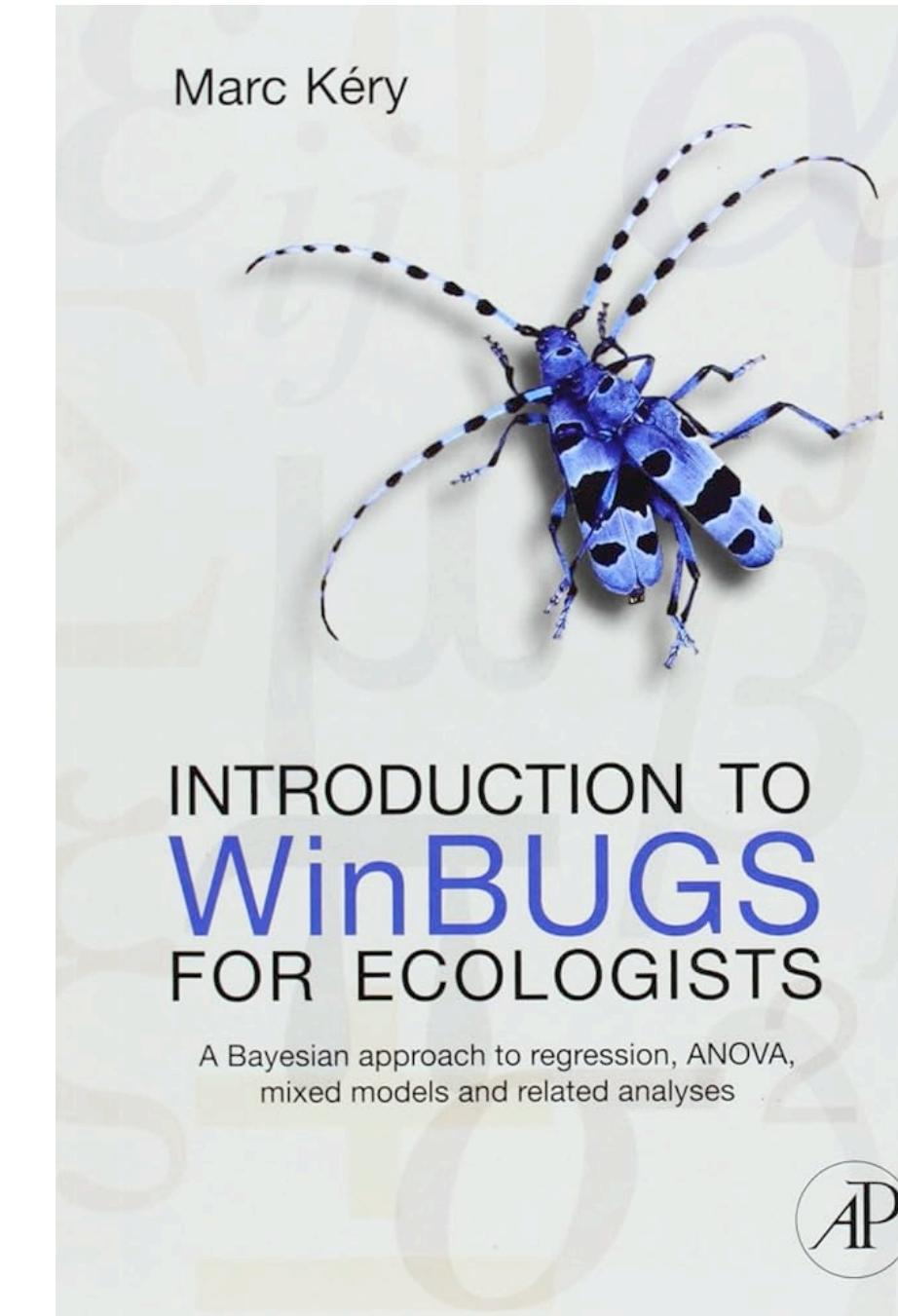
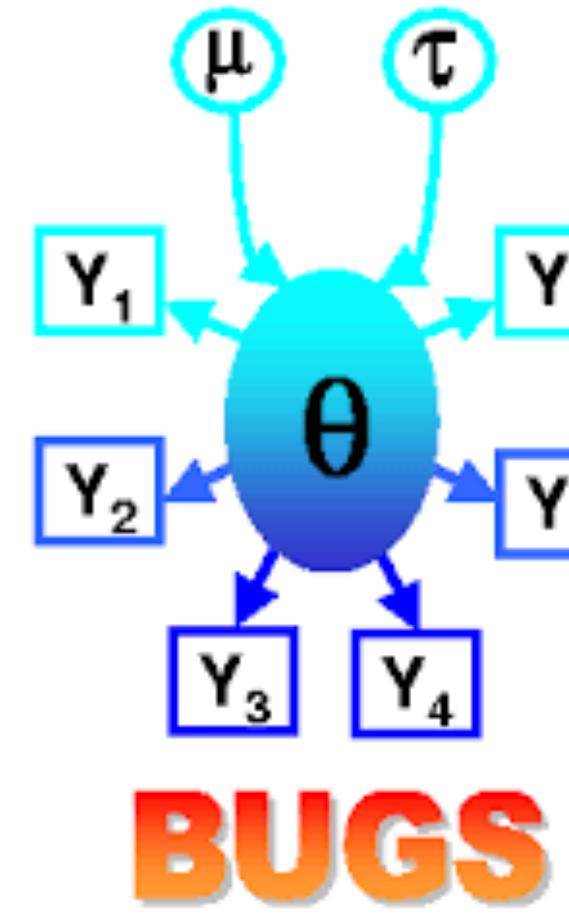
Modelos integrados de distribución de especies

- El estado latente es la distribución real (no observada) de las especies puede representarse con un **Proceso Puntual de Poisson**.
- Esta distribución verdadera se muestrea mediante distintos procesos de observación, generando los datos de sólo presencia, abundancia y presencia-ausencia que observamos.
- Como los procesos de observación pueden ser imperfectos, se pueden considerar distintos errores de observación.



ISDMs

Herramientas



JAGS



INLA
r-inla inlabru



ISDMs

Usos

ECOGRAPHY

Research
Integration of presence-only data from several sources: a case study on dolphins' spatial distribution

Sara Martino^a, Daniela Silvia Pace^a, Stefano Moro, Edoardo Casoli, Daniele Ventura, Alessandro Frachea, Margherita Silvestri, Antonella Arcangeli, Giancarlo Giacomini, Giandomenico Ardizzone and Giovanna Jona Lasinio

DOI: 10.1111/ddi.12631

BIODIVERSITY RESEARCH WILEY Diversity and Distributions A Journal of Ecological Applications

Using a novel model approach to assess the distribution and conservation status of the endangered Baird's tapir

Cody J. Schank^{1,2} | Michael V. Cove³ | Marcella J. Kelly⁴ | Eduardo Mendoza⁵ | Georgina O'Farrill⁶ | Rafael Reyna-Hurtado⁷ | Ninon Meyer^{7,8} | Christopher A. Jordan^{2,9,10} | Jose F. González-Maya¹¹ | Diego J. Lizcano^{12,13} | Ricardo Moreno^{8,14} | Michael T. Dobbins¹⁵ | Victor Montalvo¹⁶ | Carolina Sáenz-Bolaños^{16,17} | Eduardo Carillo Jimenez¹⁶ | Nereyda Estrada¹⁸ | Juan Carlos Cruz Díaz^{16,17} | Joel Saenz¹⁶ | Manuel Spínola¹⁶ | Andrew Carver¹⁹ | Jessica Fort¹⁹ | Clayton K. Nielsen¹⁹ | Francisco Botello^{20,21} | Gilberto Pozo Montuy²² | Marina Rivero^{7,23} | Jesús Antonio de la Torre^{23,24} | Esteban Brenes-Mora^{25,26} | Oscar Godínez-Gómez⁵ | Margot A. Wood^{27,28} | Jessica Gilbert²⁹ | Jennifer A. Miller¹

Received: 7 April 2021 | Revised: 24 August 2021 | Accepted: 5 September 2021
DOI: 10.1111/ddi.13416

RESEARCH ARTICLE Diversity and Distributions WILEY

Integrating citizen-science and planned-survey data improves species distribution estimates

Viviane Zulian¹ | David A. W. Miller² | Gonçalo Ferraz¹

Biological Conservation 241 (2020) 108374
Contents lists available at ScienceDirect
 ELSEVIER Biological Conservation journal homepage: www.elsevier.com/locate/biocon



Integrating multiple data sources and multi-scale land-cover data to model the distribution of a declining amphibian

Jonathan P. Rose^{a,*}, Brian J. Halstead^a, Robert N. Fisher^b

^a U.S. Geological Survey, Western Ecological Research Center, Dixon Field Station, 800 Business Park Dr, Suite D, Dixon, CA 95620, USA
^b U.S. Geological Survey, Western Ecological Research Center, San Diego Field Station, 4165 Spruance Road, Suite 200, San Diego, CA 92101, USA

SCIENTIFIC REPORTS

OPEN ed: 12 April 2018 | Integrating data from different survey types for population monitoring of an endangered species: the case of the Eld's deer
ed: 8 May 2019 | ed online: 23 May 2019

Diana E. Bowler¹, Erlend B. Nilsen¹, Richard Bischof², Robert B. O'Hara³, Thin Thin Yu⁴, Tun Oo⁵, Myint Aung⁵ & John D. C. Linnell¹

Statistical Report

Ecology, 102(1), 2021, e03204
© 2020 by the Ecological Society of America

Integrating distance sampling and presence-only data to estimate species abundance

MATTHEW T. FARR^{1,2,4}, DAVID S. GREEN^{1,2,3}, KAY E. HOLEKAMP^{1,2} AND ELISE F. ZIPKIN^{1,2}

Methods in Ecology and Evolution

Methods in Ecology and Evolution 2014, 5, 751–760
doi: 10.1111/2041-210X.12221

Quantifying range-wide variation in population trends from local abundance surveys and widespread opportunistic occurrence records

Jörn Pagel^{1,2,*}, Barbara J. Anderson^{3,4}, Robert B. O'Hara⁵, Wolfgang Cramer⁶, Richard Fox⁷, Florian Jeltsch¹, David B. Roy⁸, Chris D. Thomas⁴ and Frank M. Schurr^{2,9}

Received: 25 November 2020 | Revised: 8 February 2021 | Accepted: 11 February 2021
DOI: 10.1111/ddi.13259

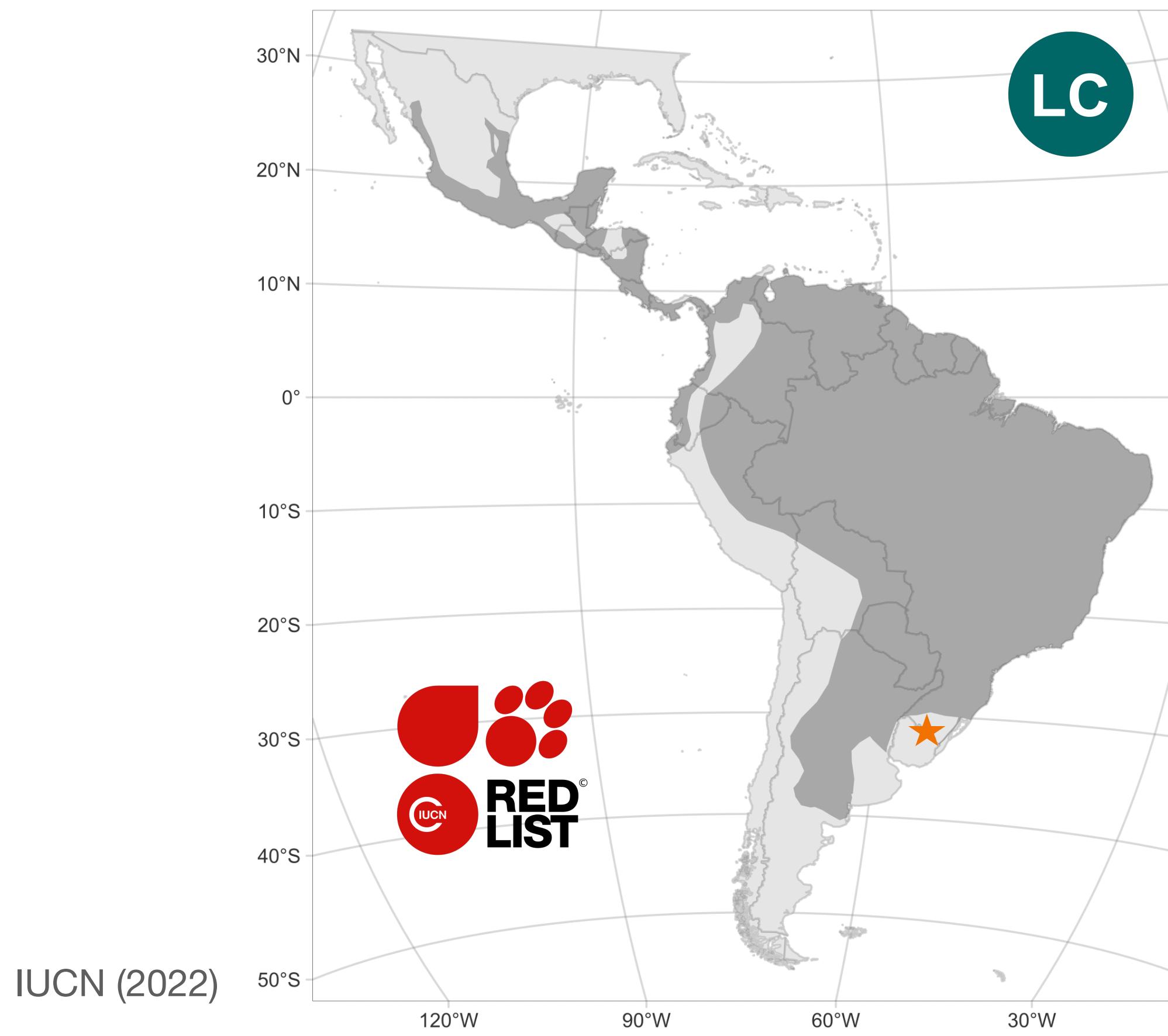
BIODIVERSITY RESEARCH Diversity and Distributions WILEY

Model-based integration of citizen science data from disparate sources increases the precision of bird population trends

Lionel R. Hertzog¹ | Claudia Frank^{2,3} | Sebastian Klimek¹ | Norbert Röder⁴ | Hannah G. S. Böhner⁴ | Johannes Kamp^{2,3}

Yaguarundí

Herpailurus yagouaroundi



Top: observed in Argentina by hhulsberg, and bottom: in Mexico by albamaya (iNaturalist.org)



JULANA
Jugando en la Naturaleza



Bushnell

M maximo

53°F 11 °C

2015-08-11 16:26:36

Objetivo

Dinámica del rango de distribución

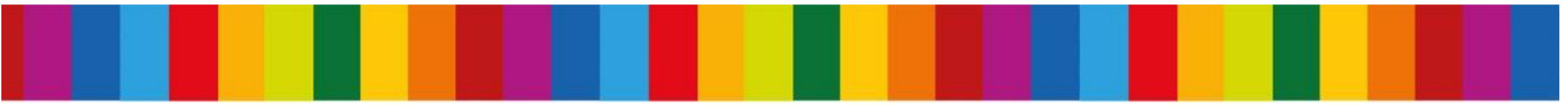
- Desarrollar un **modelo integrado de distribución de especies (ISDM)** para modelar la dinámica temporal de toda el área de distribución geográfica de *Herpailurus yagouaroundi*.



MYSTERY BOX

Métodos





Integrating presence-only and presence–absence data to model changes in species geographic ranges: An example in the Neotropics

Florencia Grattarola, Diana E. Bowler & Petr Keil

This repository includes the data, code, model and outputs for our manuscript on the use of integrated species distribution models (IDMs) to study the change over time of the yaguarundi's geographic distribution range.

Find here:

- [Data](#): PA and PO data to run the model + spatial data
- [Code](#): code for all data processing + IDM run in JAGS
- [Model](#): model file in BUGS language
- [Docs](#): model definitions + diagnostics + outputs + figures



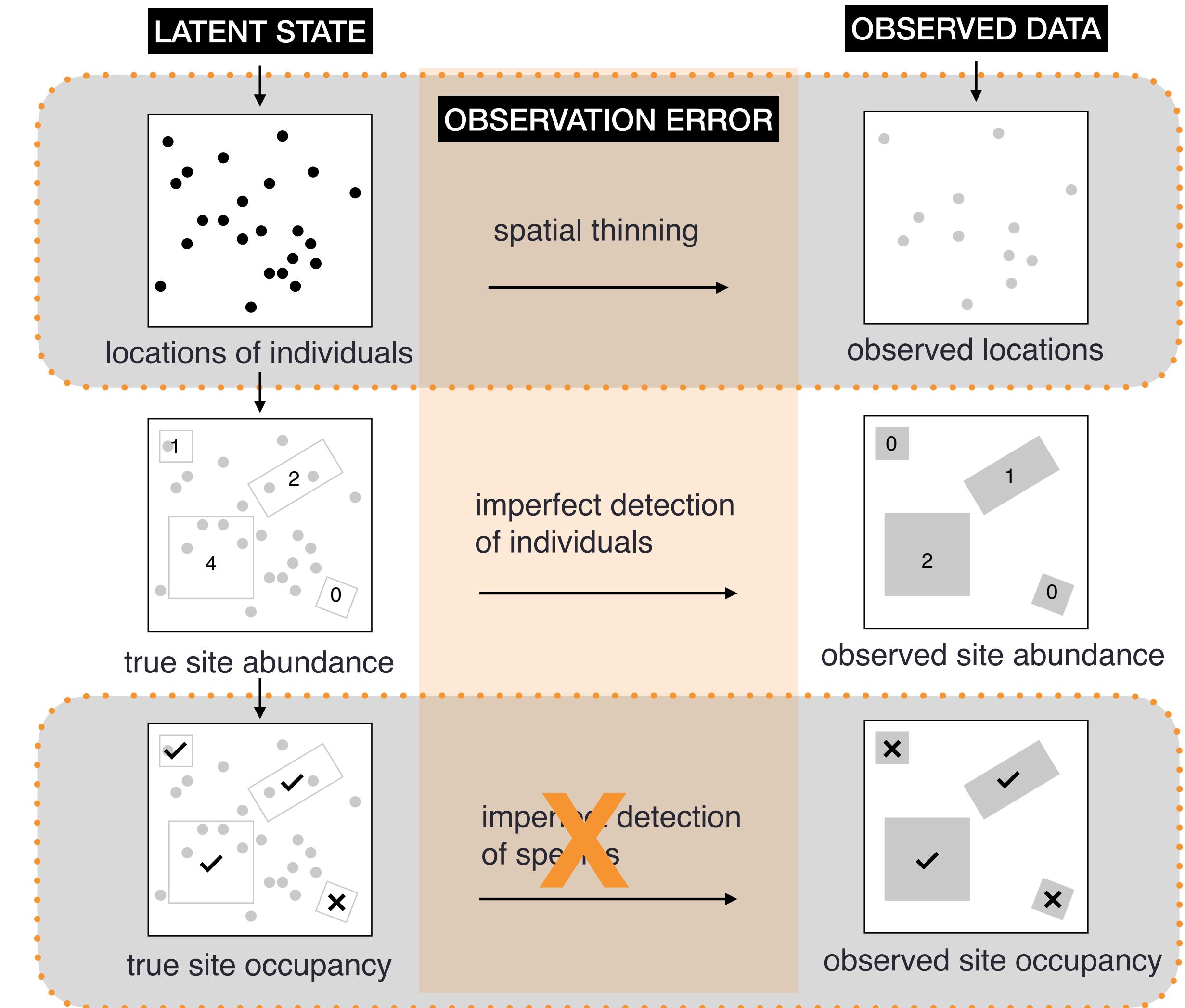
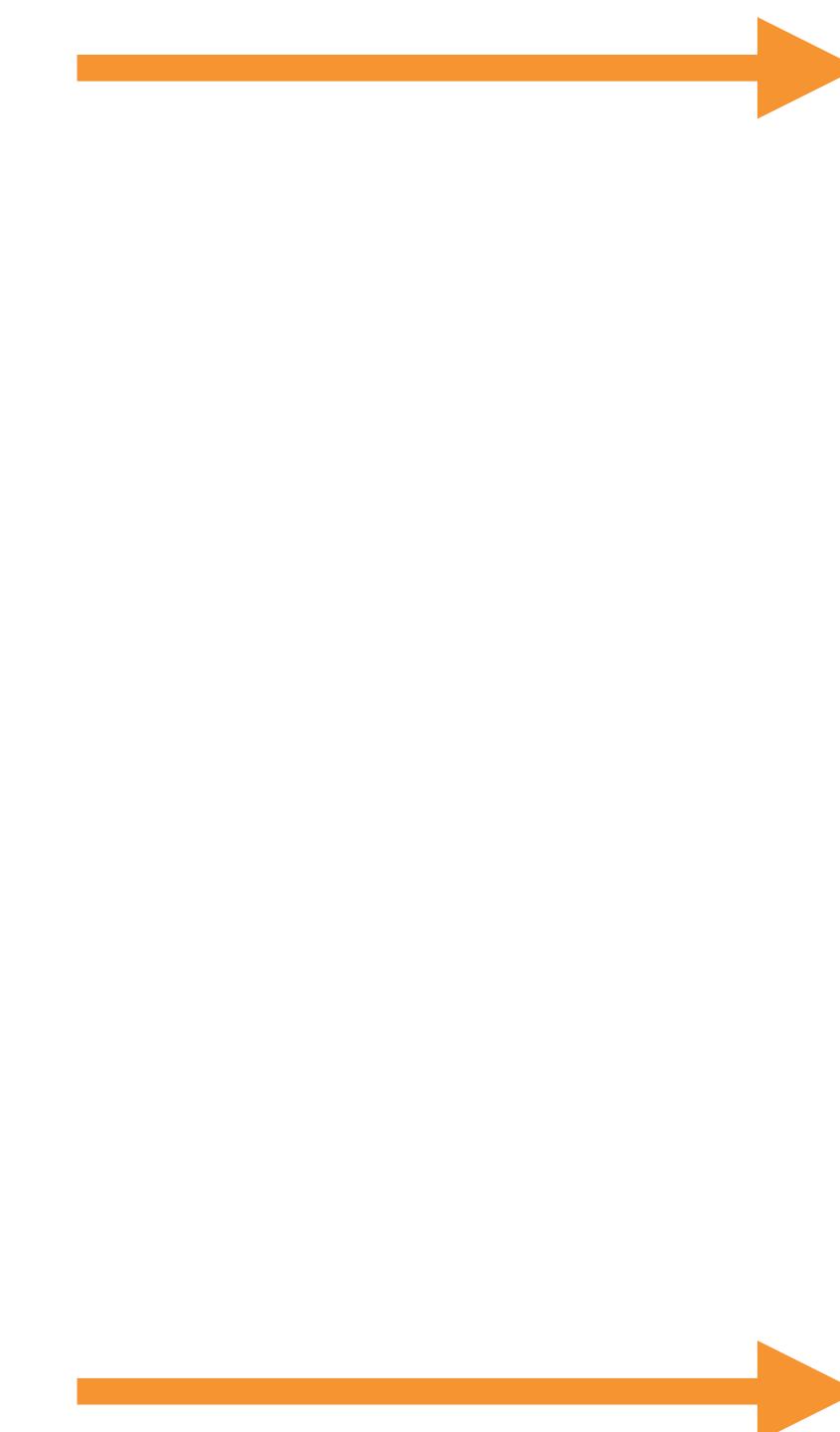
Código Open Access

https://github.com/bienflorence/yaguarundi_IDM

Nuestro ISDM

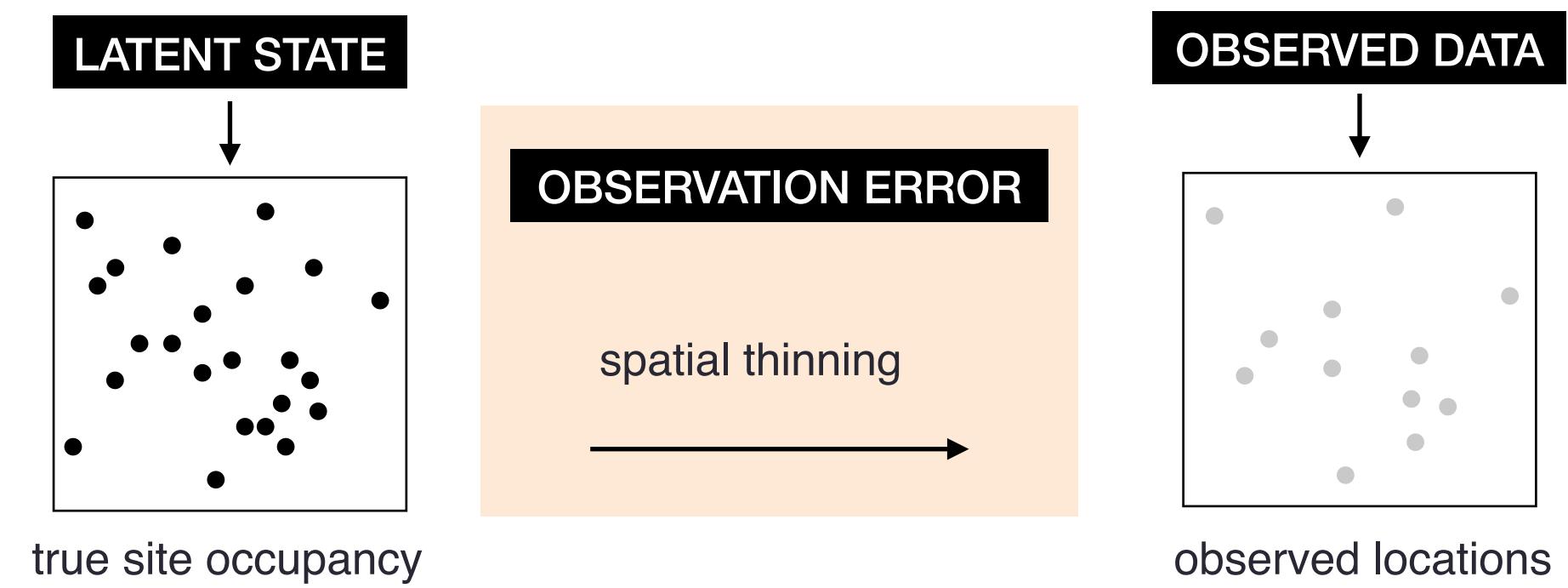
Presence-only
(PO)

