Maxent overview

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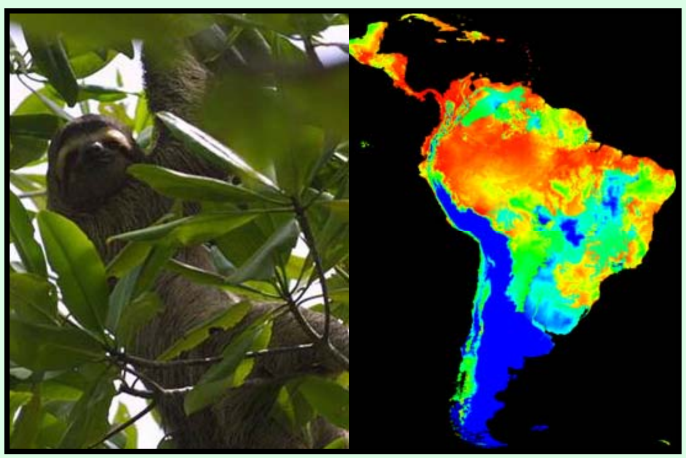
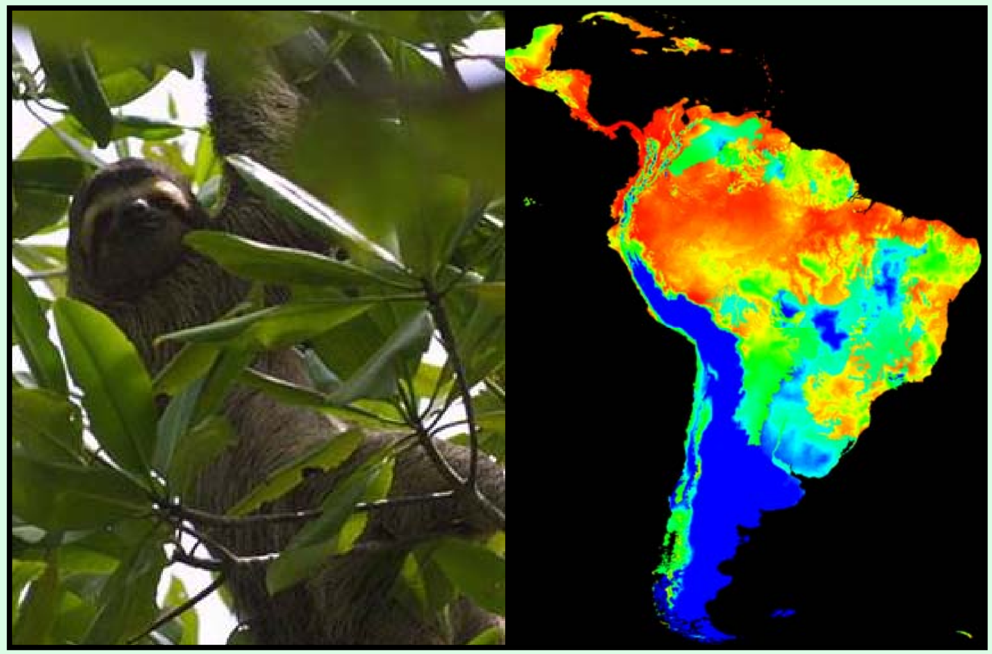


Based on:

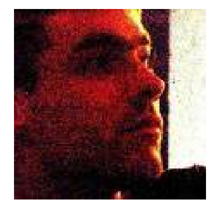
Phillips, S.J., R.P. Anderson, and R.E. Schapire. 2006. Maximum entropy modeling of species geographic distributions. *Ecological Modelling*, 190:231-259.



Steven Phillips

Rob Anderson

Rob Schapire



Miro Dudík

Maximum Entropy (Maxent) method

Precise mathematical definition

Continuous and categorical environmental data

Continuous output

Interpretability in ecological dimensions

Maximum Entropy (Maxent) method

Features: environmental variables or functions thereof

Maxent has various classes of features

Maximum Entropy (Maxent) method

Classes of features:

Linear features	…	variable itself
Quadratic features	…	square of variable
Product features	…	product of two variables

Discrete features (categorical) … variable itself

Maximum Entropy (Maxent) method

Estimates *target probability distribution*

by finding probability distribution (statistical model) of *maximum entropy* (i.e., most spread out, closest to uniform)

subject to *constraints*

Maximum Entropy (Maxent) method

Constraints: what we know about the features

Data from the sample points (the known occurrence localities, in our case)

Maximum Entropy (Maxent) method

Constraints:

Linear features	…	…	mean
Quadratic features	…	…	variance
Product features	…	…	covariance

Discrete features (categorical) … proportion

Maximum Entropy (Maxent) method

Constraints:

Linear features	…	…	mean
Quadratic features	…	…	variance
Product features	…	…	covariance
Threshold/hinge features		…	fit an arbitrary response
Discrete features (categorical)		…	proportion

Statistical model:

Gibbs probability distribution q_λ of the form

$$q_\lambda(x)$$

Each element x is a pixel of the study region

Statistical model:

Gibbs probability distribution q_λ of the form

$$q_\lambda(x) = e^{\boldsymbol{\lambda} \bullet \boldsymbol{f}(x)}$$

Each element x is a pixel of the study region

$\boldsymbol{\lambda}$ is a vector of n real-valued coefficients (feature weights)

Statistical model:

Gibbs probability distribution q_λ of the form

$$q_\lambda(x) = e^{\boldsymbol{\lambda} \cdot \boldsymbol{f}(x)}$$

Each element x is a pixel of the study region

$\boldsymbol{\lambda}$ is a vector of n real-valued coefficients (feature weights)