Presence-absence
(PA)



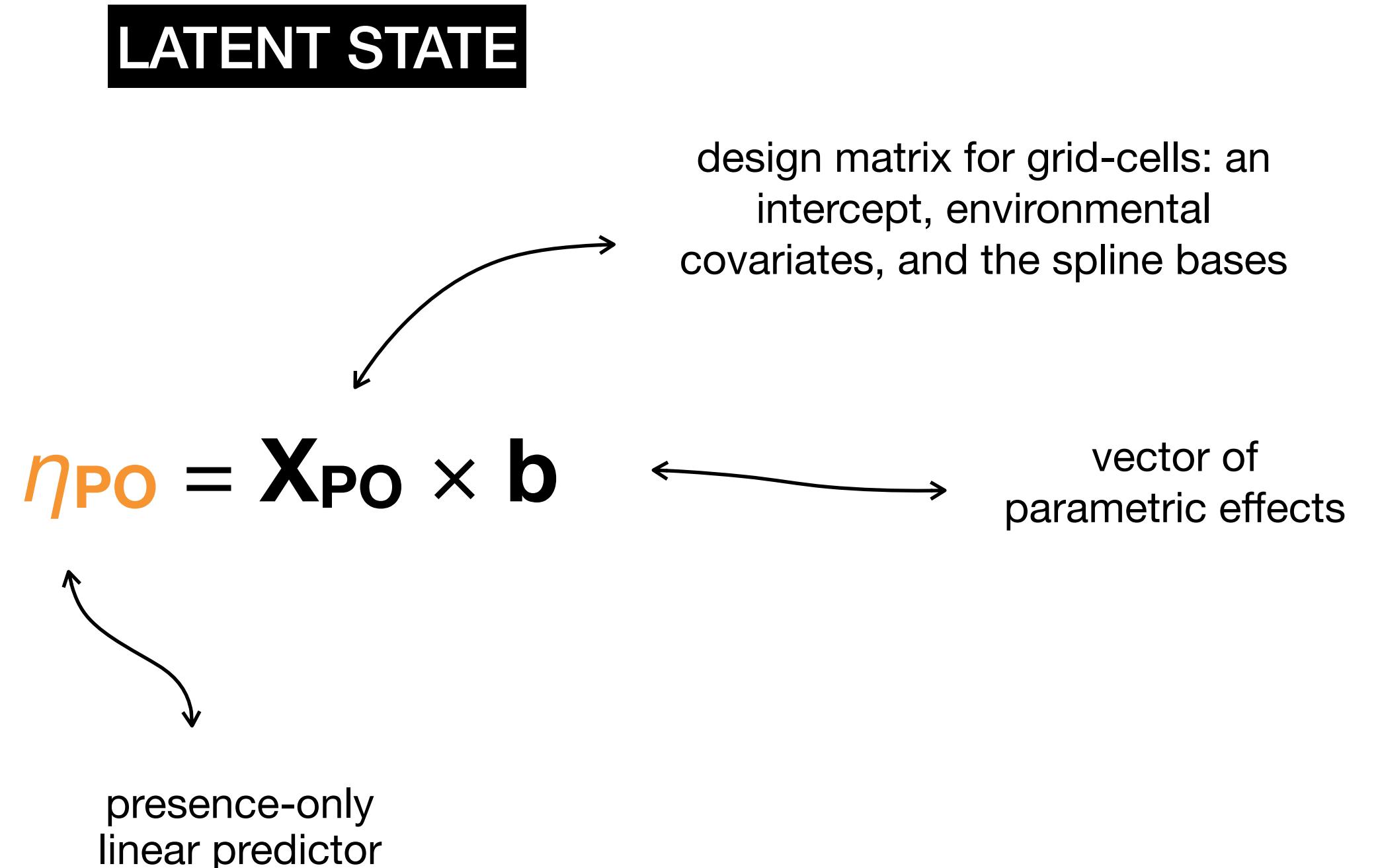
Nuestro ISDM

Modelado de presence-only (PO)



Nuestro ISDM

Modelado de presence-only (PO)



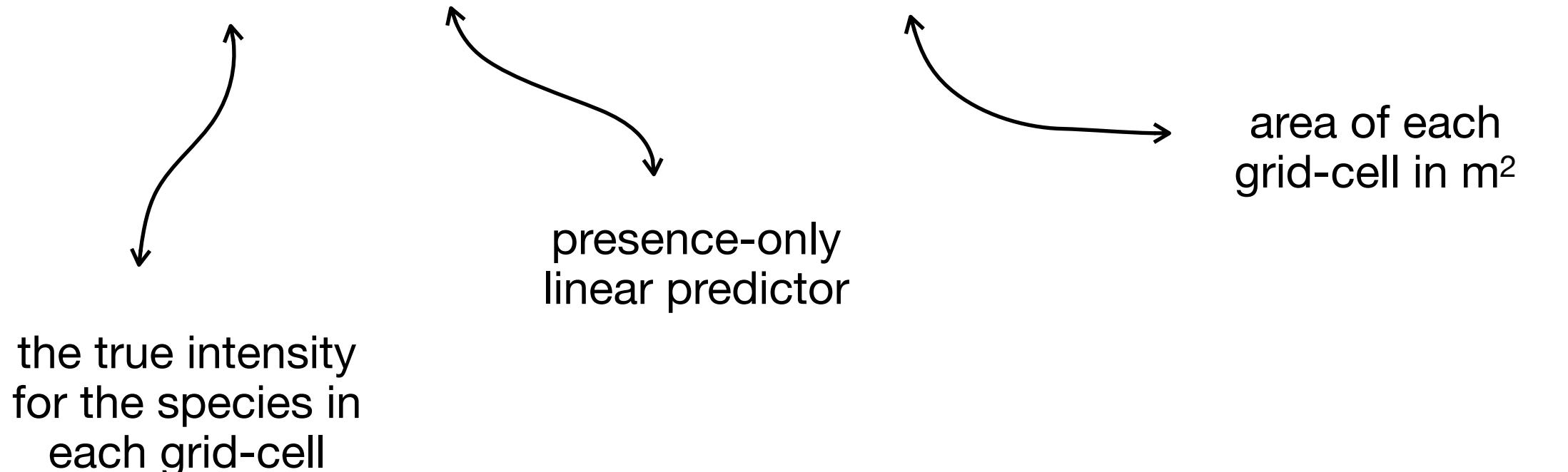
Nuestro ISDM

Modelado de presence-only (PO)

LATENT STATE

$$\eta_{PO} = \mathbf{X}_{PO} \times \mathbf{b}$$

$$\log(v_j) = \eta_{POj} + \log(\text{area}_{POj})$$



Nuestro ISDM

Modelado de presence-only (PO)

LATENT STATE

$$\eta_{\text{PO}} = \mathbf{X}_{\text{PO}} \times \mathbf{b}$$

$$\log(v_j) = \eta_{POj} + \log(\text{area}_{POj})$$

OBSERVATION ERROR

$$\lambda_j = v_j \times \text{Pret}_j$$

thinned intensity
per grid-cell

the true intensity
for the species in
each grid-cell

cell-specific
probability of
retaining a point

Nuestro ISDM

Modelado de presence-only (PO)

LATENT STATE

$$\eta_{\text{PO}} = \mathbf{X}_{\text{PO}} \times \mathbf{b}$$

$$\log(v_j) = \eta_{POj} + \log(\text{area}_{POj})$$

OBSERVATION ERROR

$$\lambda_j = v_j \times \text{Pret}_j$$

$$\text{Pret}_j = a_0 \text{country}_j \times \exp^{-a_1 \times \text{acce}_j}$$

cell-specific
probability of
retaining a point

random
intercept for
each country

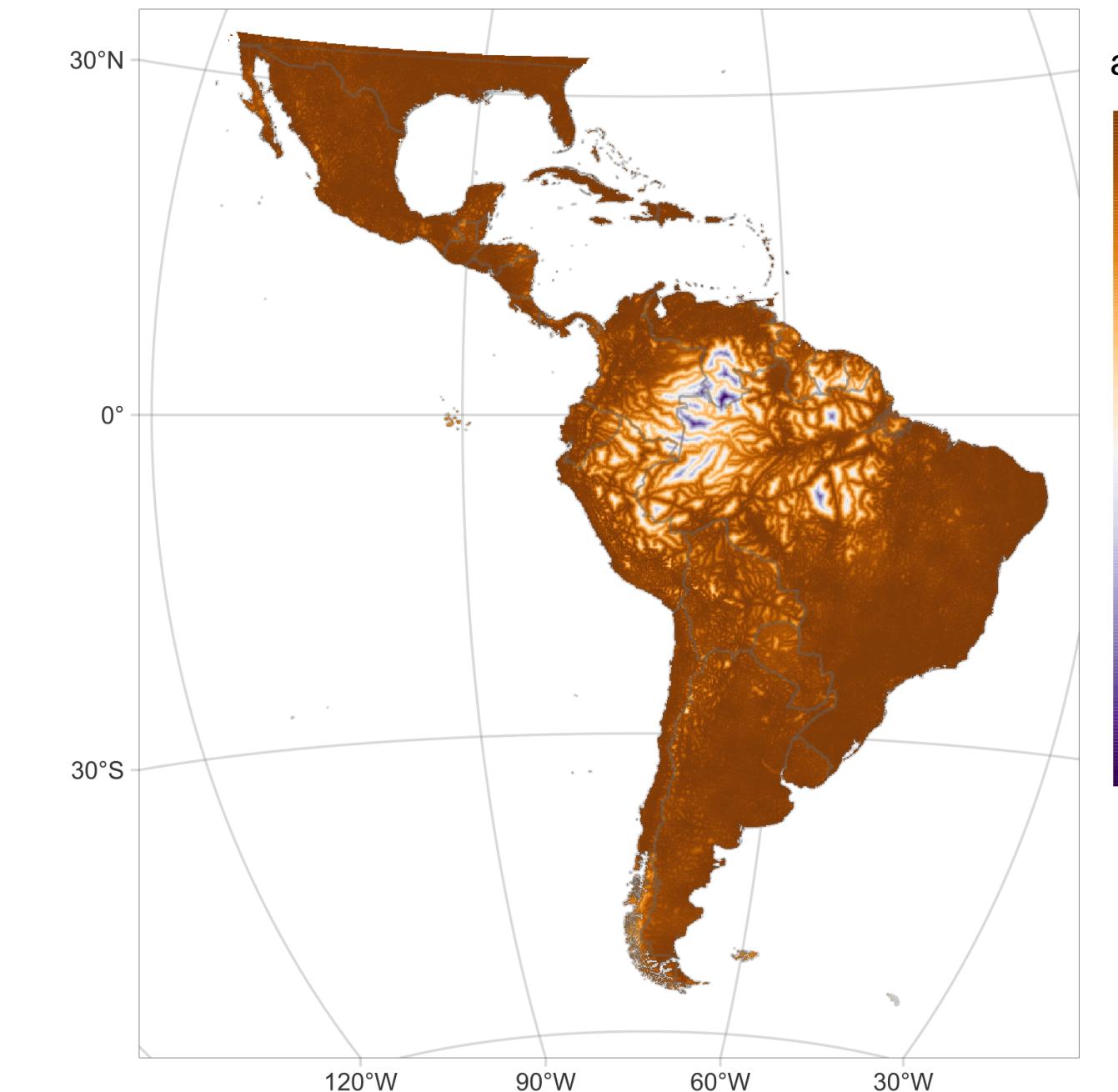
fixed slope
for grid-cell
accessibility

Variables observacionales

Modelado de presence-only (PO)

- **Accesibilidad:** esperamos que las celdas más accesibles tengan más registros que las celdas menos accesibles.

$$P_{retj} = a_0 country_j \times \exp^{-a_1 \times acce_j}$$



fixed slope
for grid-cell
accessibility

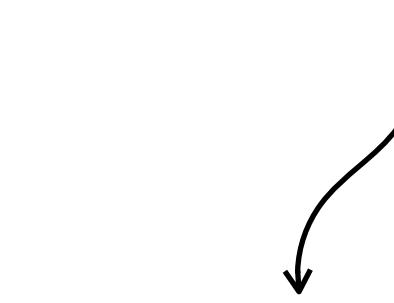
Weiss et al. (2020)

Variables observacionales

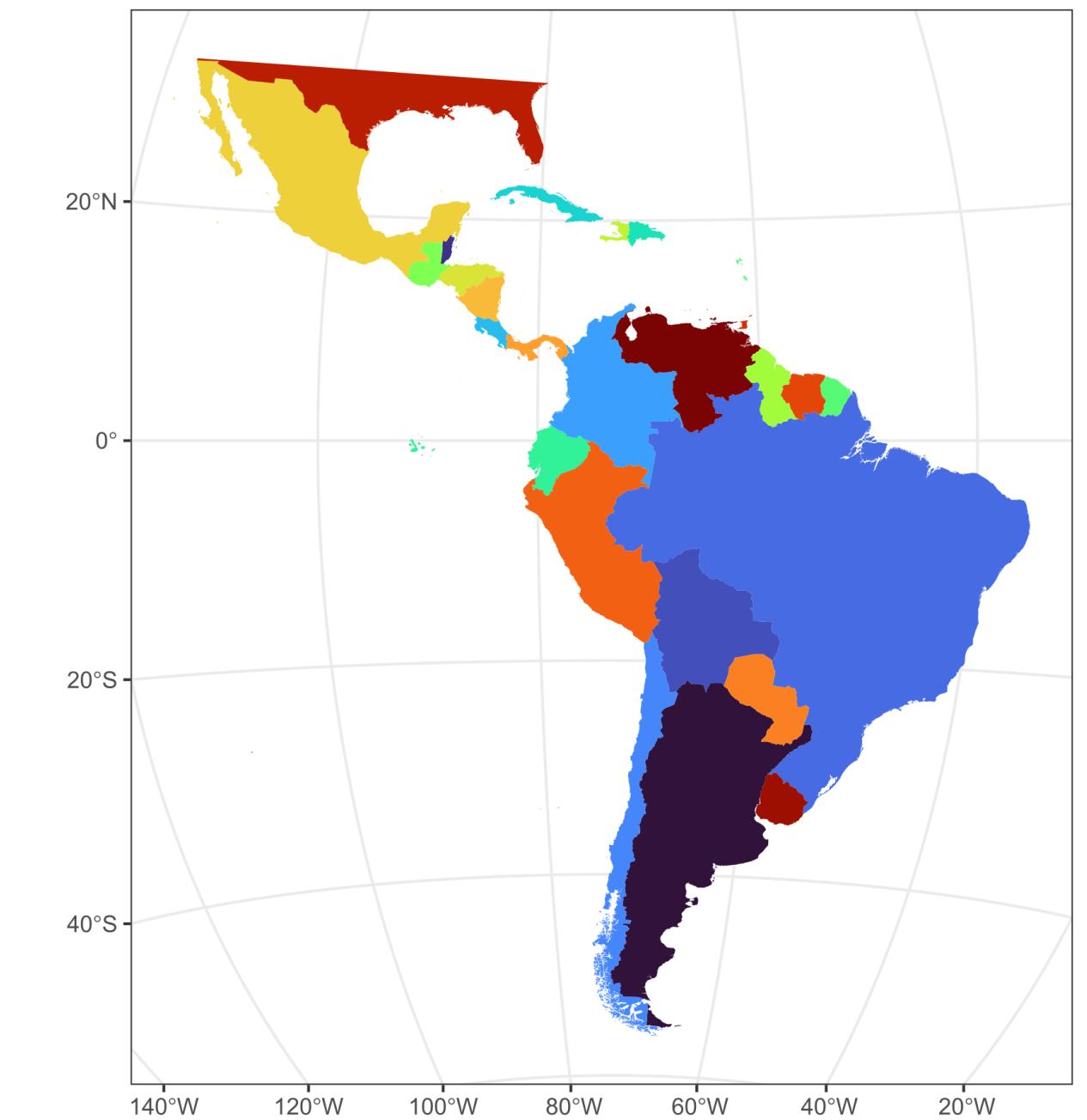
Modelado de presence-only (PO)

- **País de origen:** diferencias en las capacidades de publicación de datos y los niveles de participación de la ciencia comunitaria entre países.

$$P_{retj} = a_0 \text{country}_j \times \exp^{-a_1 \times \text{acce}_j}$$



random
intercept for
each country



Nuestro ISDM

Modelado de presence-only (PO)

LATENT STATE

$$\eta_{\text{PO}} = \mathbf{X}_{\text{PO}} \times \mathbf{b}$$

$$\log(v_j) = \eta_{POj} + \log(\text{area}_{POj})$$

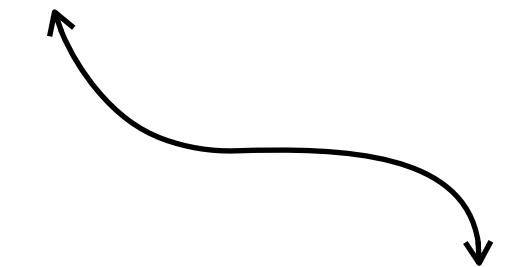
OBSERVATION ERROR

$$\lambda_j = v_j \times \text{Pret}_j$$

$$\text{Pret}_j = a_0 \text{country}_j \times \exp^{-a_1 \times \text{acce}_j}$$

OBSERVED DATA

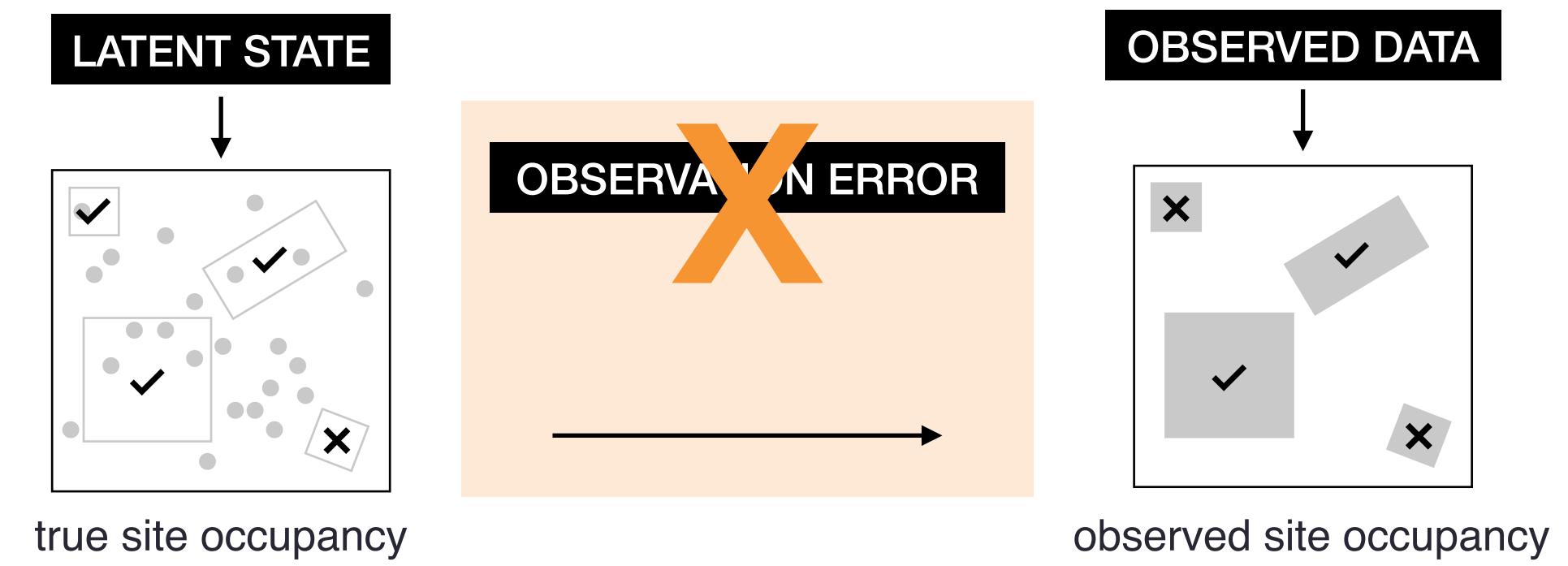
$$Y_{POj} \sim \text{Poisson}(\lambda_j)$$



the observed count data
in each j-th grid cell

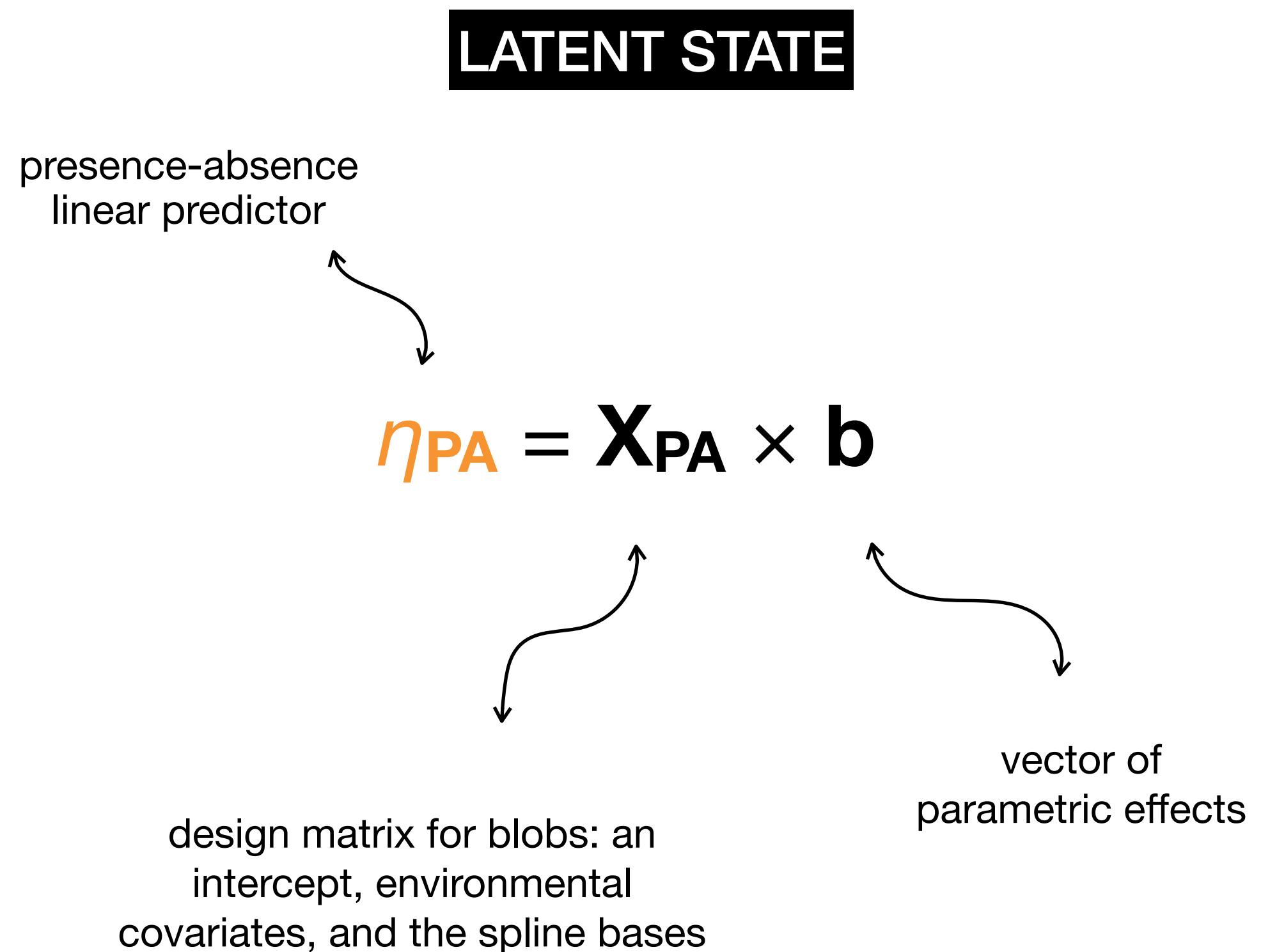
Nuestro ISDM

Modelado de presence-absence (PA)



Nuestro ISDM

Modelado de presence-absence (PA)



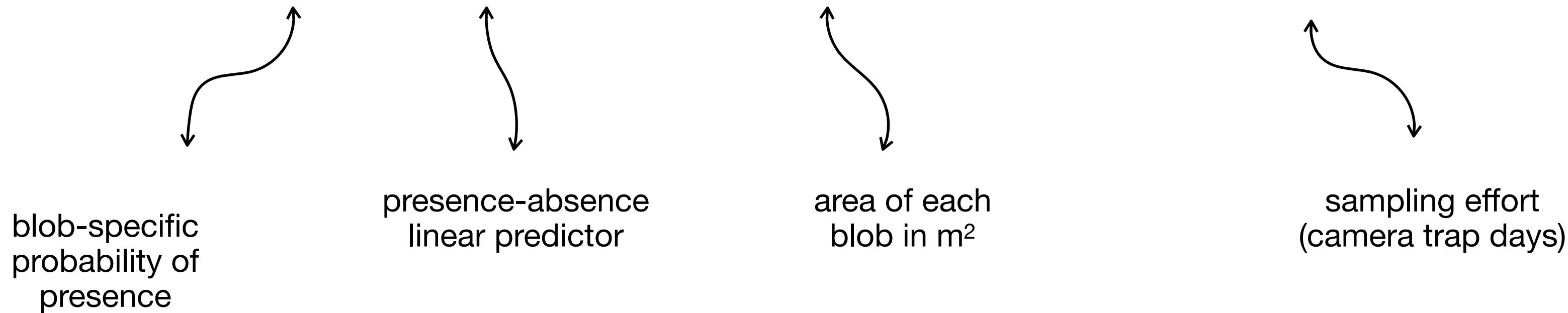
Nuestro ISDM

Modelado de presence-absence (PA)

LATENT STATE

$$\eta_{PA} = \mathbf{X}_{PA} \times \mathbf{b}$$

$$cloglog(\psi_i) = \eta_{PAi} + \log(\text{area}_{PAi}) + \beta \times \log(\text{effort}_i)$$



Nuestro ISDM

Modelado de presence-absence (PA)

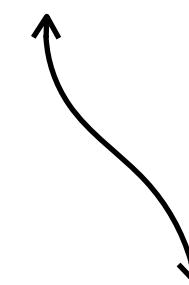
LATENT STATE

OBSERVED DATA

$$\eta_{PA} = \mathbf{X}_{PA} \times \mathbf{b}$$

$$cloglog(\psi_i) = \eta_{PAi} + log(area_{PAi}) + \beta \times log(effort_i)$$

$$y_{PAi} \sim Bernoulli(\psi_i)$$



the observed presence (1) or absence (0) value in each i-th blob

Nuestro ISDM

Predicciones

$$\eta_{\text{pred}} = \mathbf{X}_{\text{PO}} \times \mathbf{b}$$

vector of parametric effects

linear predictor

design matrix for grid-cells: an intercept, environmental covariates, and the spline bases

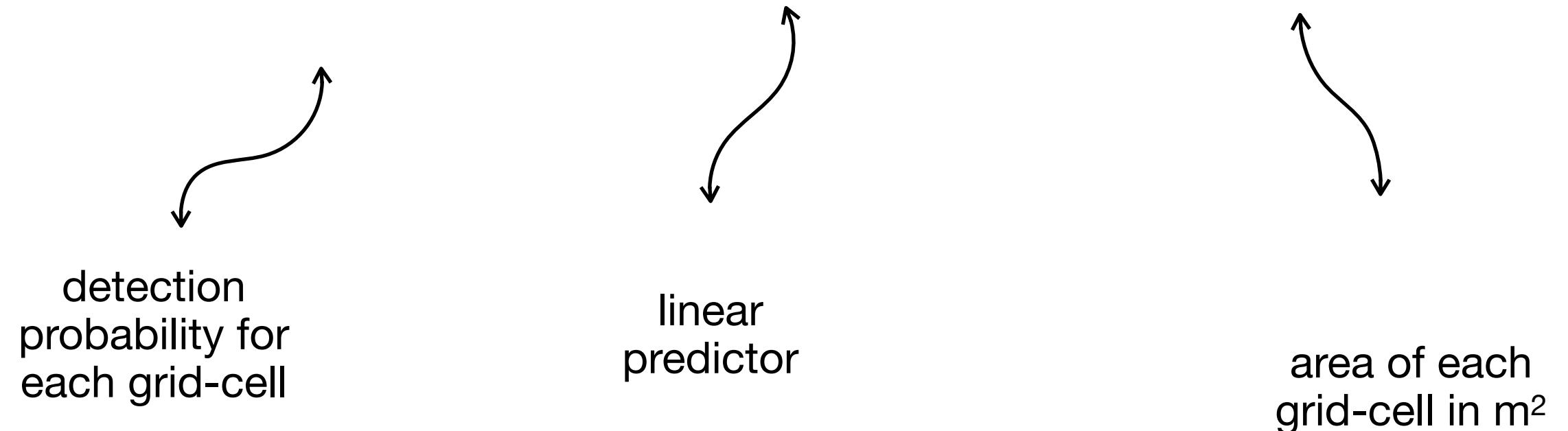
The diagram illustrates the components of a linear predictor equation. At the bottom, the equation $\eta_{\text{pred}} = \mathbf{X}_{\text{PO}} \times \mathbf{b}$ is displayed. Above the equation, the text "vector of parametric effects" is positioned above the vector \mathbf{b} , with a curved arrow pointing from the text to the vector. Below the equation, two curved arrows point from the labels "linear predictor" and "design matrix for grid-cells: an intercept, environmental covariates, and the spline bases" to the matrix \mathbf{X}_{PO} .

Nuestro ISDM

Predicciones

$$\eta_{\text{pred}} = \mathbf{X}_{\text{PO}} \times \mathbf{b}$$

$$cloglog(Pred_j) = \eta_{\text{pred}j} + \log(\text{area}_{\text{POj}})$$



Nuestro ISDM

Predicciones

$$\eta_{\text{pred}} = \mathbf{X}_{\text{PO}} \times \mathbf{b}$$

$$cloglog(Pred_j) = \eta_{\text{pred}j} + log(\text{area}_{\text{PO}j})$$

area of the species
range for the first
period

$$A_{\text{time}1} = \sum Pred_j$$

$$A_{\text{time}2} = \sum Pred_j$$

area of the species
range for the
second period

Nuestro ISDM

Predicciones

$$\eta_{pred} = X_{PO} \times b$$

$$cloglog(Pred_j) = \eta_{predj} + log(area_{Poj})$$

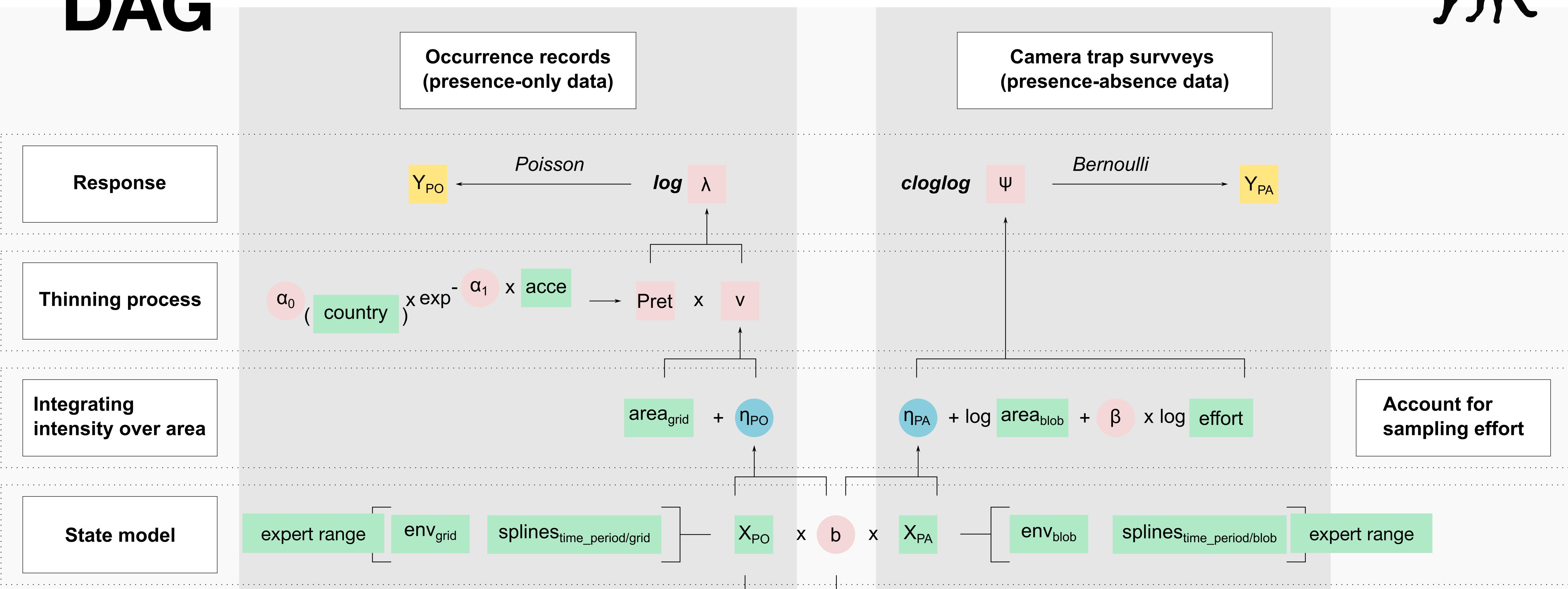
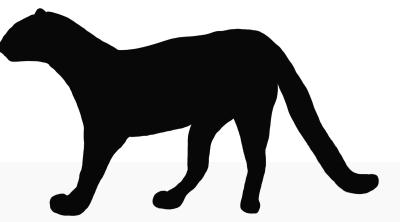
$$A_{time1} = \sum Pred_j$$

$$A_{time2} = \sum Pred_j$$

$$\Delta A = A_{time2} - A_{time1}$$

the difference in the
area between both
time periods

DAG



● estimated parameters
■ estimated variables

● linear predictors

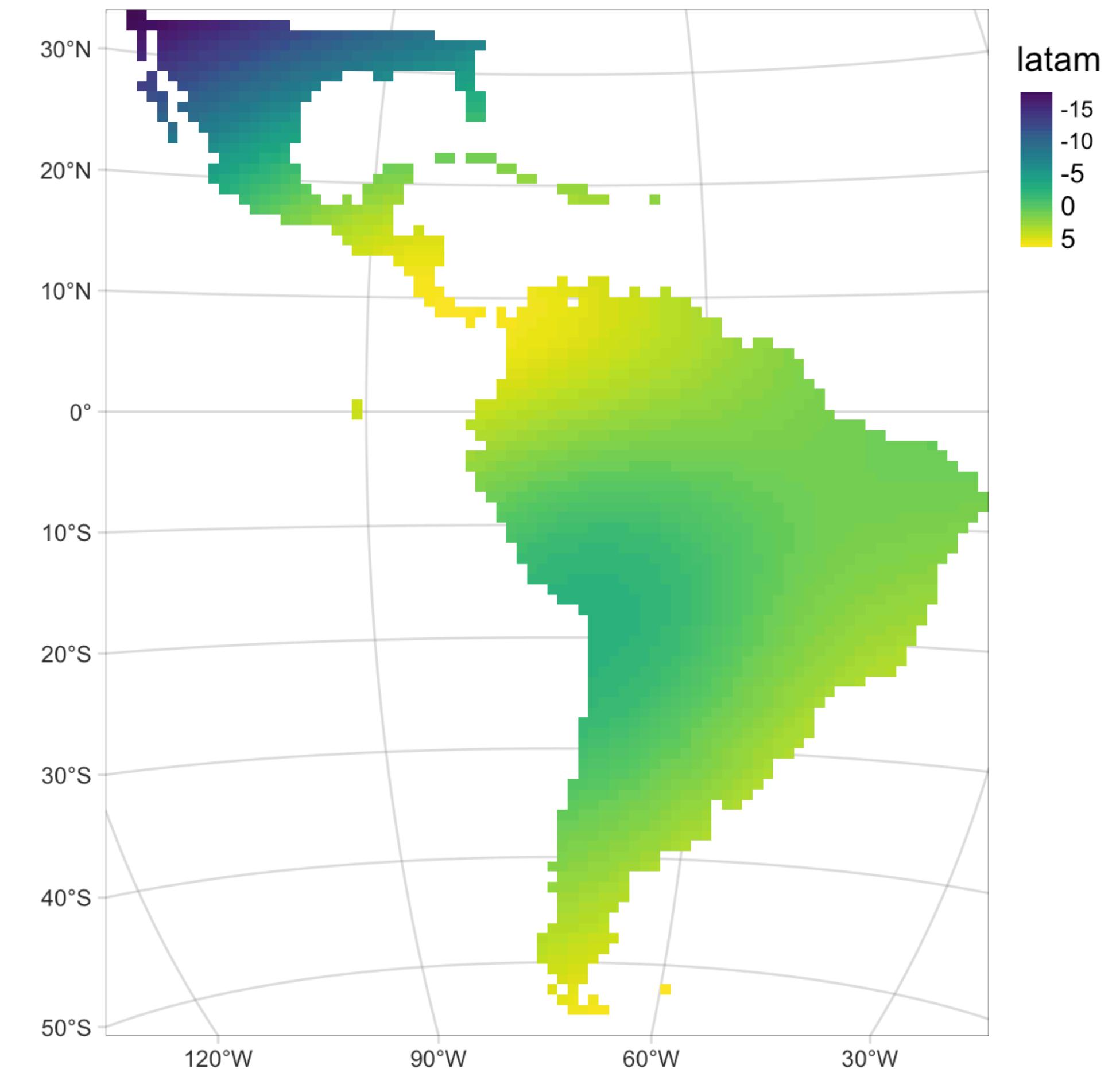
■ data

■ response

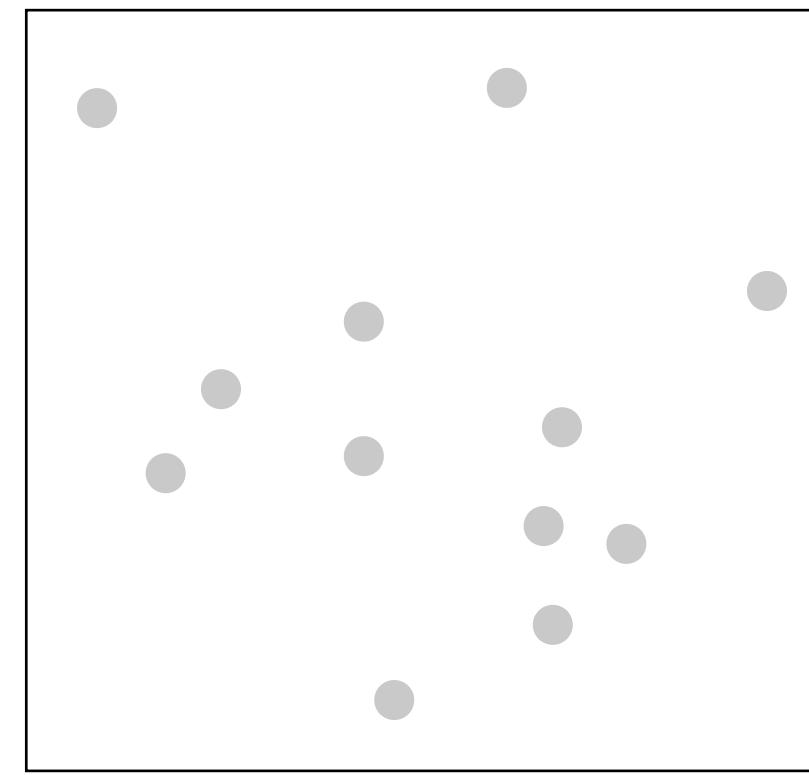
Smoothing splines

Componente espacial

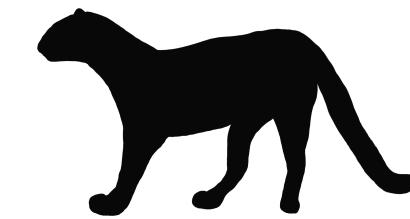
- Modelan la estructura espacial en la distribución que no tienen en cuenta las covariables ambientales.
- Usamos la función `jagam` del paquete ‘mgcv’. El número the *spline basis* fue $k = 9$



Datos de la especie



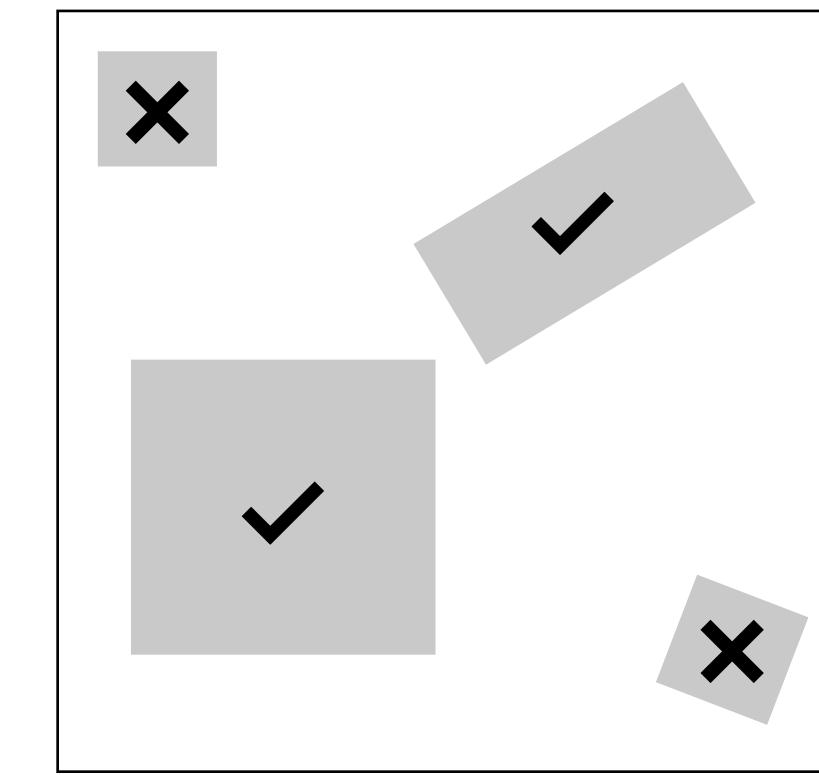
presence-only data
observed locations



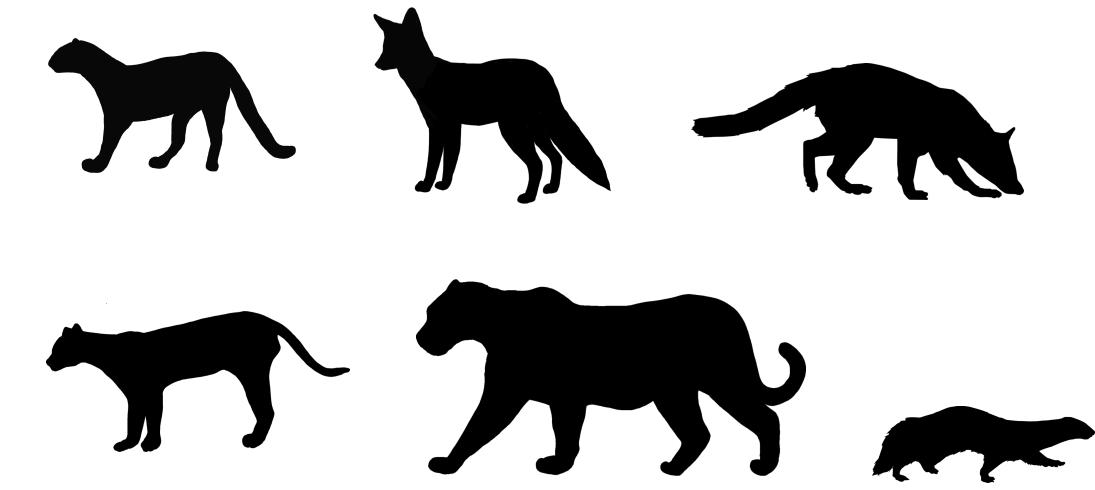
PO

GBIF.org (2022)

<https://doi.org/10.15468/DL.3CU474>



presence-absence data
observed site occupancy



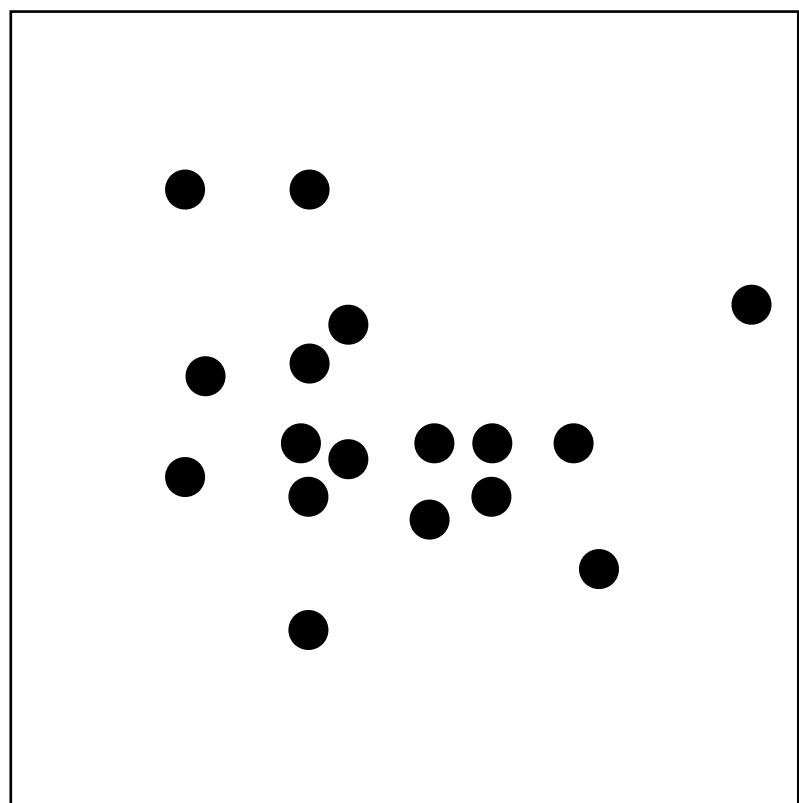
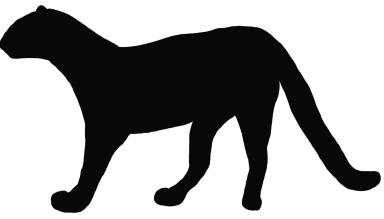
PA

Nagy-Reis et al. (2020)

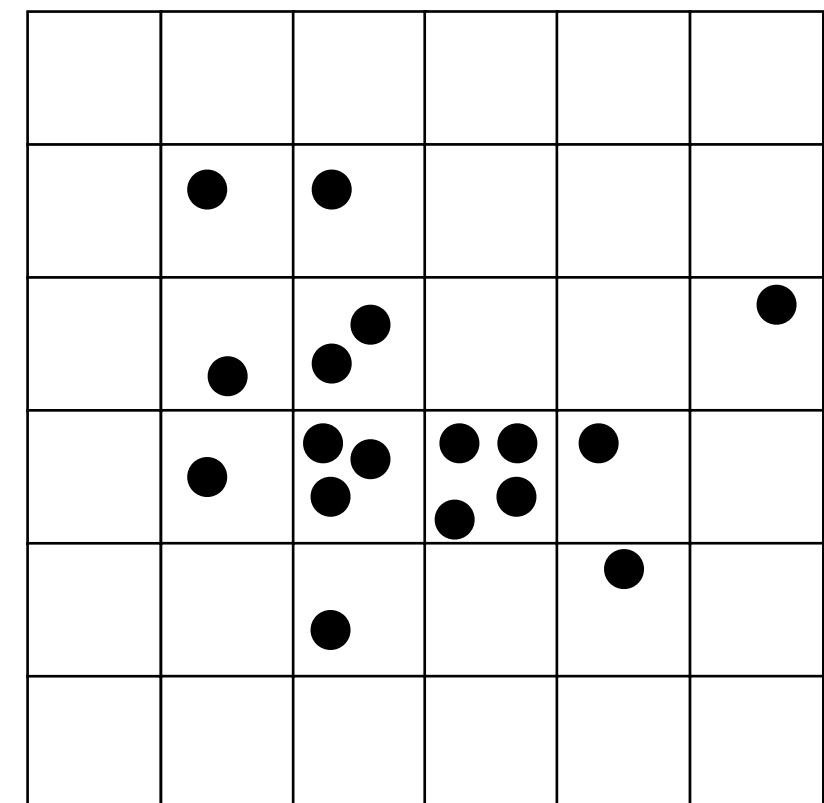
<https://doi.org/10.1002/ecy.3128>

Datos de la especie

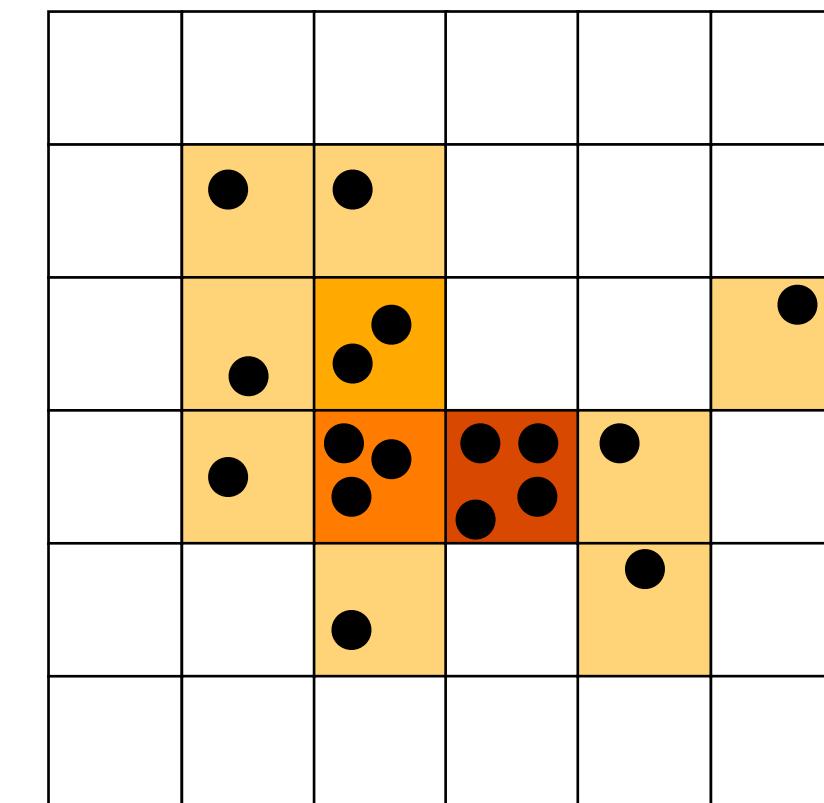
Presence-only (observed locations)



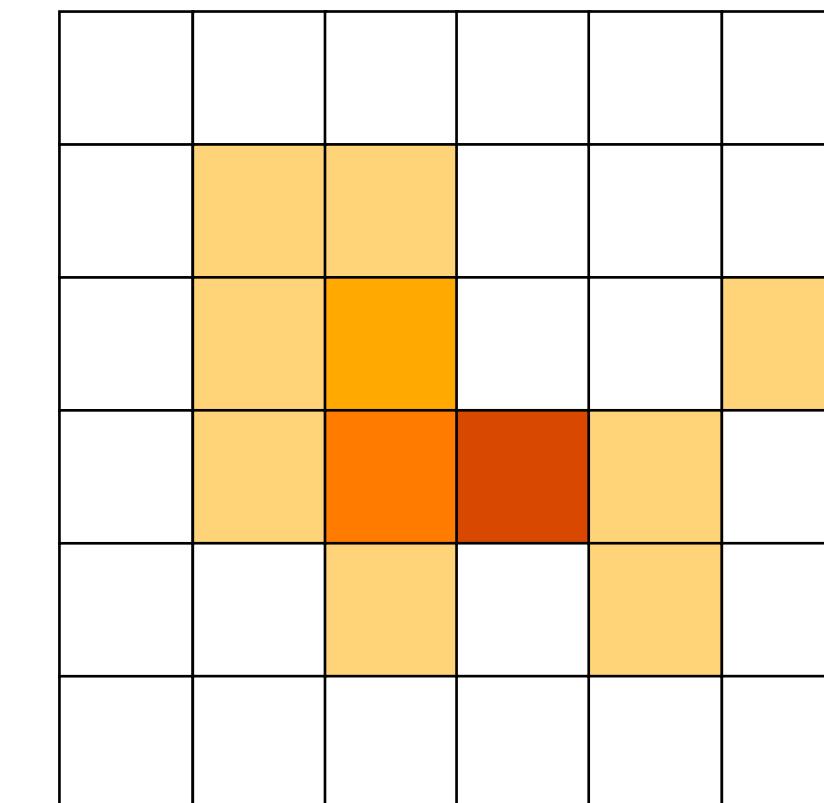
presence-only
occurrence records



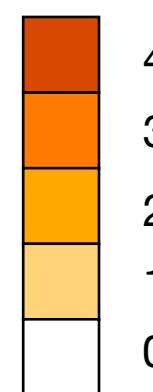
grid of 100x100 km
over the study area



counts of records
per grid-cell

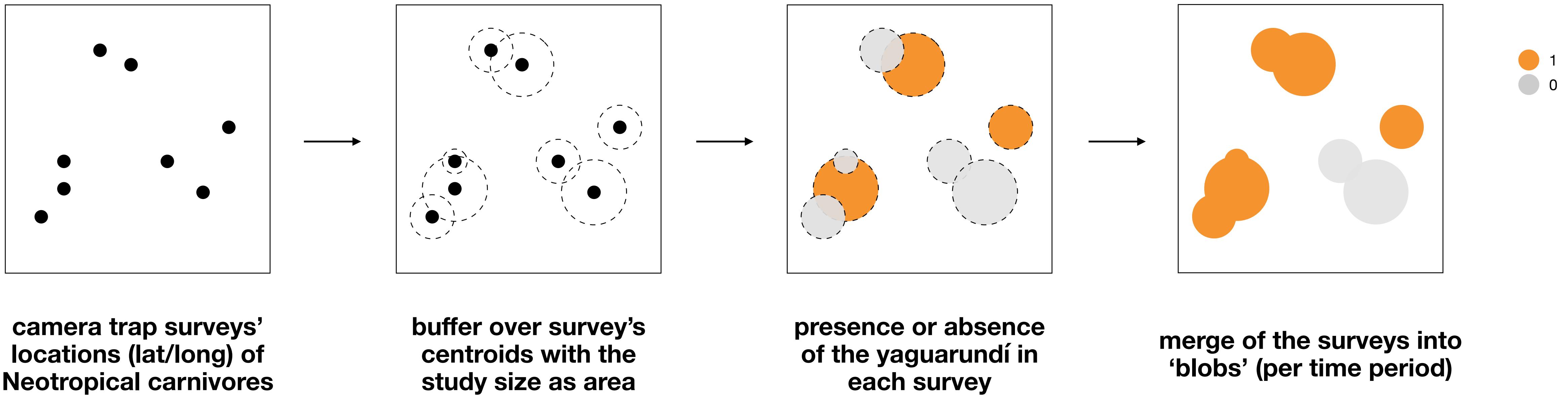
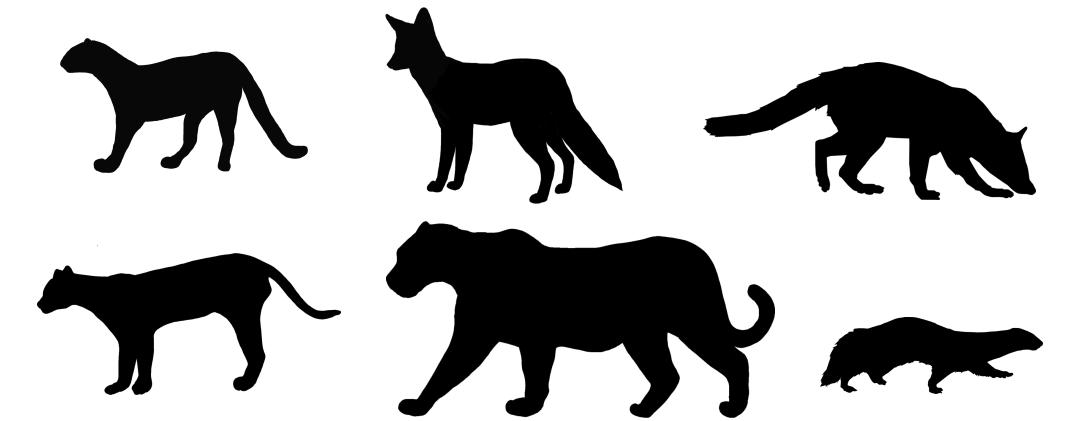


rasterisation of
100x100 grid-cell
counts



Datos de la especie

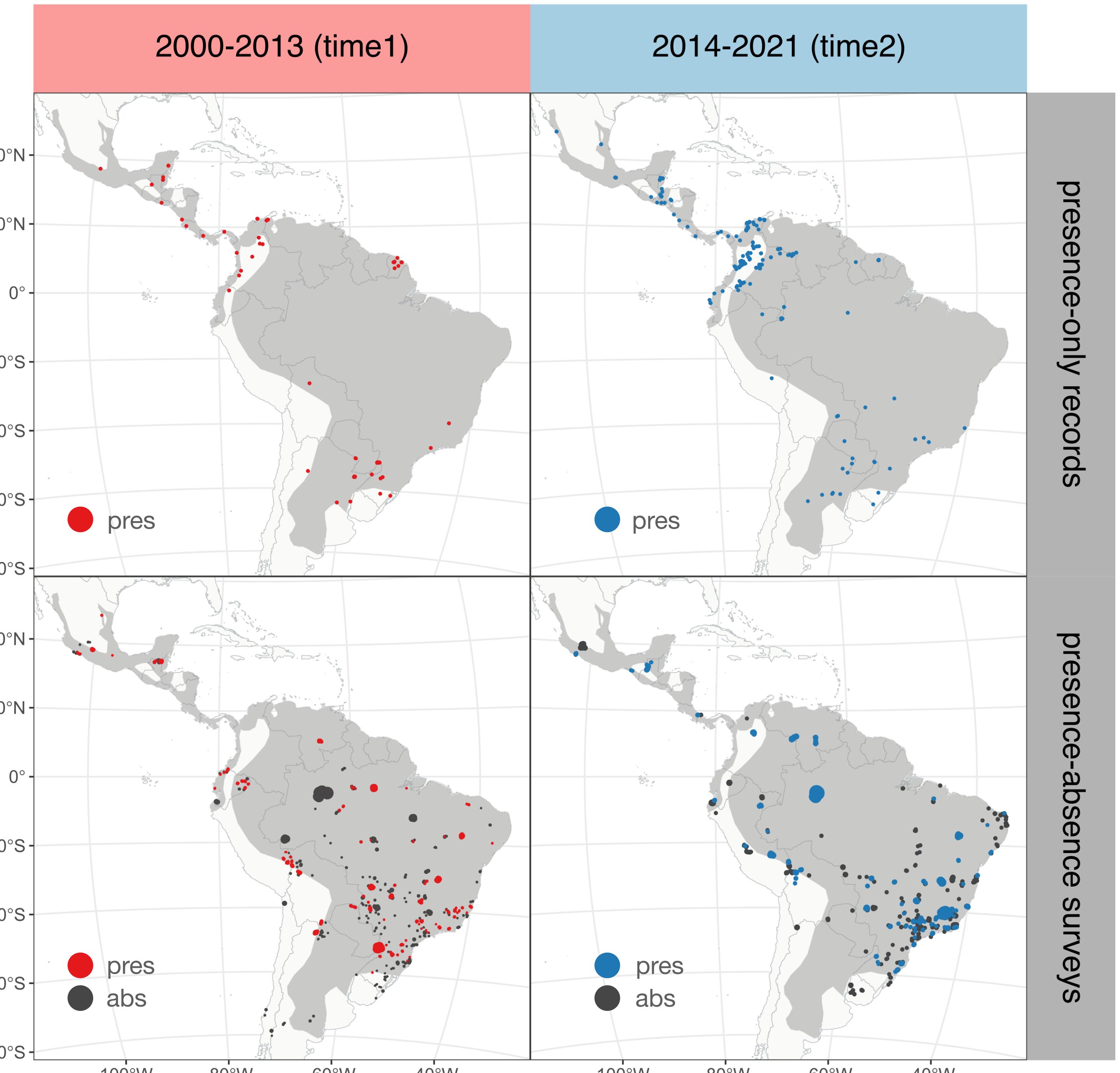
Presence-absence (observed site occupancy)



Datos

Yaguarundí

- **PO:** En el primer período se detectaron 196 registros de yaguarundí y en el segundo 234.
- **PA:** Se utilizaron datos de 8.346 estudios. El yaguarundí fue registrado en 614.

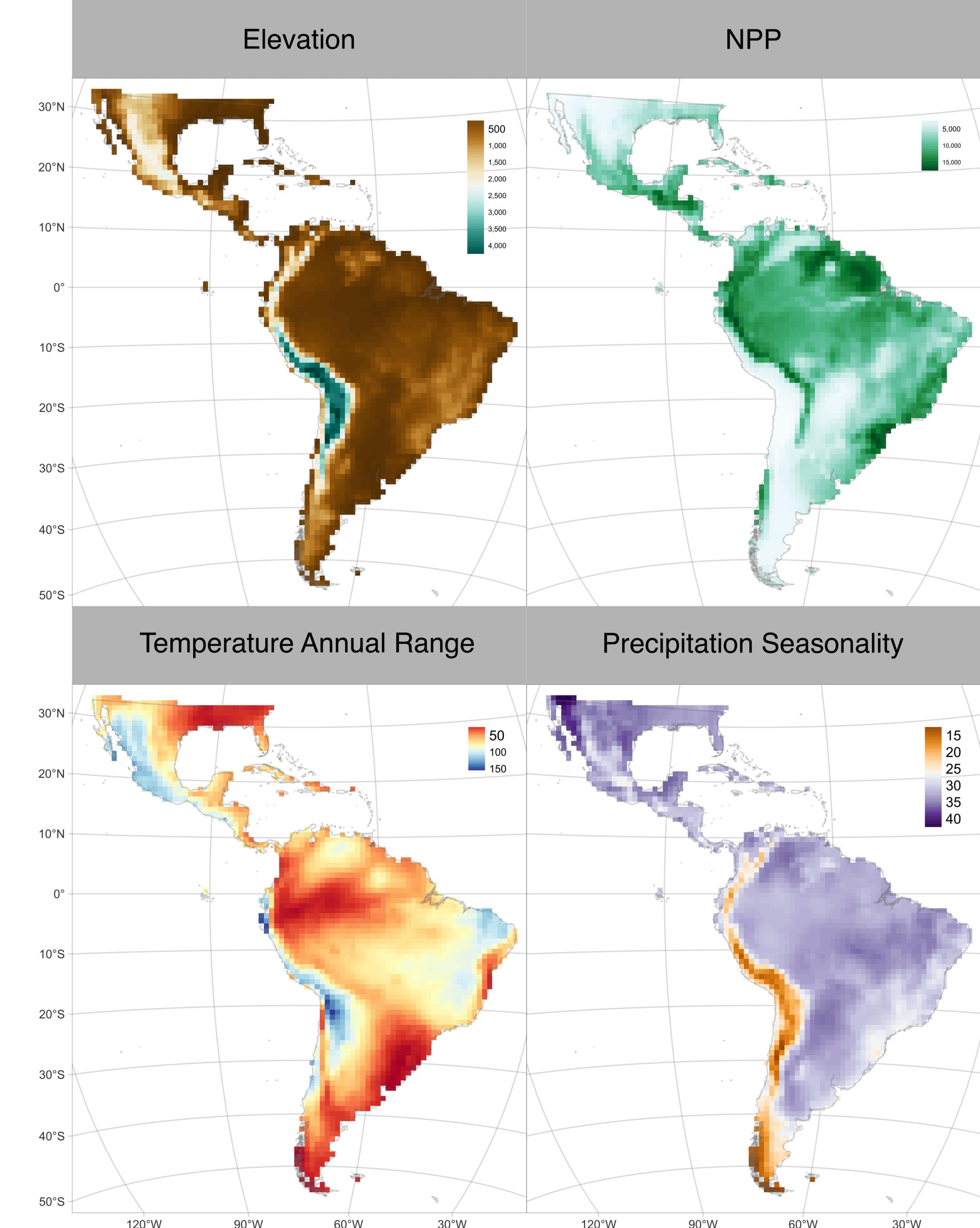


Variables ambientales

Clima, cobertura del suelo, vegetación

Usamos un conjunto de 28 covariables potenciales:

- Bioclimatic variables (WorldClim V2.1): bio1 - bio19.
- Elevation (WorldClim V2.1 SRTM elevation data)
- Land cover (MODIS - MCD12Q1): urban, barren, water, savanna, wetland, grassland.
- Net Primary Production (NPP) (MODIS - M*D17A3HGF)
- Percentage of Vegetation cover (MODIS TERRA - MOD44B): tree cover, no tree cover, non tree vegetation cover.



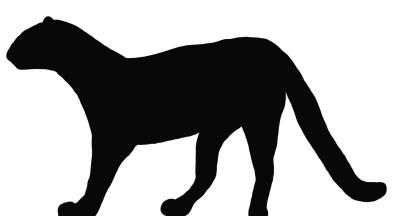
El modelo Corrida

- `jags` función del paquete ‘R2jags’ (para llamar a JAGS desde R)
 - 3 cadenas
 - 100,000 iteraciones por cadena
 - 10,000 de largo de burning
 - 10 de thinning rate

97 lines (71 sloc) | 3.01 KB

Raw Blame ⌂ ⌂ ⌂

```
1 model
2 {
3     # PRIORS -----
4
5     ## Thinning at locations with complete accessibility in PO data
6
7     # intercept of the decay function for each country of origin.
8     # It needs a flat prior between 0 and 1
9     for (c in 1:n.cntr)
10    {
11        alpha0[c] ~ dbeta(1, 1)
12    }
13
14    # steepness of the decaying distance-P.ret relationship in PO data
15    alpha1 ~ dgamma(0.5, 0.05)
16
17    ## Effect of sampling effort in PA data
18    beta ~ dnorm(0, 0.01)
19
20    ## Parametric effects of environment driving the point process intensity
21    # (it also includes an intercept)
22
23    for (r in 1:n.par)
24    {
25        b[r] ~ dnorm(0,0.01)
26    }
27
28    ## Splines (imported and adjusted form output of mgcv:::jagam)
29
30    ## prior for s(X,Y):as.factor(time)0
31    sigma.pre <- S.pre[1:n.spl, 1:n.spl] * gamma[1] +
32        S.pre[1:n.spl, (n.spl + 1):(n.spl * 2)] * gamma[2]
33    b[(n.par+1):(n.spl + n.par)] ~ dmmnorm(Z[(n.par+1):(n.spl + n.par)], sigma.pre)
34
35    ## prior for s(X,Y):as.factor(time)1
36    sigma.post <- S.post[1:n.spl, 1:n.spl] * gamma[3] +
37        S.post[1:n.spl, (n.spl + 1):(n.spl * 2)] * gamma[4]
38    b[(n.X - n.spl + 1):(n.X)] ~ dmmnorm(Z[(n.X - n.spl + 1):(n.X)], sigma.post)
39
40    ## Priors for smoothing parameter
41    for (f in 1:n.fac)
42    {
43        gamma[f] ~ dgamma(.5,.5)
44        rho[f] <- log(gamma[f])
45    }
46
47    # LIKELIHOOD -----
48
49    ## --- Presence-Absence (PA) data ---
50
51    eta.PA <- X.PA %*% b ## linear predictor
52
53    for (i in 1:n.PA)
54    {
55        # the probability of presence
56        cloglog(psi[i]) <- eta.PA[i] + log(area.PA[i]) + beta*log(effort[i])
57
58        # presences and absences come from a Bernoulli distribution
59        y.PA[i] ~ dbern(psi[i]*0.9999)
60    }
61
62    ## --- Presence-Only (PO) data ---
63
64    eta.PO <- X.PO %*% b ## linear predictor
65
66    for (j in 1:n.PO)
67    {
68        # cell-specific probability of retainin (observing) a point is a function of accessibility
69        P.ret[j] <- alpha0[country[j]] * exp( -alpha1 * acce[j])
70
71        # true mean number (nu) of points per cell i is the true intensity multiplied by cell area
72        nu[j] <- area.PO[j] * exp(eta.PO[j])
73
74        # thinning: the true lambda
75        lambda[j] <- nu[j] * P.ret[j]
76
77        # counts of observed points come from a Poisson distribution
78        y.PO[j] ~ dpois(lambda[j])
79    }
80
81    # PREDICTIONS -----
82
83    eta.pred <- X.PO %*% b
84
85    for (j in 1:n.PO)
86    {
87        # predicted probability of occurrence in grid cell j
88        cloglog(P.pred[j]) <- eta.pred[j] + log(area.PO[j])
89    }
90
91    # DERIVED QUANTITIES -----
92
93    # area in each time period, and temporal change of area
94    A.pre <- sum(P.pred[1:n.PO.half])
95    A.post <- sum(P.pred[(n.PO.half+1):n.PO])
96    delta.A <- A.post - A.pre
97 }
```



El modelo

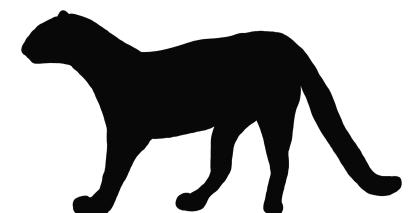
Corrida

- jags función del paquete ‘R2jags’ (para llamar a JAGS desde R)
- 3 cadenas
- 100,000 iteraciones por cadena
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Quick Model References

For more details please see [here](#)

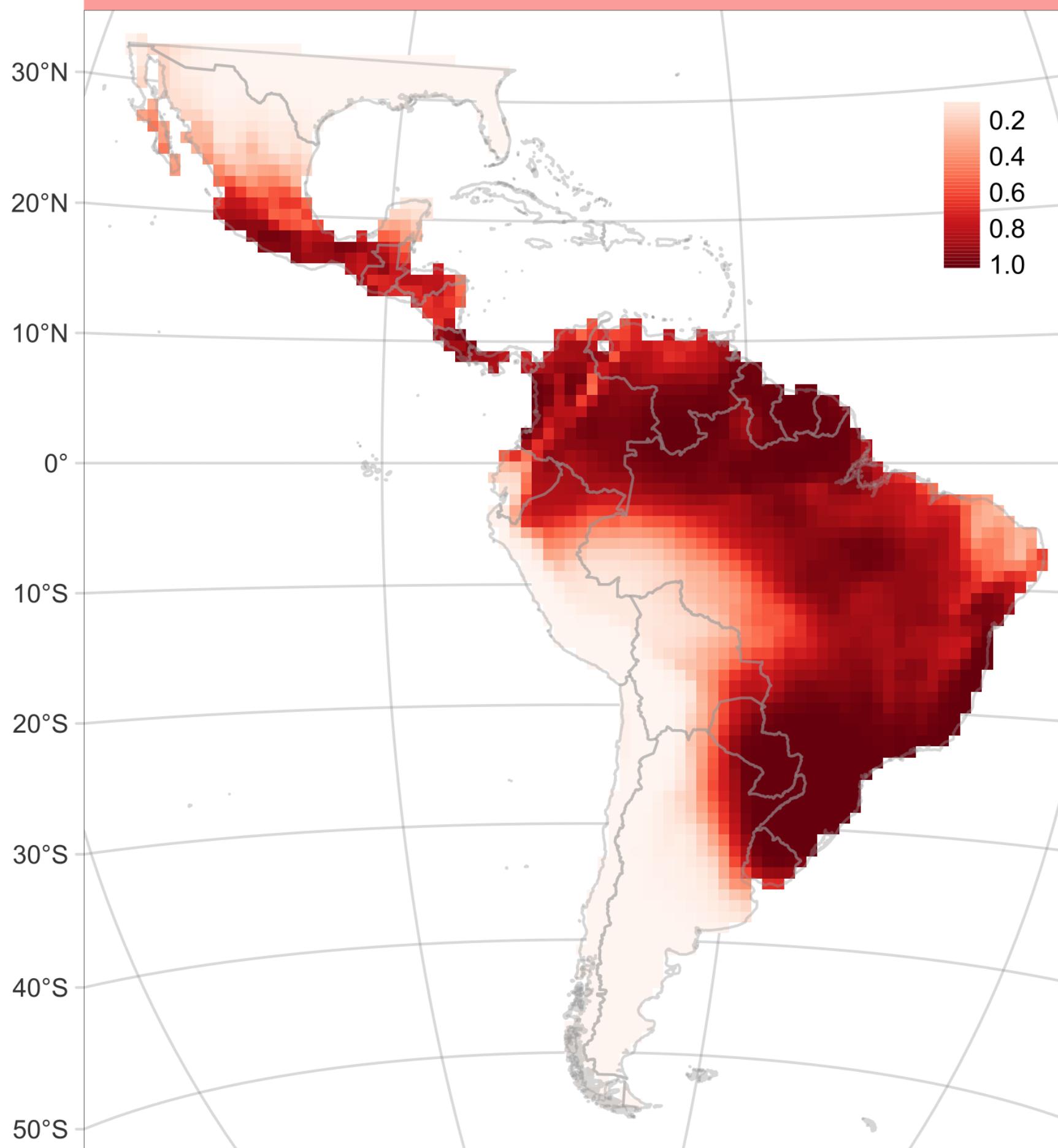
| Model term | Definition | Equation notation |
|-------------|---|----------------------|
| n.PA | number of blobs for both time periods (pre and pos) | n_{PA} |
| i | index identifying blobs | $i \in 1:n_{PA}$ |
| y.PA[i] | presence (1) or absence (0) value in each i-th blob (overlapping surveys' area), can be for pre- or post- period | y_{PA_i} |
| X.PA | design matrix including vector of 1s (for intercept) and all the covariates and spline bases for each blob, for both time periods | \mathbf{X}_{PA} |
| area.PA[i] | area of i-th blob in meters for both time periods | $area_{PA_i}$ |
| effort[i] | sampling effort for i-th blob in the given period for both time periods | $effort_{PA_i}$ |
| n.PO | number of grid-cells for both time periods concatenated (pre and pos) | n_{PO} |
| j | index identifying grid cells | $j \in 1:n_{PO}$ |
| n.PO.half | number of grid-cells for one time period | $n_{PO}/2$ |
| y.PO[j] | count of observed points in j-th grid-cell, can be for pre- or post- period | y_{PO_j} |
| X.PO | design matrix including vector of 1s (for intercept) and all the covariates and spline bases for each grid-cell for both time periods | \mathbf{X}_{PO} |
| area.PO[j] | area of each grid-cell in meters for both time periods | $area_{PO_j}$ |
| acce[j] | accessibility from urban areas based on travel time for j-th grid-cell for both time periods | $acce_j$ |
| country[j] | country name for j-th grid-cell for both time periods | $country_j$ |
| n.X | total number of columns in X ('X.PA' or 'X.PO') | n_X |
| n.cntr | total number of countries | n_{cntr} |
| c | index identifying countries | $c \in 1:n_{cntr}$ |
| n.par | number of parameters considered (intercept and covariates) | n_{par} |
| r | index identifying parameters | $r \in 1:n_{par}$ |
| n.fac | number of factors of time in X ('X.PA' or 'X.PO') | n_{fac} |
| f | index identifying factors | $f \in 1:n_{fac}$ |
| n.spl | number of spline bases functions in in X ('X.PA' or 'X.PO') | n_{spl} |
| S.pre | spline values for the first time period (pre) | S_{pre} |
| S.post | spline values for the second time period (post) | S_{post} |
| Z | a vector of zeros (0) of the length of the splines | Z |
| sigma.pre | variance of splines for the first time period (pre) | σ_{pre} |
| sigma.post | variance of splines for the second time period (post) | σ_{post} |
| b | vector of parametric effects of covariates driving the point process intensity (it also includes an intercept) | $b_r \in \mathbf{b}$ |
| alpha0 | intercept of the thinning process in the presence-only data | α_0 |
| alpha1 | slope -steepness- of the thinning process in the presence-only data (decaying distance-P.ret relationship) | α_1 |
| beta | coefficient of the effect of sampling effort in the presence-absence data | β |
| gamma | prior for splines smoothing parameter | γ |
| eta.PA | linear predictor for presence-absence data | η_{PA} |
| eta.PA[i] | expected presence-absence for the i-th blob | η_{PA_i} |
| eta.PO | linear predictor for presence-only data | η_{PO} |
| eta.PO[j] | expected count points for the j-th grid-cell | η_{PO_j} |
| psi[i] | blob-specific probability of presence | ψ_i |
| P.ret[j] | cell-specific probability of retaining (observing) a point as a function of accessibility and country of origin | P_{ret_j} |
| nu[j] | true mean number of points per grid-cell (the true intensity) | ν_j |
| lambda[j] | thinning of the true intensity | λ_j |
| eta.pred | linear predictor for the predicted probability of occurrence | η_{pred} |
| eta.pred[j] | predicted count points for the j-th grid-cell | η_{pred_j} |
| P.pred[j] | predicted probability of occurrence for the j-th grid-cell | P_{pred_j} |
| A.pre | range area in the first time period (pre) | A_{pre} |
| A.post | range area in the second time period (post) | A_{post} |
| delta.A | temporal change of range area (post-pre) | ΔA |



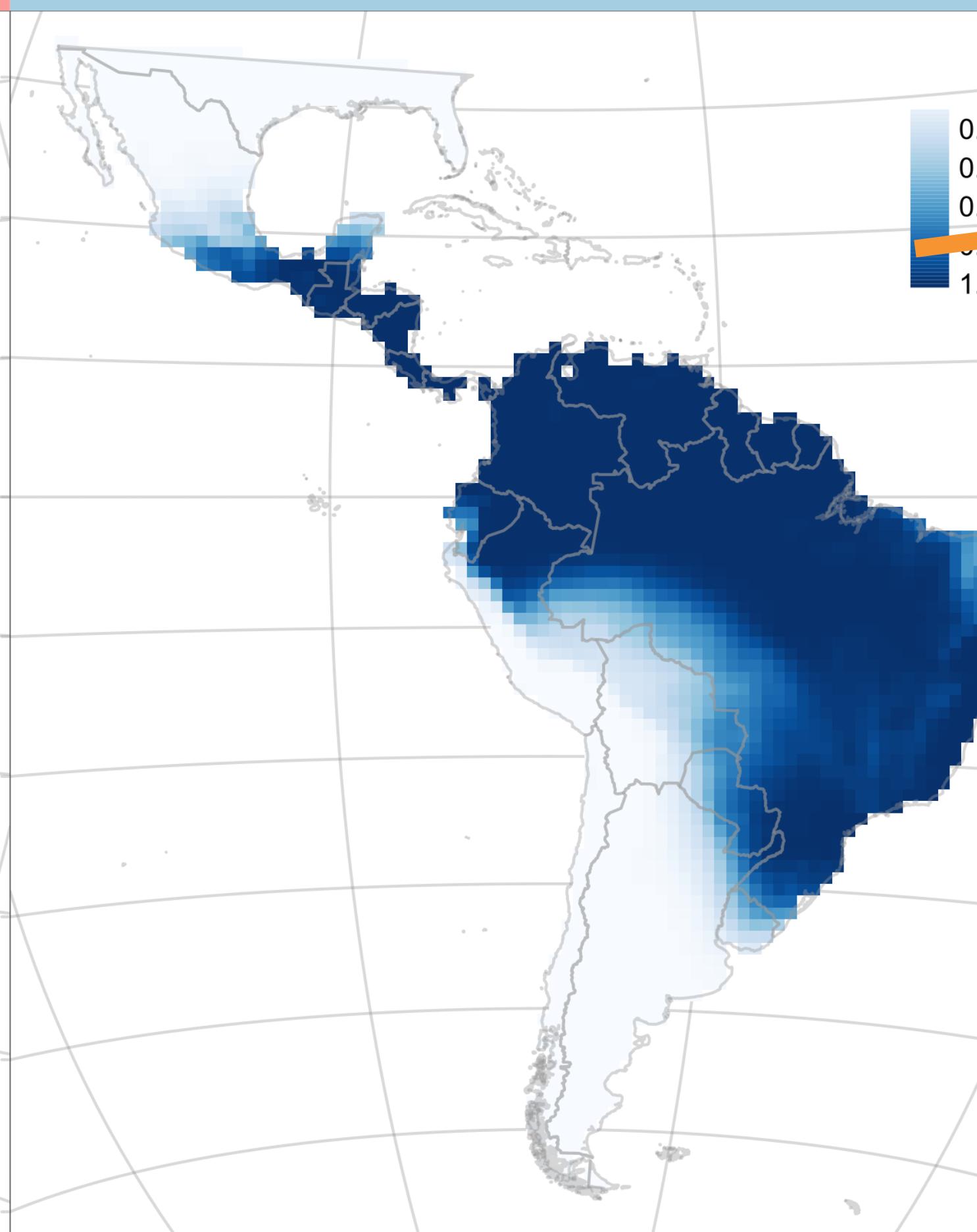
Resultados y Discusión



Range_{time1} (2000-2013)



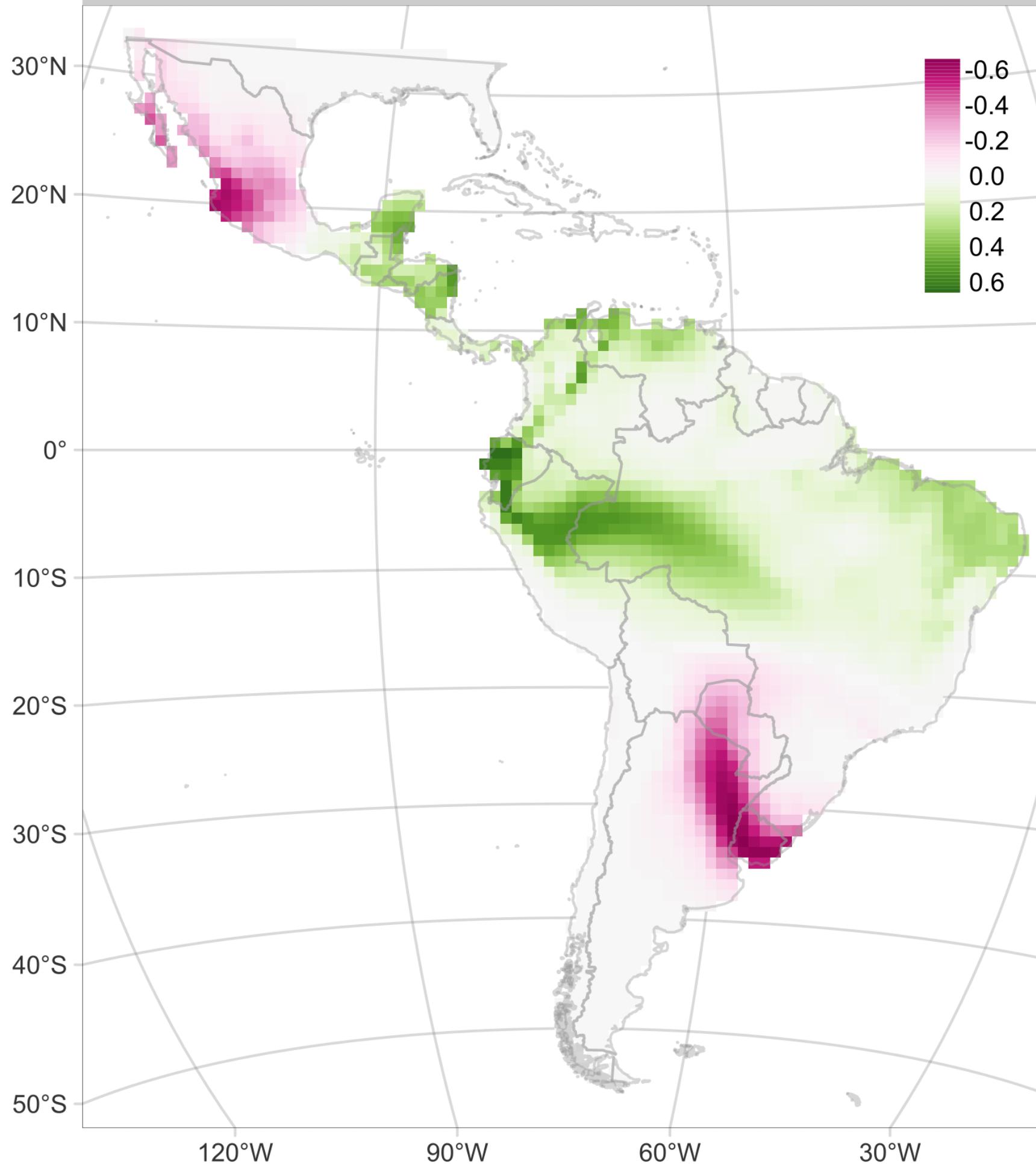
Range_{time2} (2014-2021)



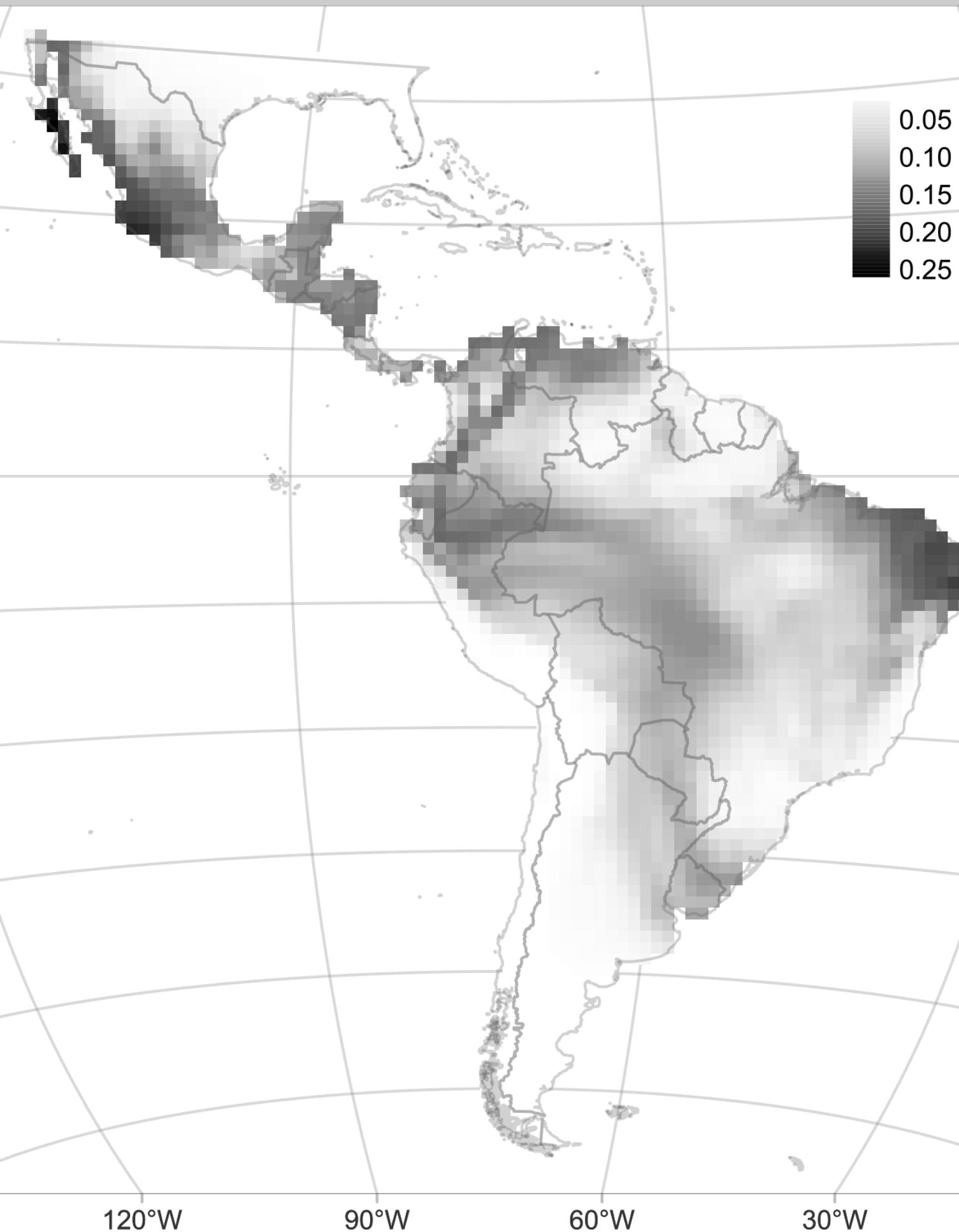
IUCN range



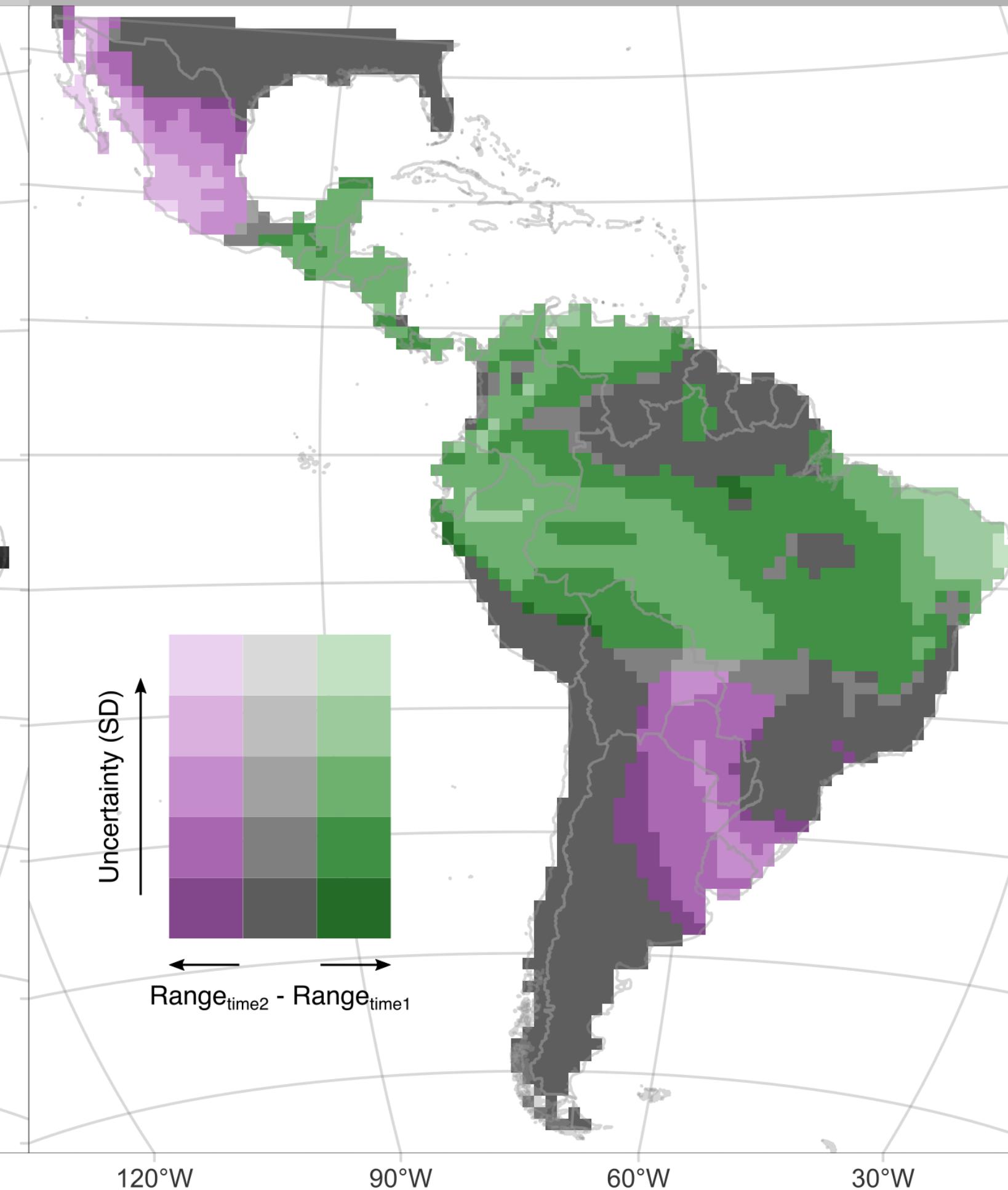
$\text{Range}_{\text{time}2} - \text{Range}_{\text{time}1}$



Uncertainty (SD)



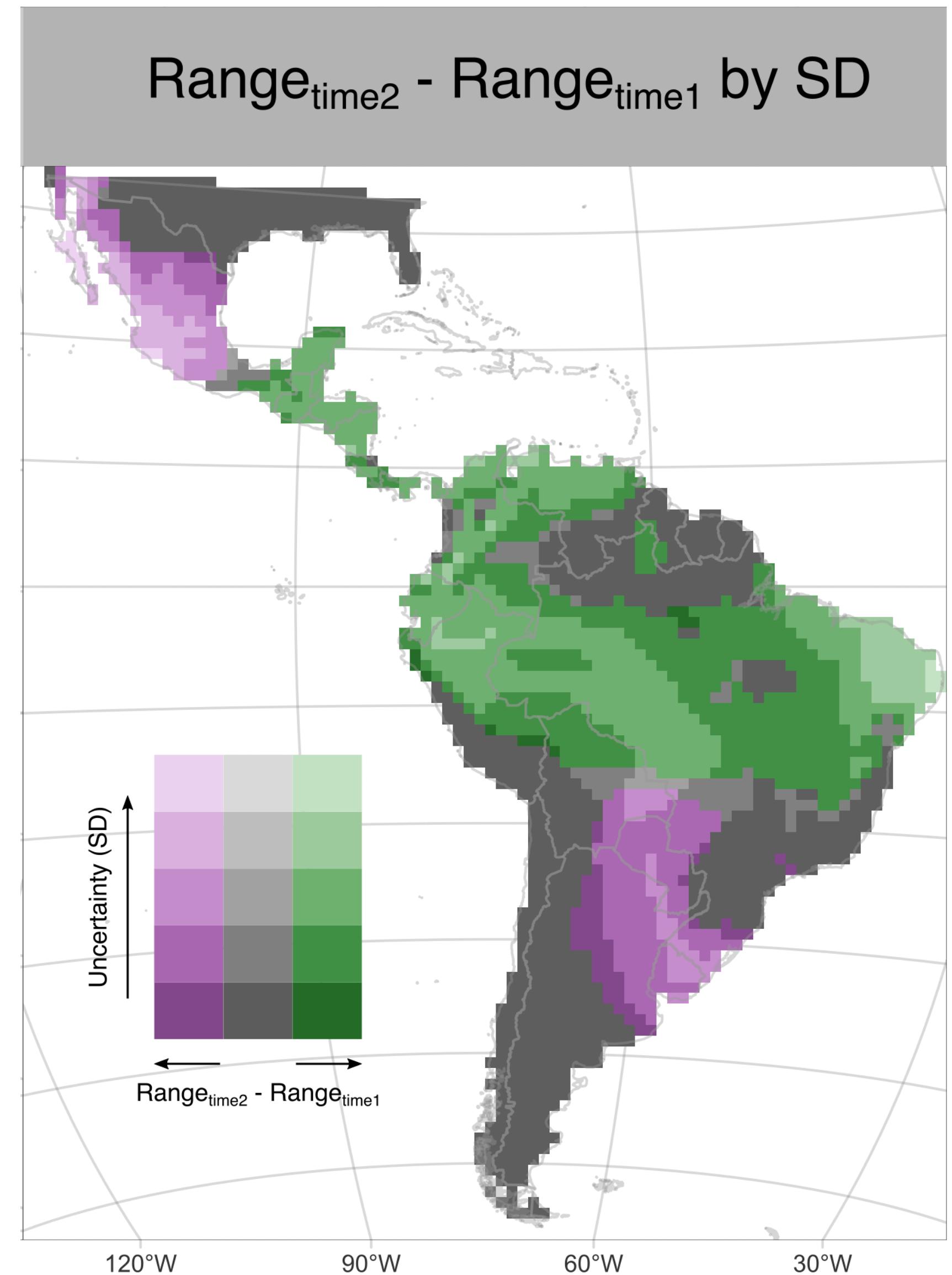
$\text{Range}_{\text{time}2} - \text{Range}_{\text{time}1}$ by SD



Rango de la especie

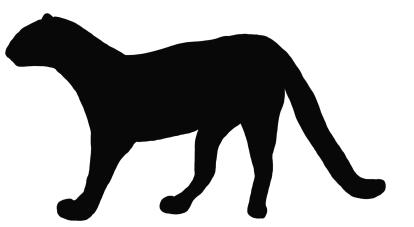
Cambio temporal

- **Retracción** del límite sur del área de distribución en Argentina, Uruguay y Paraguay y del límite norte en México.
- **Mantuvo** su presencia en el centro y sureste de Brasil.
- **Expansión** en la Amazonia brasileña y colombiana, cerca de la región del Sertão en el noreste de Brasil y en la frontera de México con Guatemala.



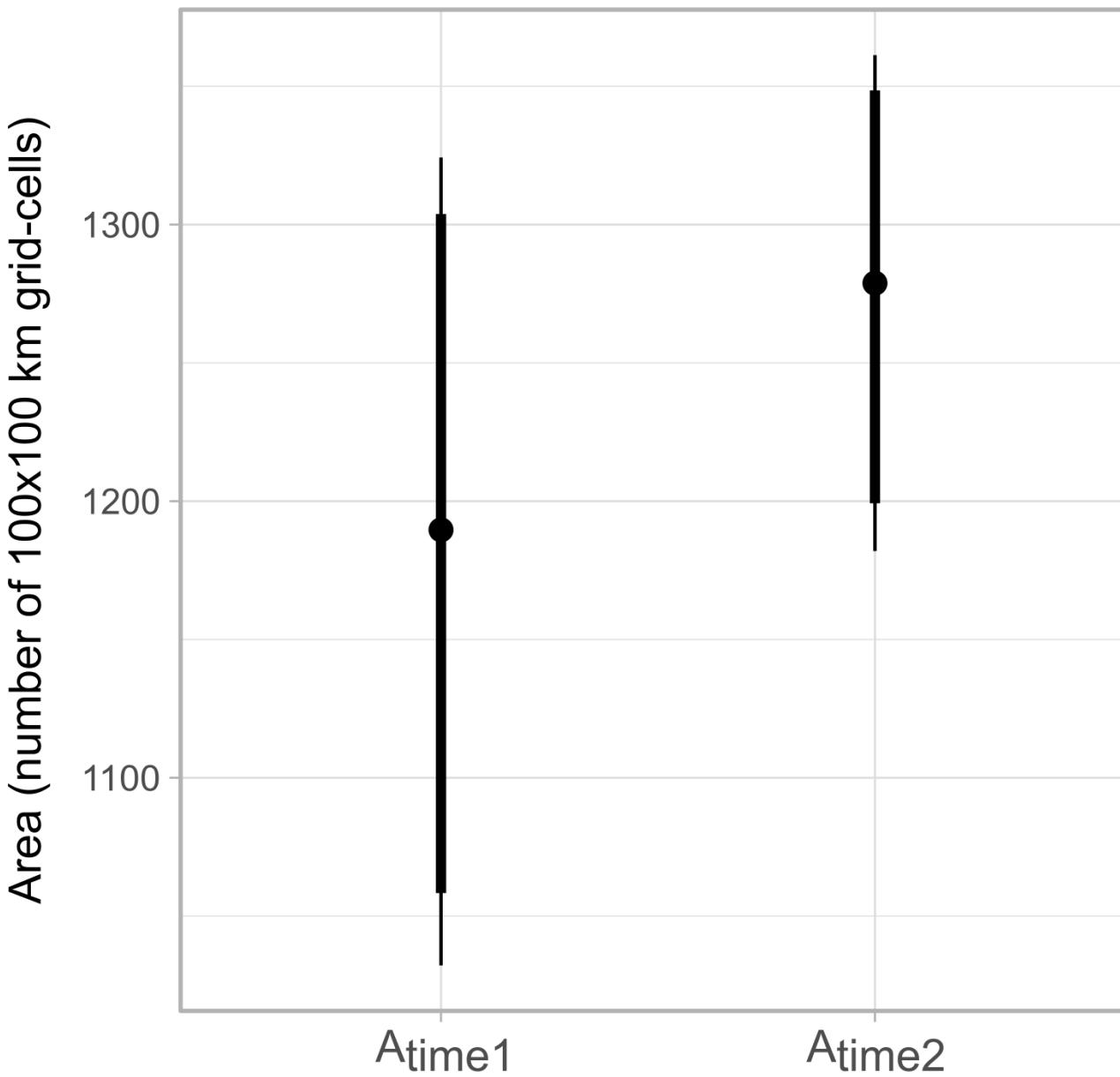
Rango de la especie

Cambio en el área



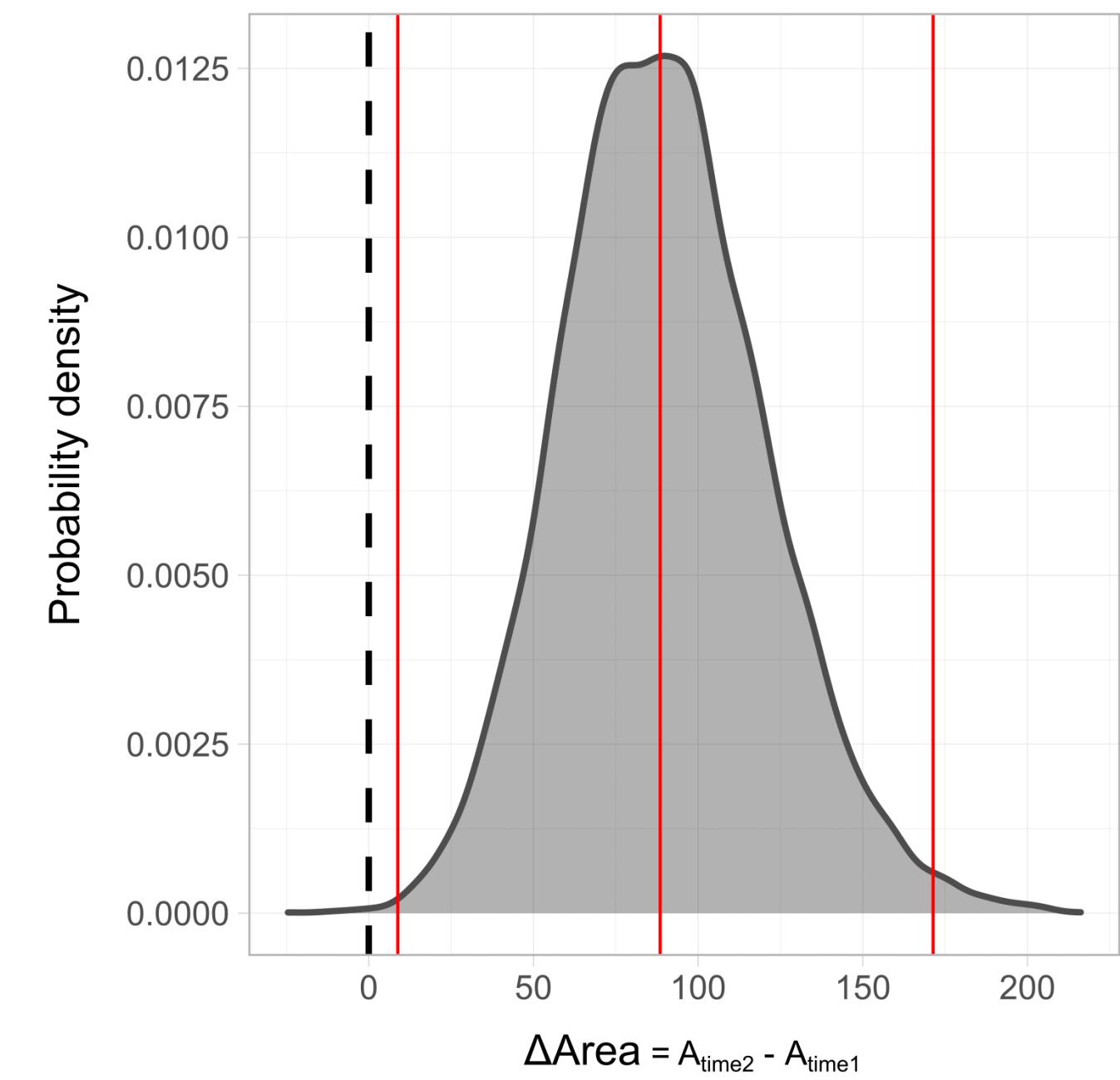
- Entre ambos períodos, se observa un aumento del área de distribución del yaguarundí, **ampliando su área de distribución** (número de celdas).

a



Densidades posteriores del área
prevista en ambos periodos de tiempo

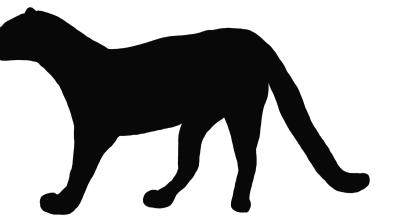
b



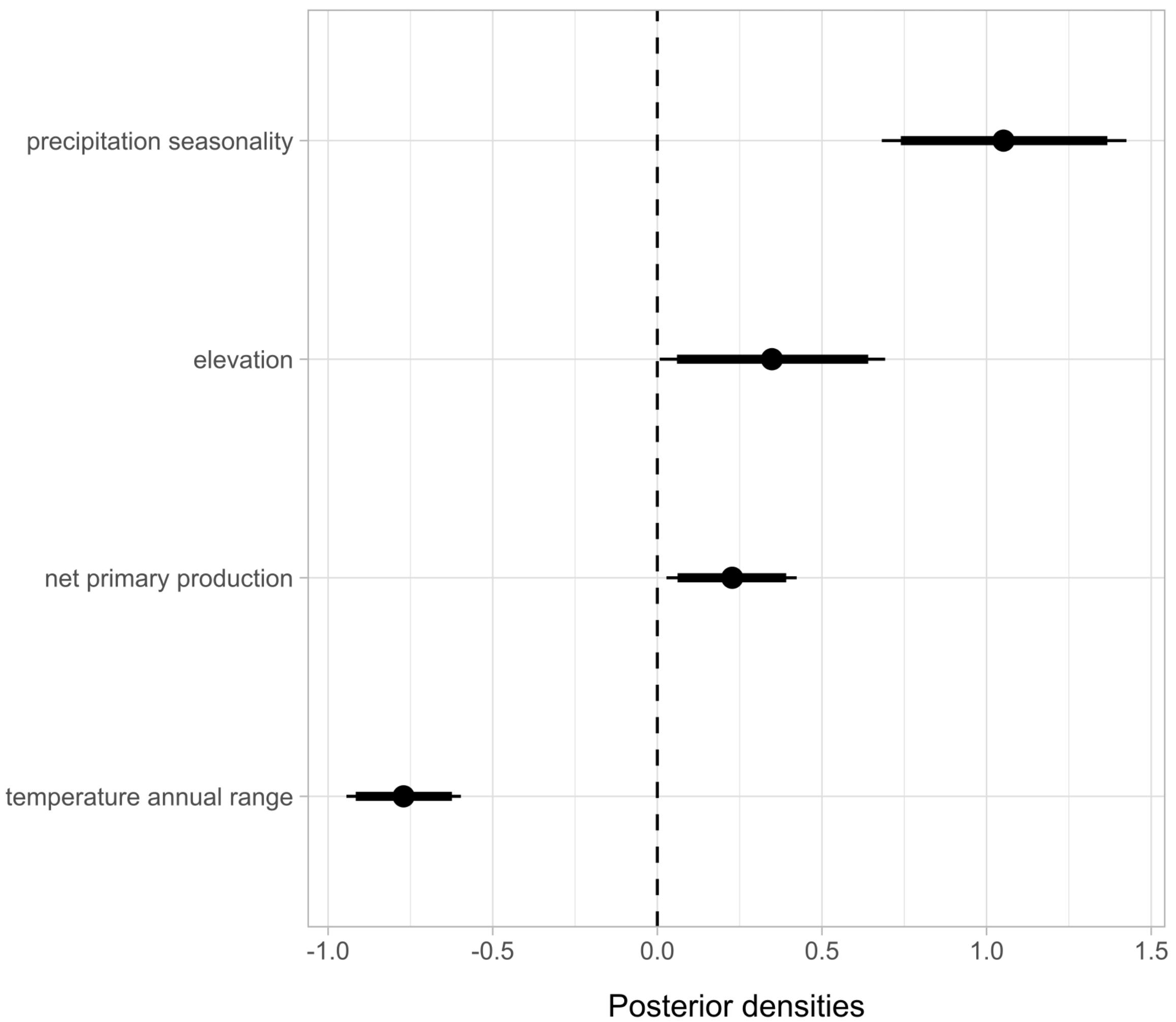
Distribución posterior del cambio de rango,
(línea discontinua = sin cambio de rango)

Rango de la especie

Inferencia ecológica



- El yaguarundí prefiere zonas con precipitaciones estacionales (**+Prec**).
- Prefiere altitudes más elevadas (**+Elev**).
- Prefiere zonas verdes productivas con buena cobertura vegetal (**+NPP**).
- Evita los desiertos y las zonas semiáridas (**-Temp**).



Conclusiones



SDM integrado

El modelo

- Asumió una intensidad de patrón puntual de Poisson (libre de escala)
- Integró datos de cámaras-trampa con las ocurrencias puntuales de GBIF.
- Tuvo en cuenta el esfuerzo de muestreo y la autocorrelación espacial



SDM integrado

Cambio temporal

- La integración de los datos nos permitió aumentar el tamaño de la muestra, la extensión geográfica y el scope ambiental de cada período.
- Pudimos estimar el cambio temporal en el área de distribución geográfica de la especie incluso en un lapso de tiempo relativamente corto.



SDM integrado

Solución a la falta de datos

- Los datos no estructurados son cada vez más comunes en América Central y del Sur.
- Estos datos se han considerado problemáticos, pero utilizando los ISDM podemos combinarlos con datos de alta calidad para mejorar nuestra comprensión de cómo las especies cambian sus áreas de distribución geográfica a lo largo del tiempo.



¿Y ahora qué?



¿Y ahora qué?

Nuevos desafíos

- **Otras especies:** ¿Qué está pasando con otras especies? ¿Podemos detectar áreas donde se acumulan más cambios?
- **Causas:** ¿Podemos atribuir estos cambios a algún factor, como el cambio de uso del suelo o el cambio climático?
- **Interacción:** ¿Cómo modelar los efectos de la co-currencia? ¿podemos adaptar nuestro modelo para modelar conjuntamente más de una especie?

¿Y ahora qué?

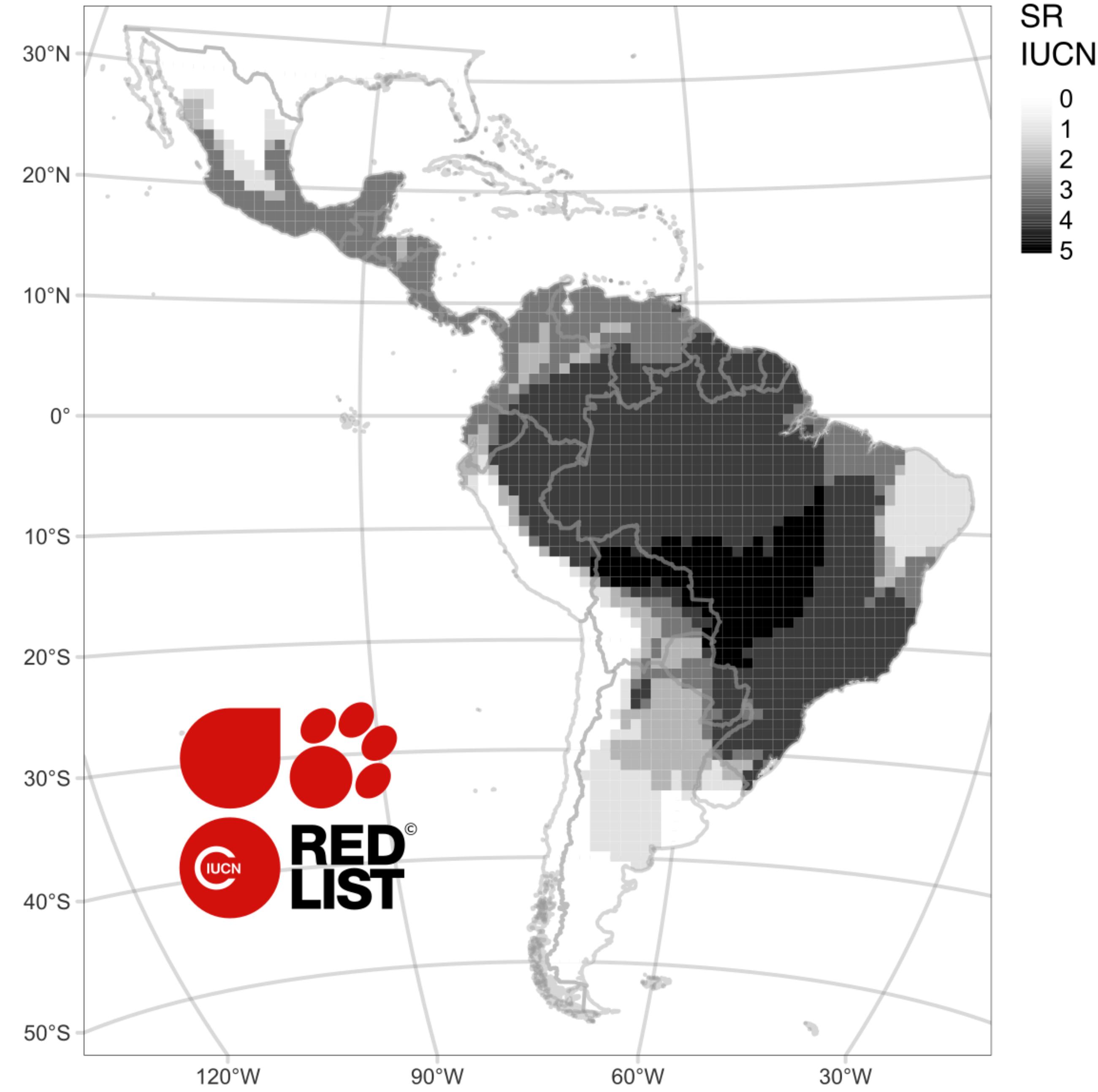
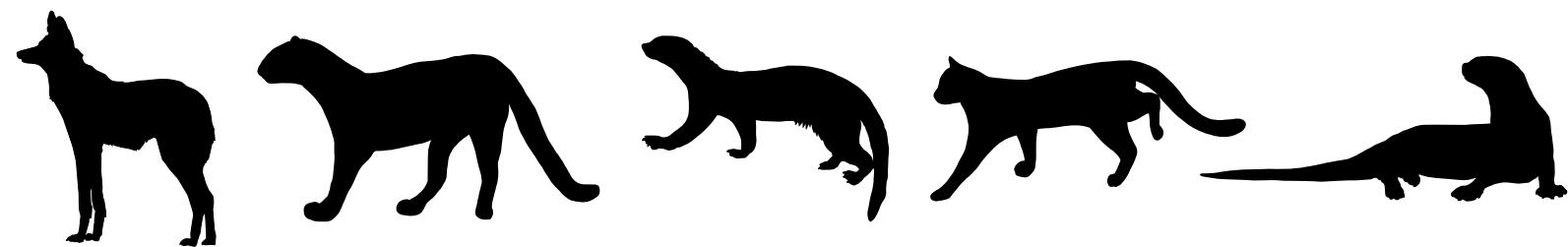
Nuevos desafíos

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- **Interacción:** ¿Cómo modelar los efectos de la co-currencia? ¿podemos adaptar nuestro modelo para modelar conjuntamente más de una especie?

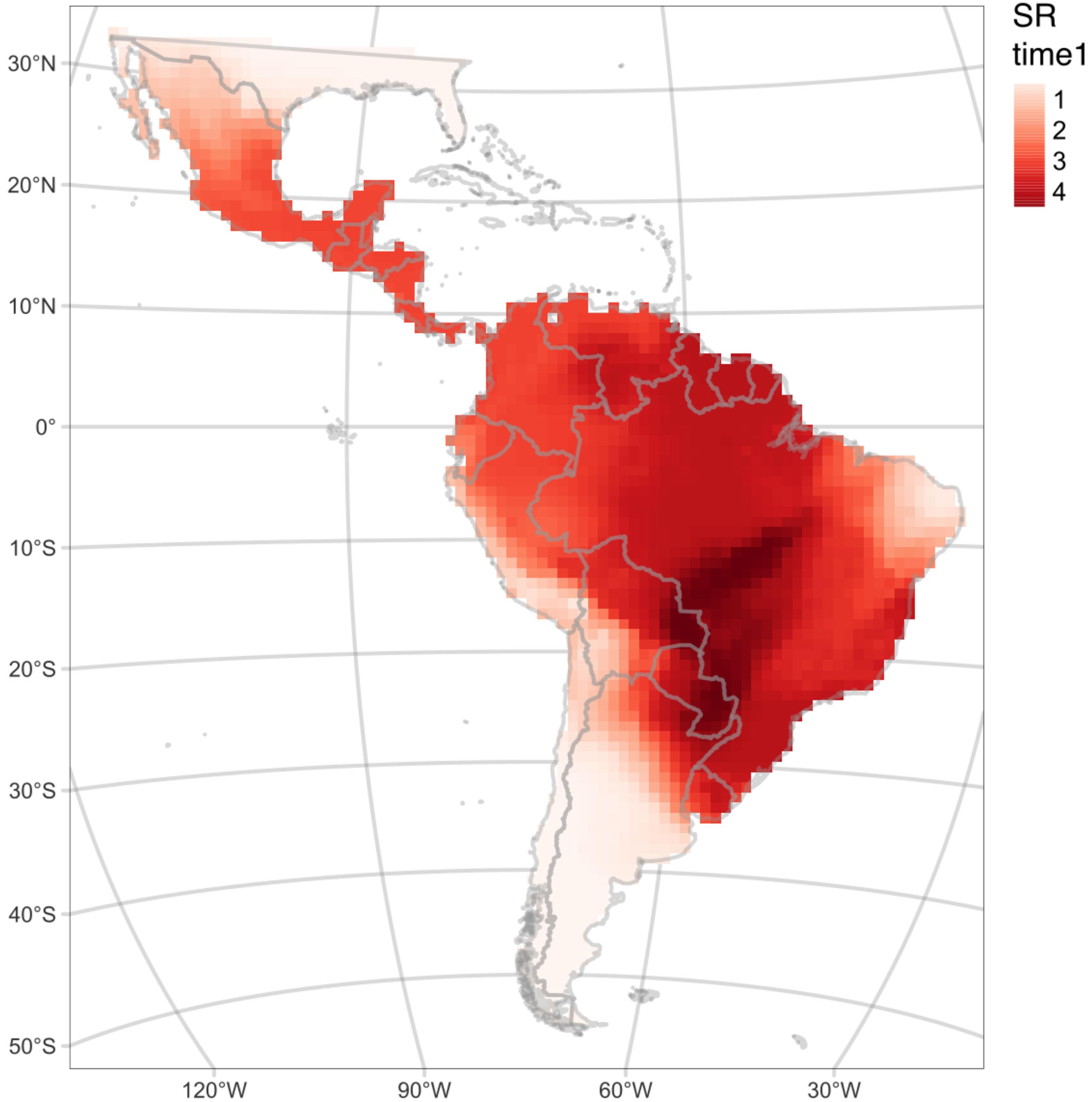
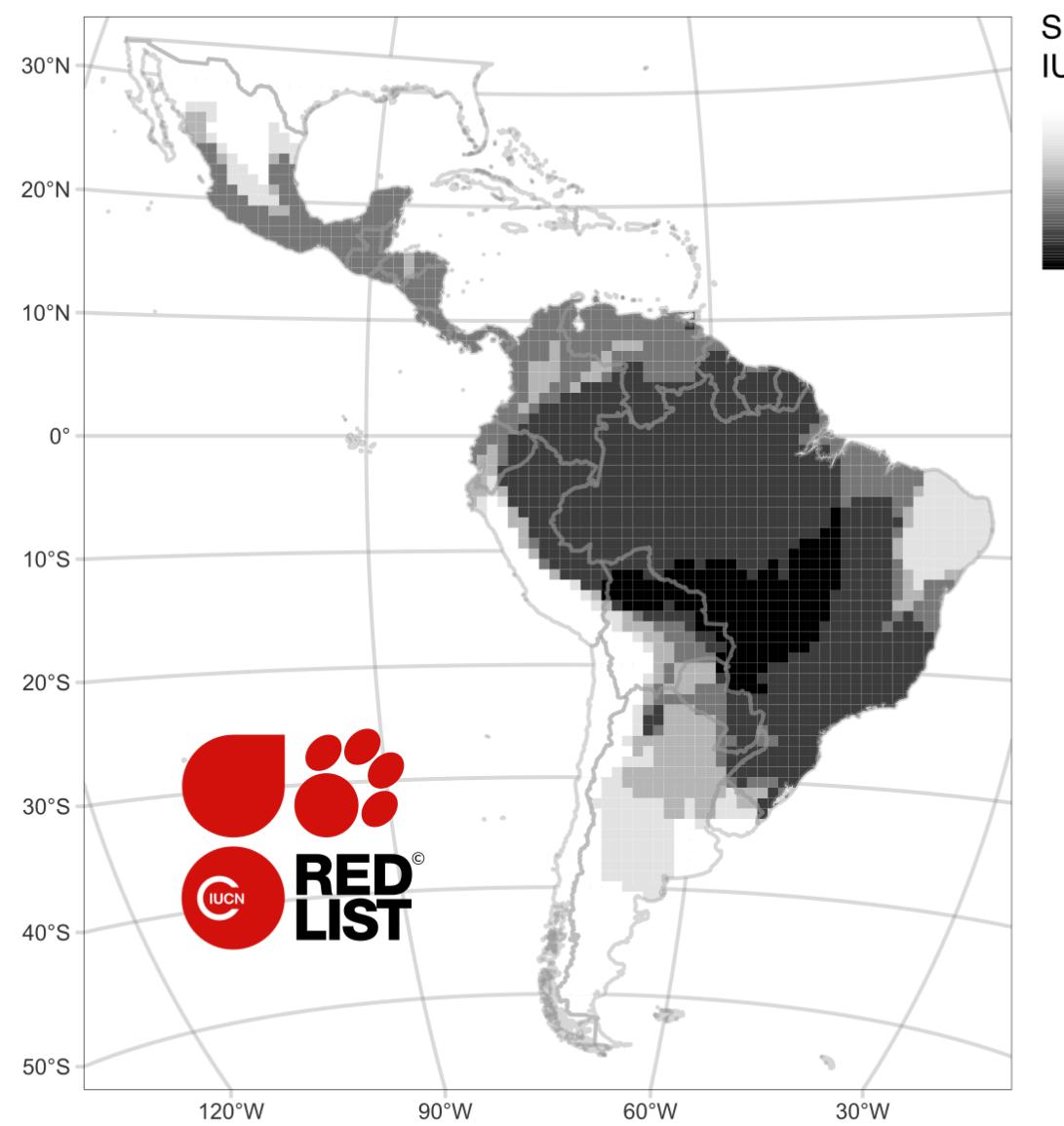
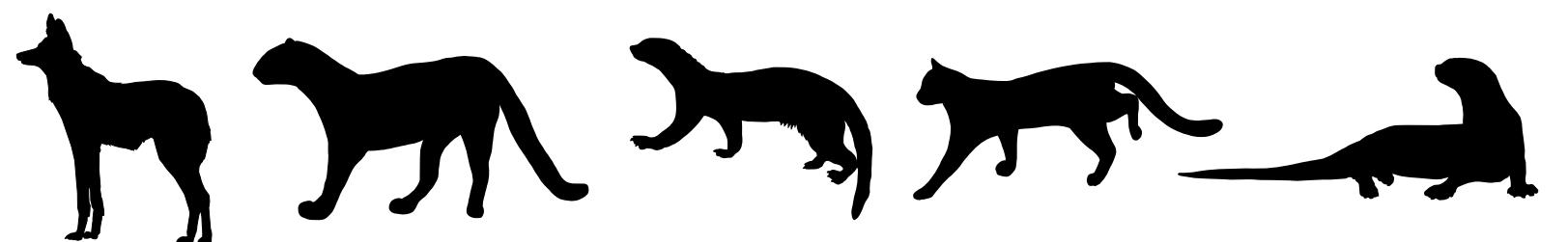


jaguarundi (*Herpailurus yagouaroundi*) by @hhulsberg, ocelot (*Leopardus pardalis*) by @cotingidae, crab-eating fox (*Cerdocyon thous*) by @farpost, maned wolf (*Chrysocyon brachyurus*) by @constanzamcl, tayra (*Eira barbara*) by @christoph_moning, margay (*Leopardus wiedii*) by @bigsam, coati (*Nasua nasua*) by @douglasmeye, and giant river otter (*Pteronura brasiliensis*) by @npdowling (iNaturalist.org).

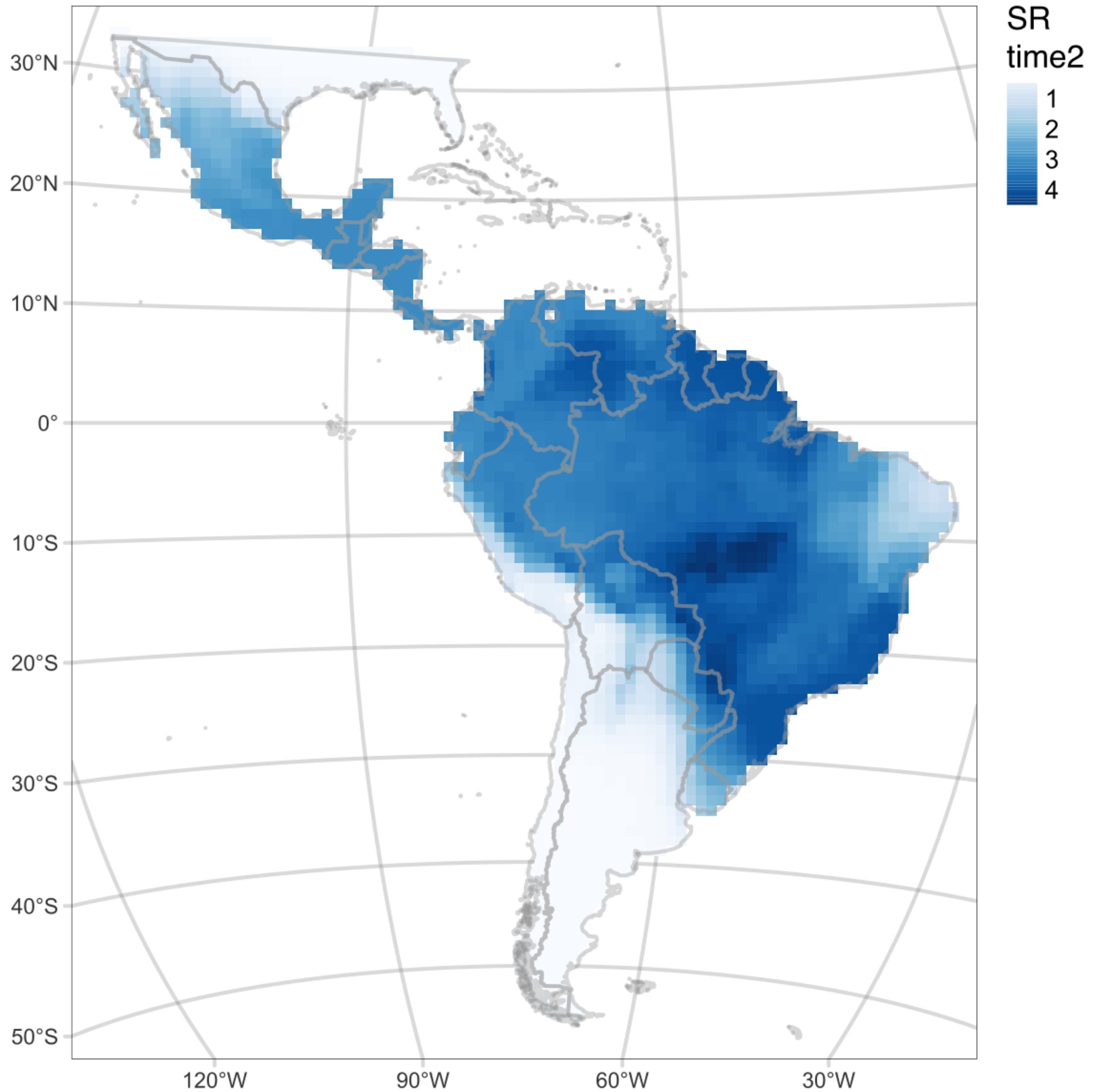
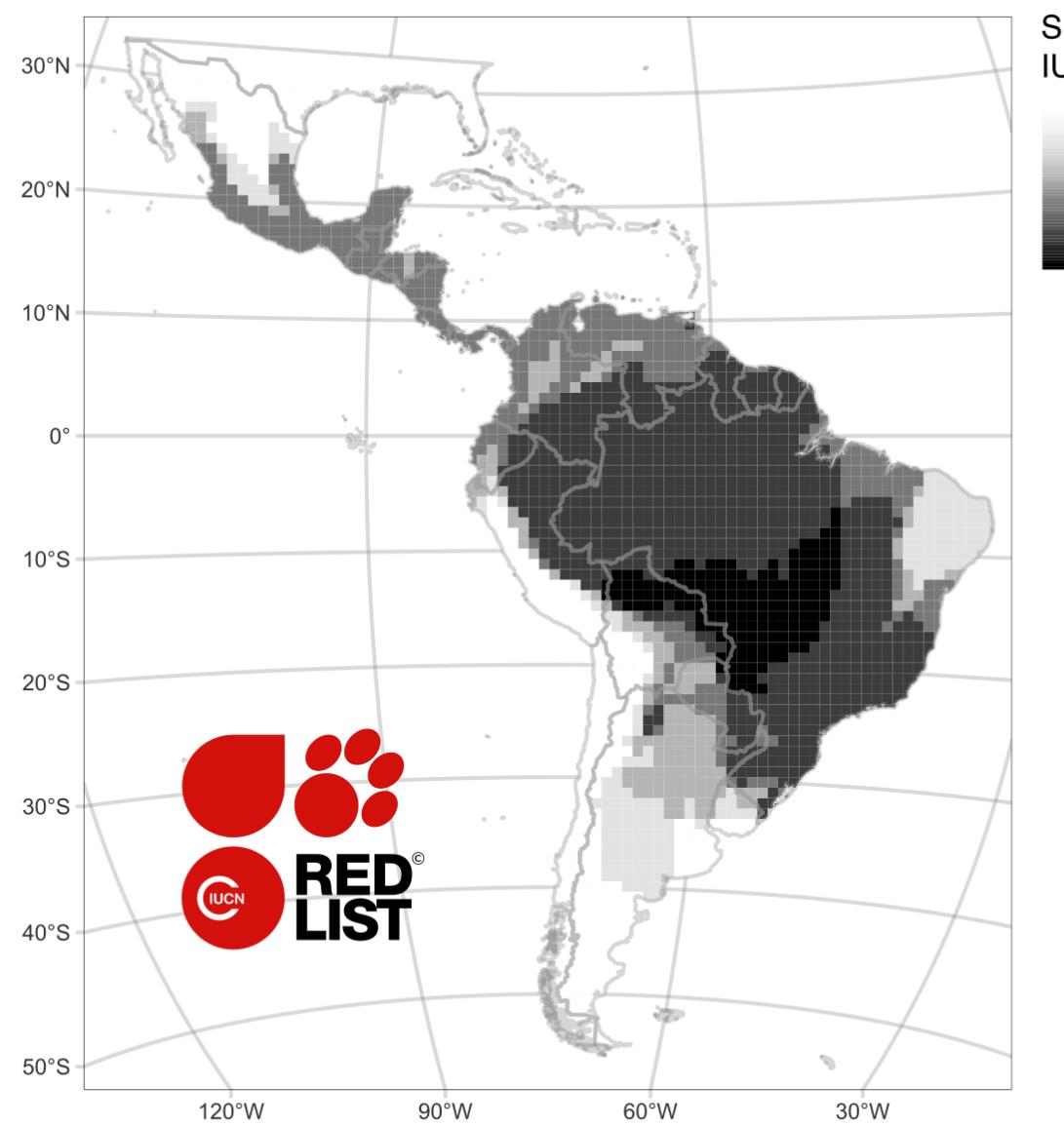
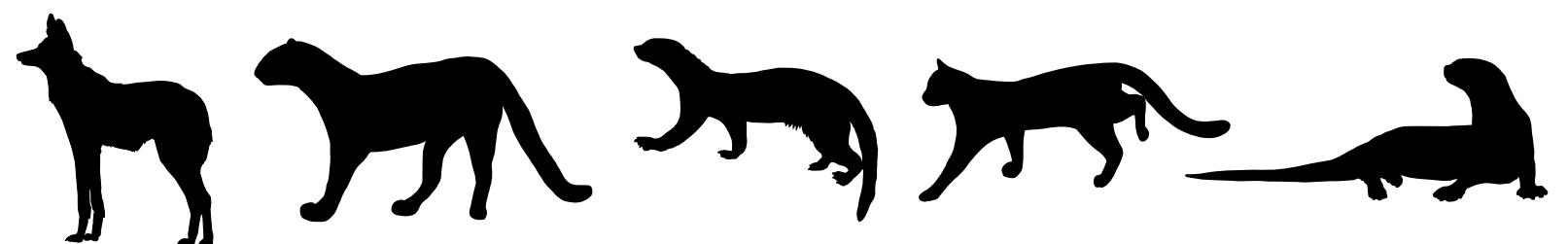
Riqueza de especies IUCN



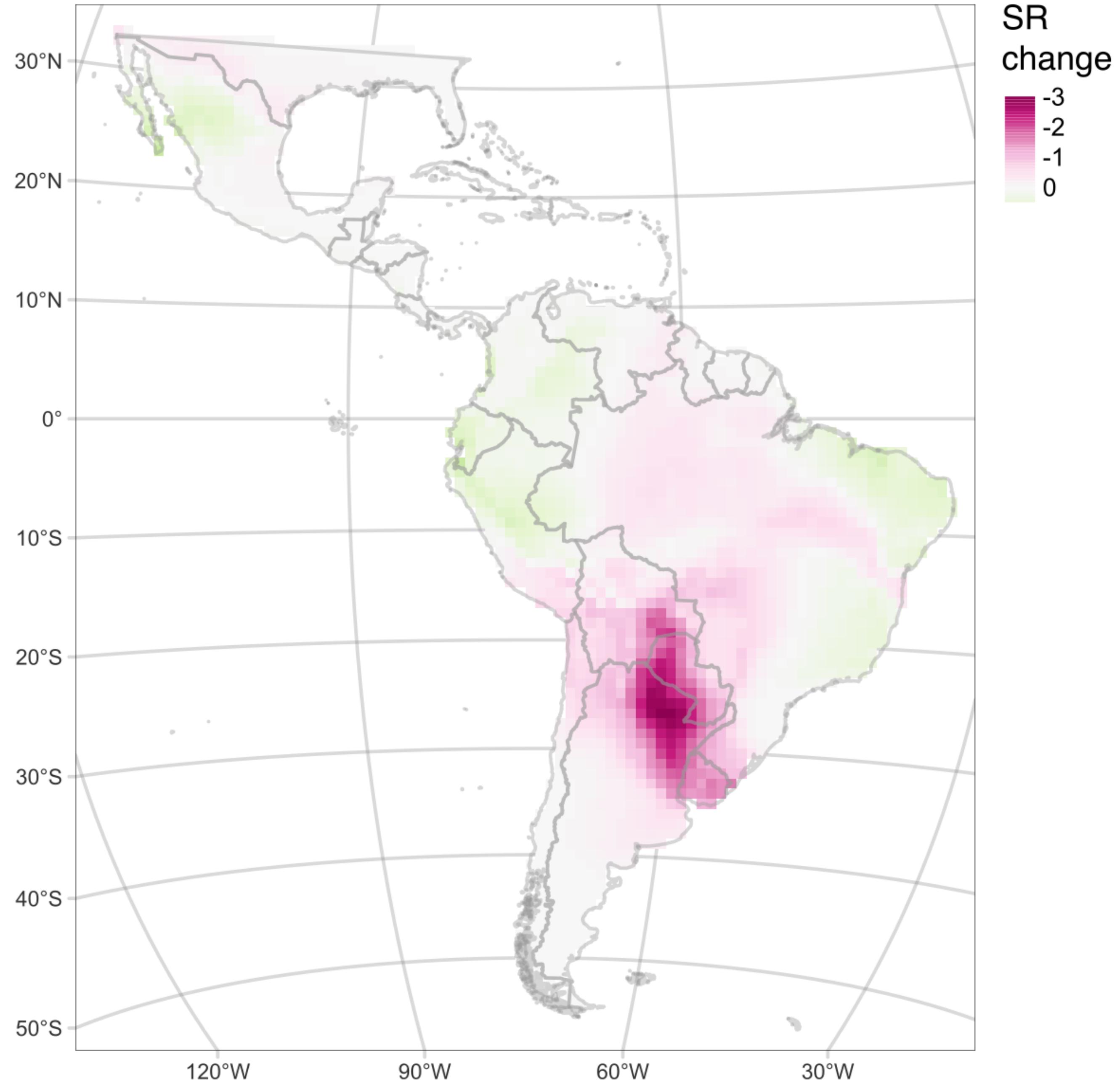
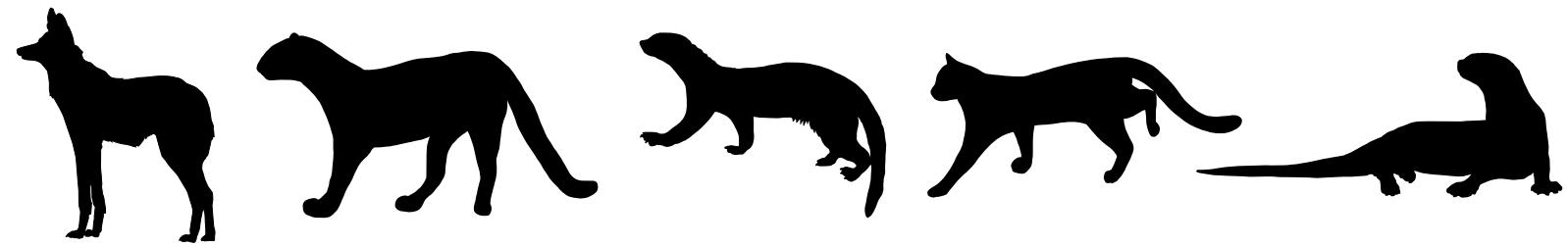
Riqueza de especies



Riqueza de especies



Cambio en la riqueza de especies



Y ahora qué?

Desafíos

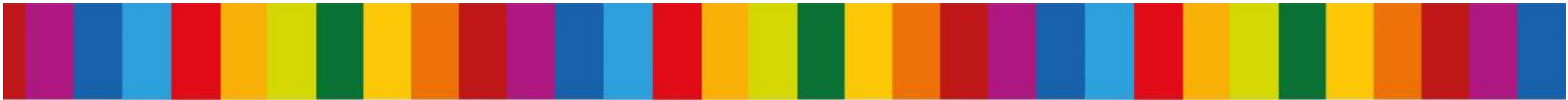
Aumentar la cantidad de datos disponibles en América Latina

- **Involucrar** a más personas en la ciencia comunitaria, por ejemplo, a través de iNaturalist.
- **Digitalizar** nuevos estudios con cámaras trampa, de bibliografía pero también de iniciativas de locales de nuestra región.



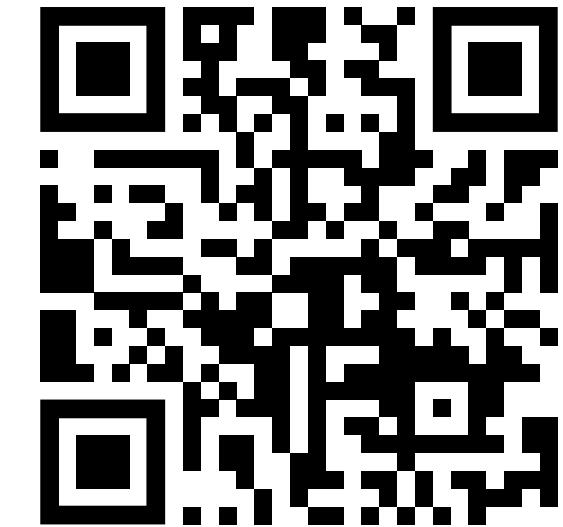
NaturalistaUY

¡Gracias!



**Daiana E. Bowler,
and Petr Keil**

Journal of
Biogeography



GitHub



Agradecimientos

REES (Research Excellence in Environmental Sciences) fondo de la Faculty of Environmental Sciences, Czech University of Life Sciences in Prague.

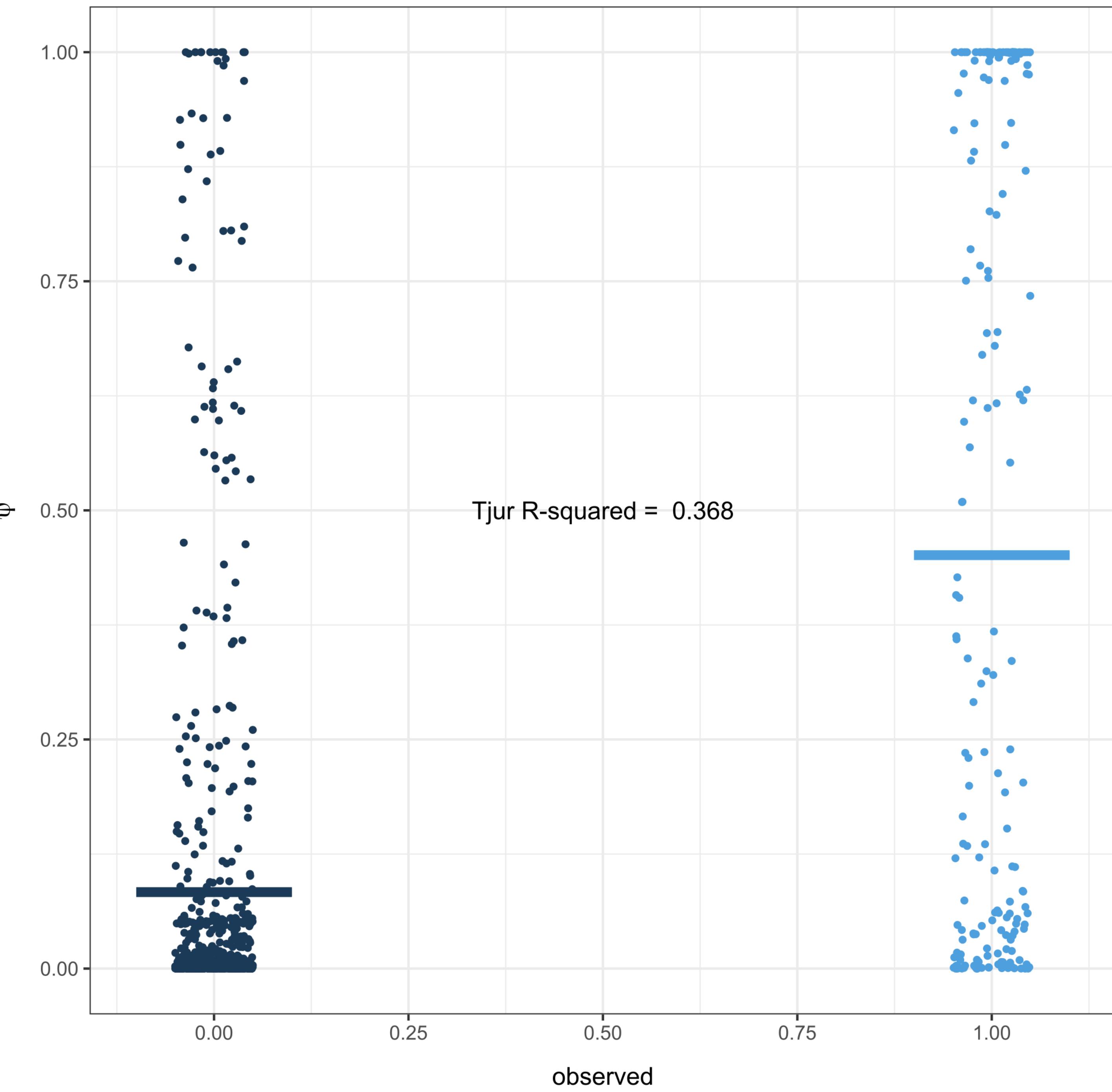
European Research Council. Grant Number: 101044740

Créditos

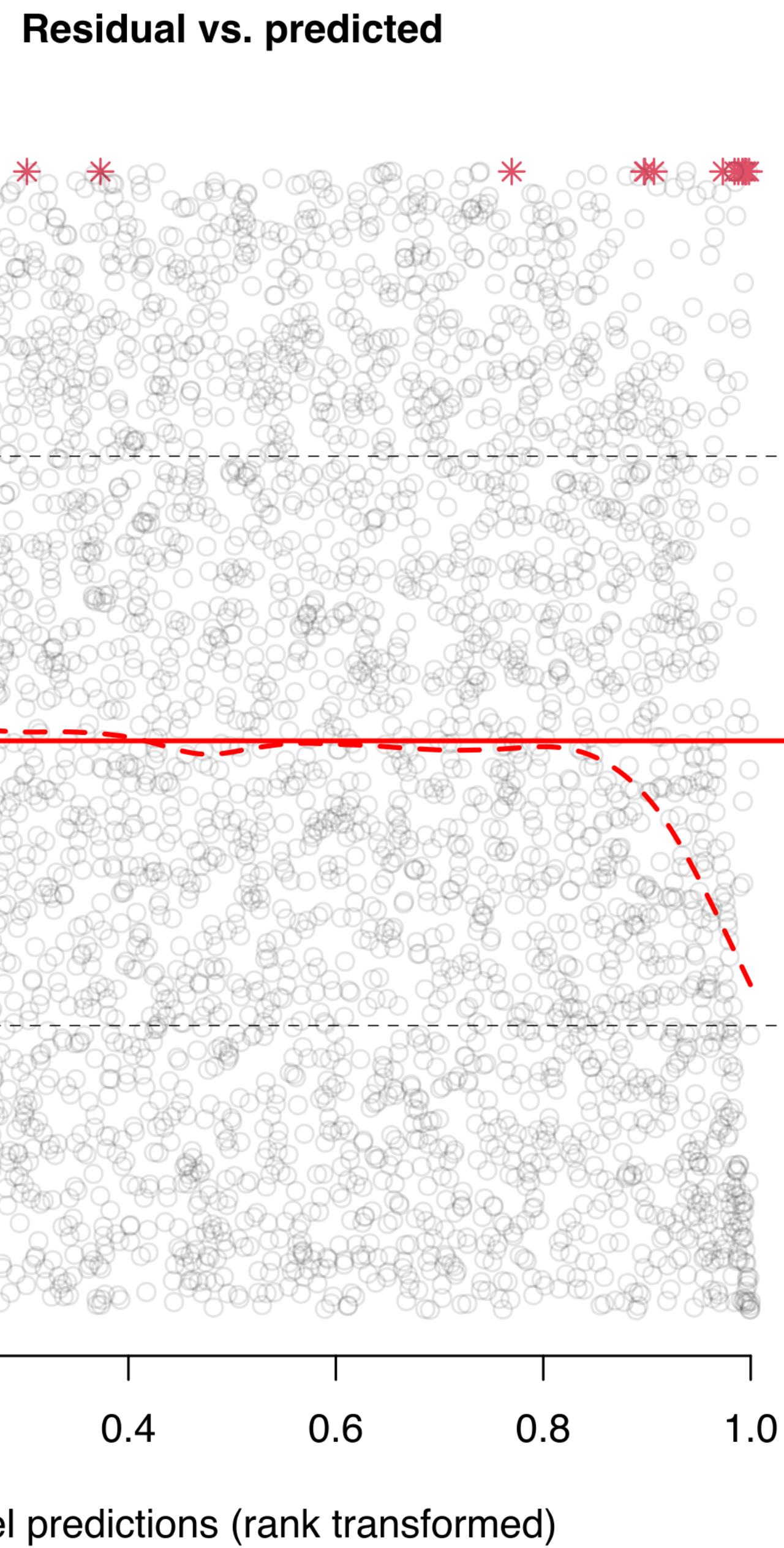
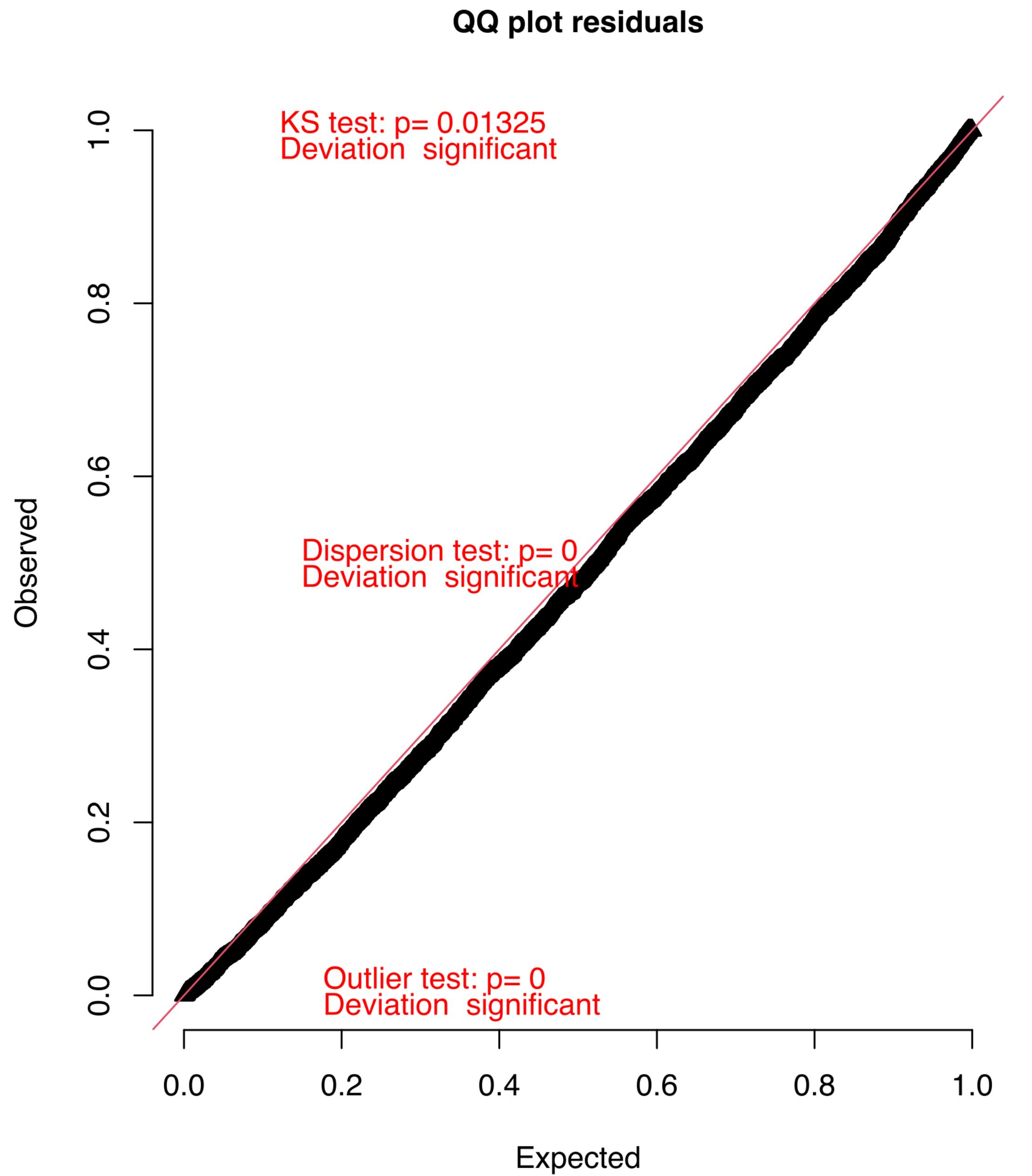
Fotos por Hugo Hulsberg (CC-BY-NC), albamaya (CC-BY-NC), Christoph Moning (CC-BY), Bernard Foy (CC-BY-NC), Scott Ramos (CC-BY-NC), drewdavis74 (CC-BY-NC), ddavilareyes (CC-BY-NC), alexcg223 (CC-BY-NC) - [iNaturalist](#). Siluetas por Gabriela Palomo-Muñoz (CC BY-NC) y Margot Michaud (CC0) - [PhyloPic](#).



Tjur R2

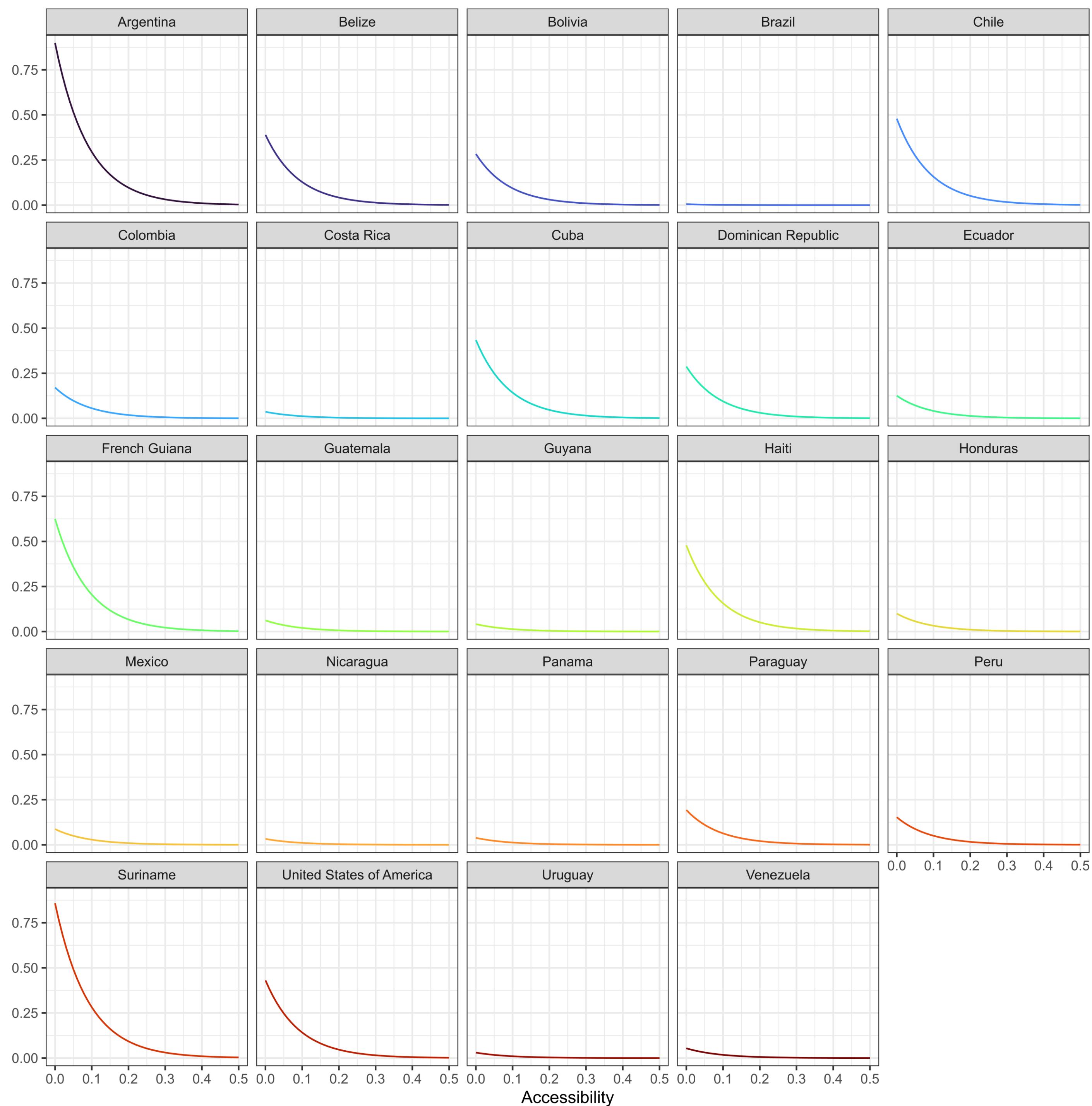


DHARMA residual

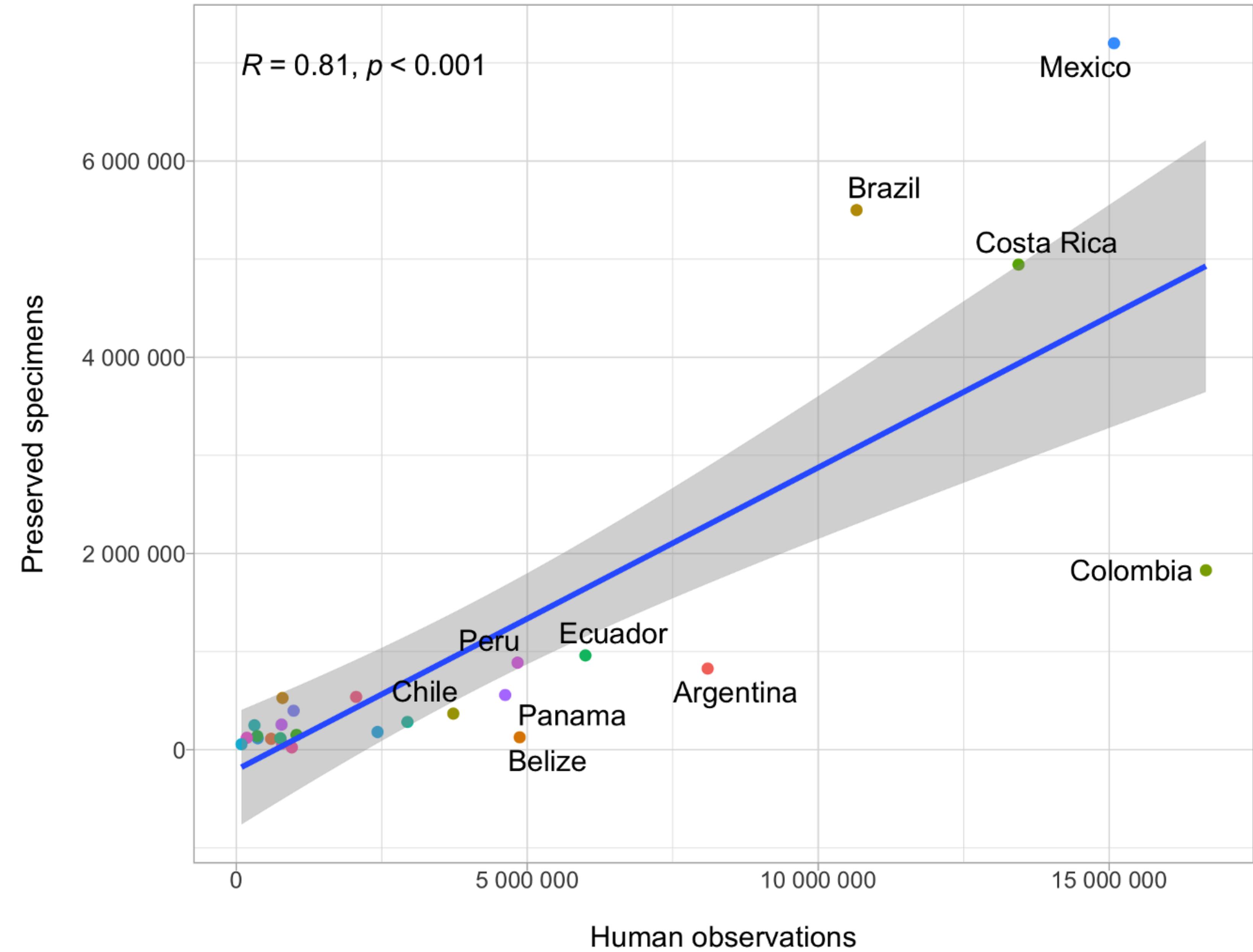


País

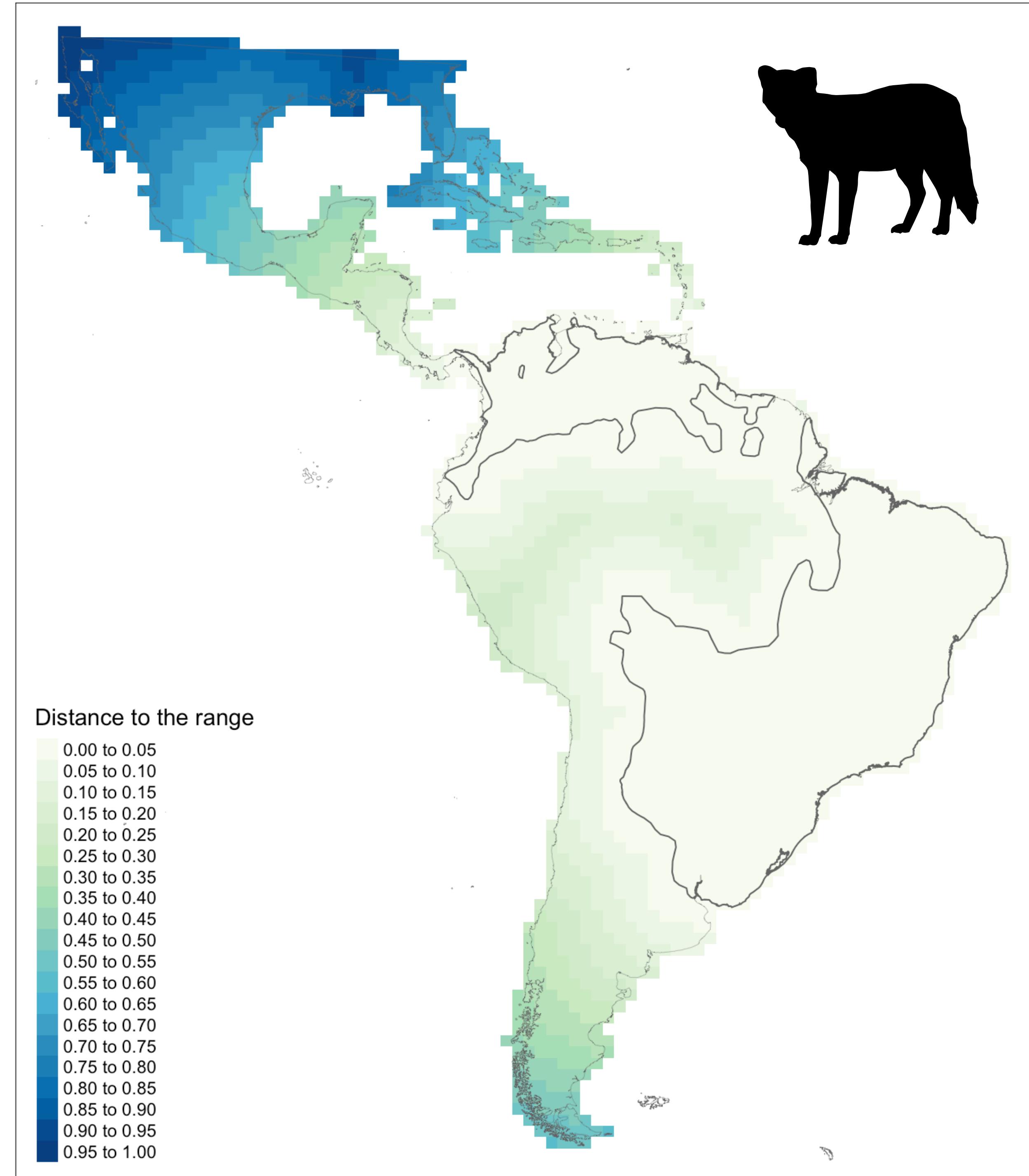
$$P_{retj} = a_0 \text{country}_j \times \exp^{-a1 \times \text{acce}_j}$$



País

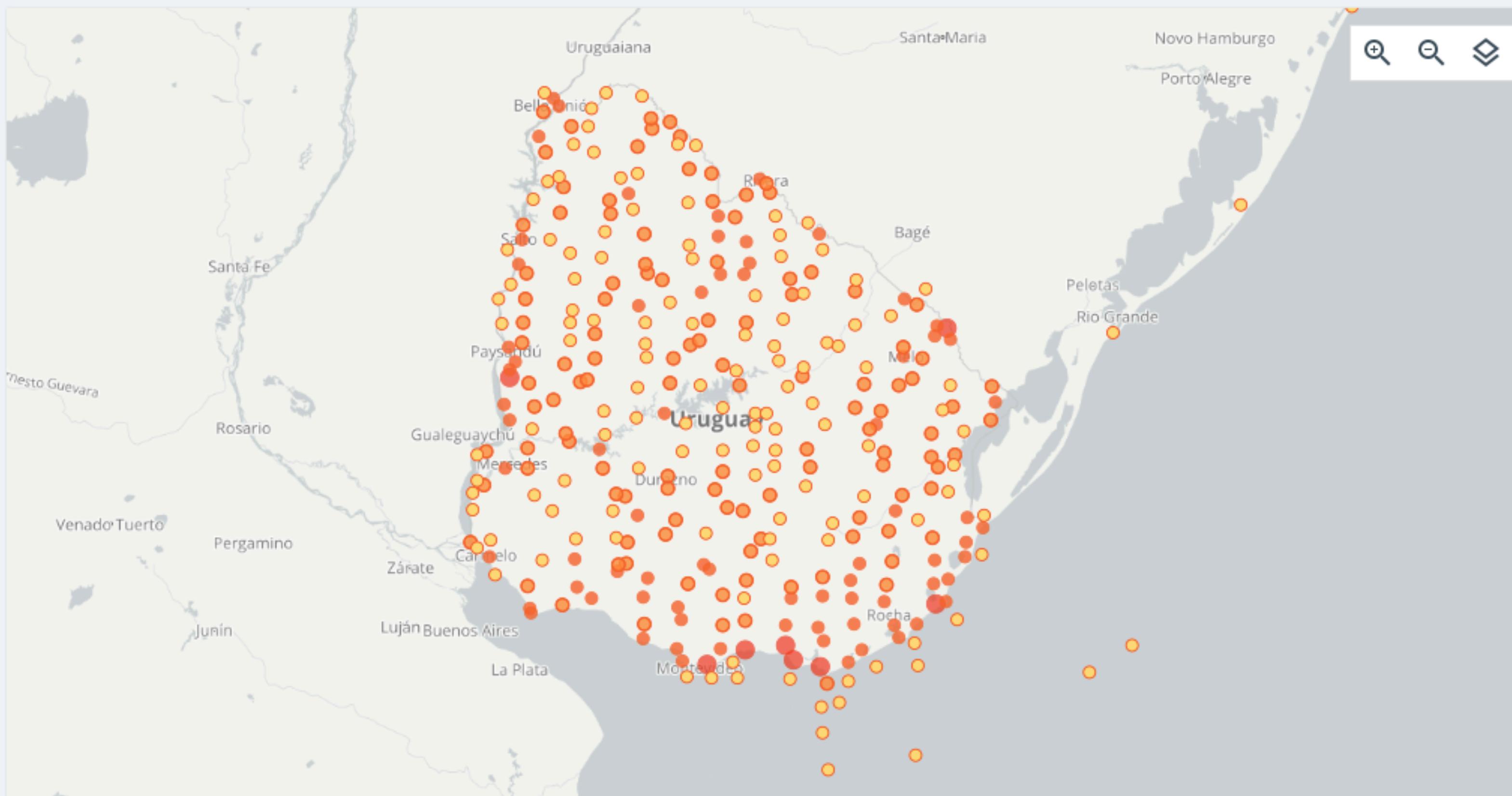


Expert range map as a covariate



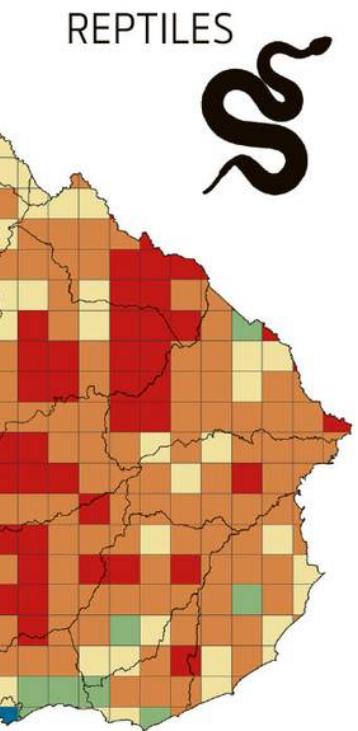
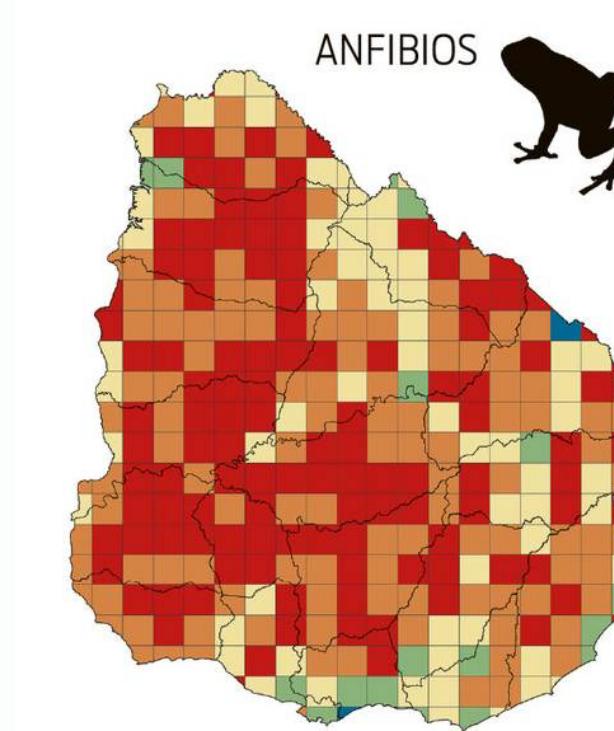
[Mapa](#) [Tabla](#) [Galería](#) [Conjuntos de datos](#) [Descargar](#)[Nombre científico](#) [Departamento/Estado/Provincia](#) [Año](#) [Base del registro](#) [Publicador](#) [más](#)

44.501 resultados con coordenadas



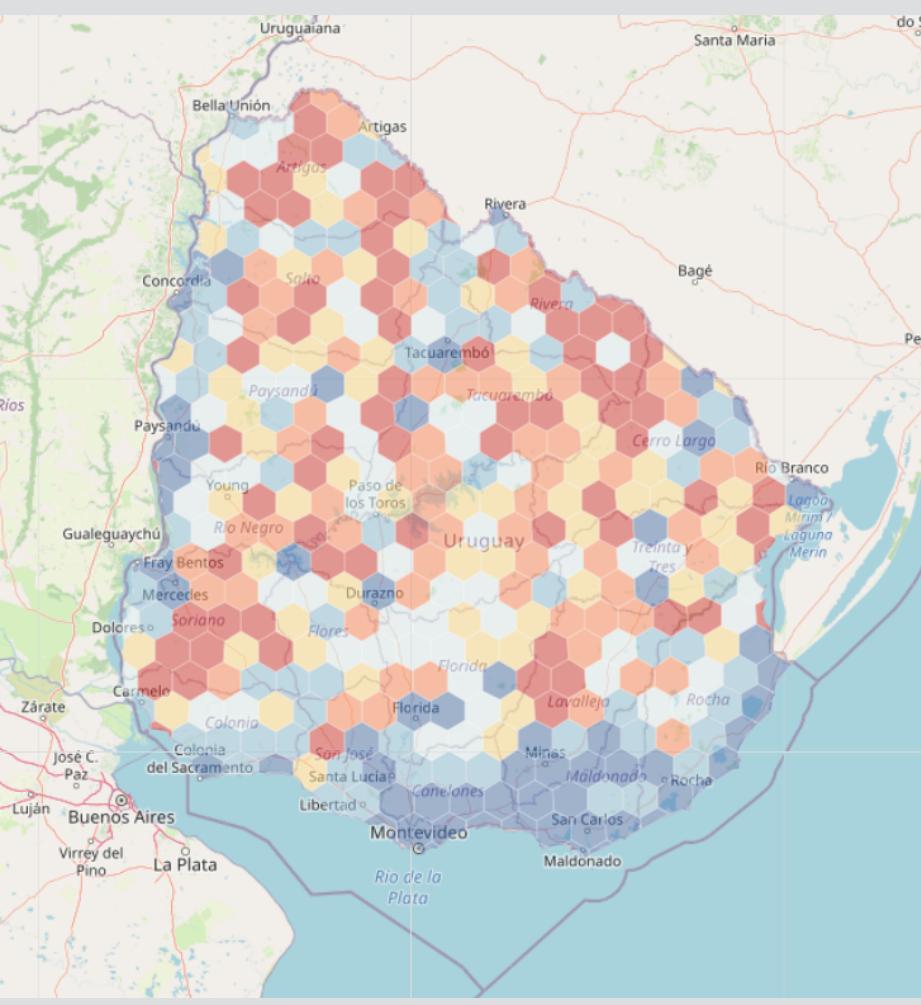
ÁREAS DE PRIORIDAD PARA FUTUROS MUESTREOS

Nula Baja Media Alta Muy alta



BIODIVERSIDATA: THE URUGUAYAN CONSORTIUM OF BIODIVERSITY DATA

OPEN SCIENCE | DATA MOBILISATION



NATURALISTAUY | COMMUNITY SCIENCE

THE OBSERVERS' BIAS