$\boldsymbol{f}$ is the vector of all n features

Statistical model:

Gibbs probability distribution q_λ of the form

$$q_\lambda(x) = e^{\boldsymbol{\lambda} \cdot \boldsymbol{f}(x)}/Z_\lambda$$

Each element x is a pixel of the study region

$\boldsymbol{\lambda}$ is a vector of n real-valued coefficients (feature weights)

$\boldsymbol{f}$ is the vector of all n features

Z_λ is a normalizing constant that ensures that q_λ sums to 1

Statistical model:

Gibbs probability distribution q_λ of the form

$$q_\lambda(x) = e^{\boldsymbol{\lambda} \cdot \boldsymbol{f}(x)} / Z_\lambda$$

Each element x is a pixel of the study region

The probabilities of all pixels sum to 1

Statistical model:

Gibbs probability distribution q_λ of the form

$$q_\lambda(x) = e^{\boldsymbol{\lambda} \cdot \mathbf{f}(x)}/Z_\lambda$$

Each element *x* is a pixel of the study region

The probabilities of all pixels sum to 1

These probabilities are *not* probabilities of occurrence, but rather values representing the relative suitability of the environmental conditions in each pixel

Cumulative output:

“raw” probabilities for individual pixels are extremely small

“cumulative” probability is the sum of the probabilities of that particular pixel and all other pixels with equal or lower probability,

multiplied by 100 to give a percentage

Cumulative output:

t% of randomly sampled pixels with have cumulative value of *t* or less

Expectation: use of a threshold of *t* to make a binary model from the continuous cumulative output will yield an omission rate of *t*%

and minimum predicted area among such models

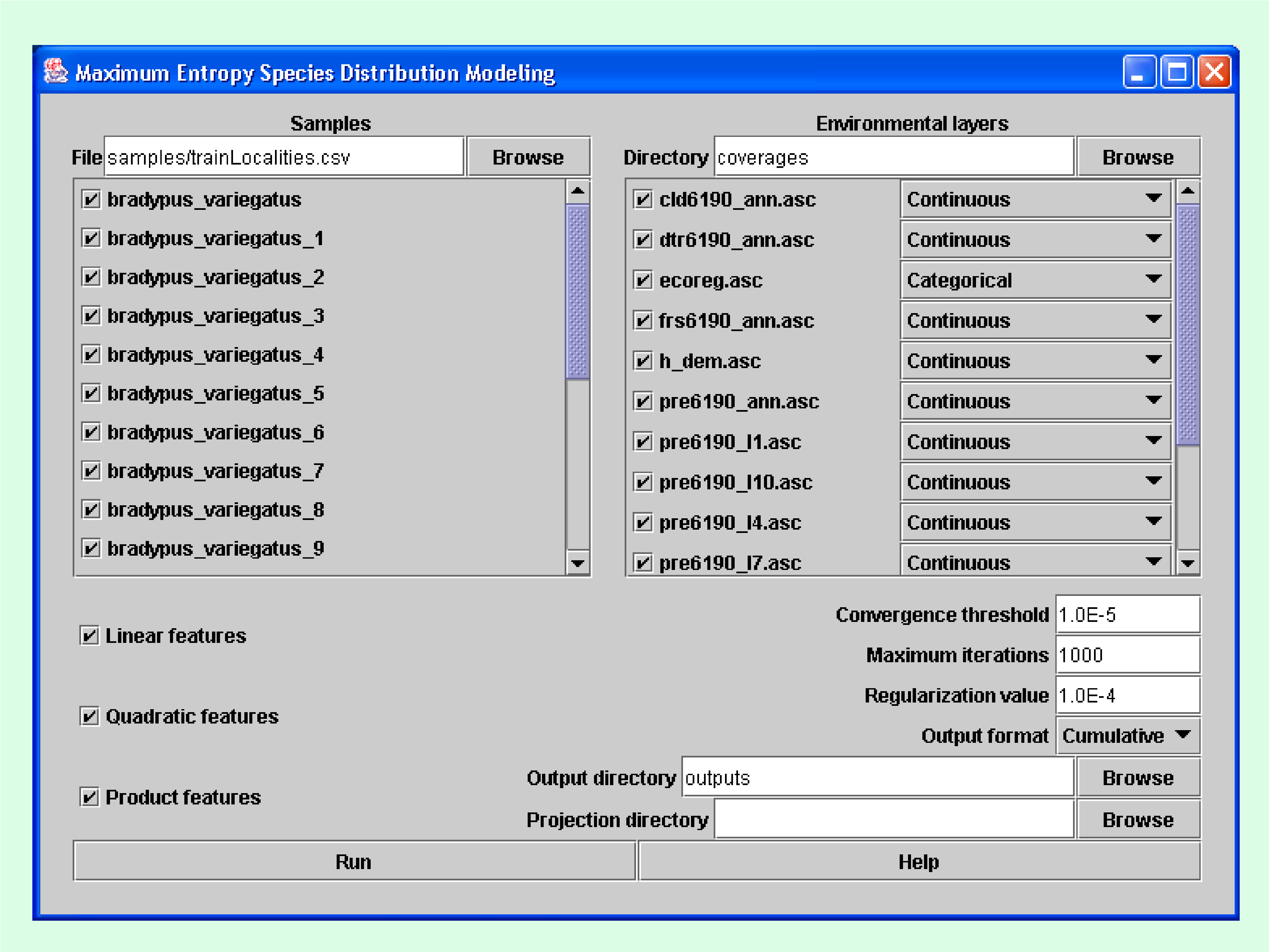
(!!)

Logistic output:

“raw” probabilities for individual pixels are extremely small

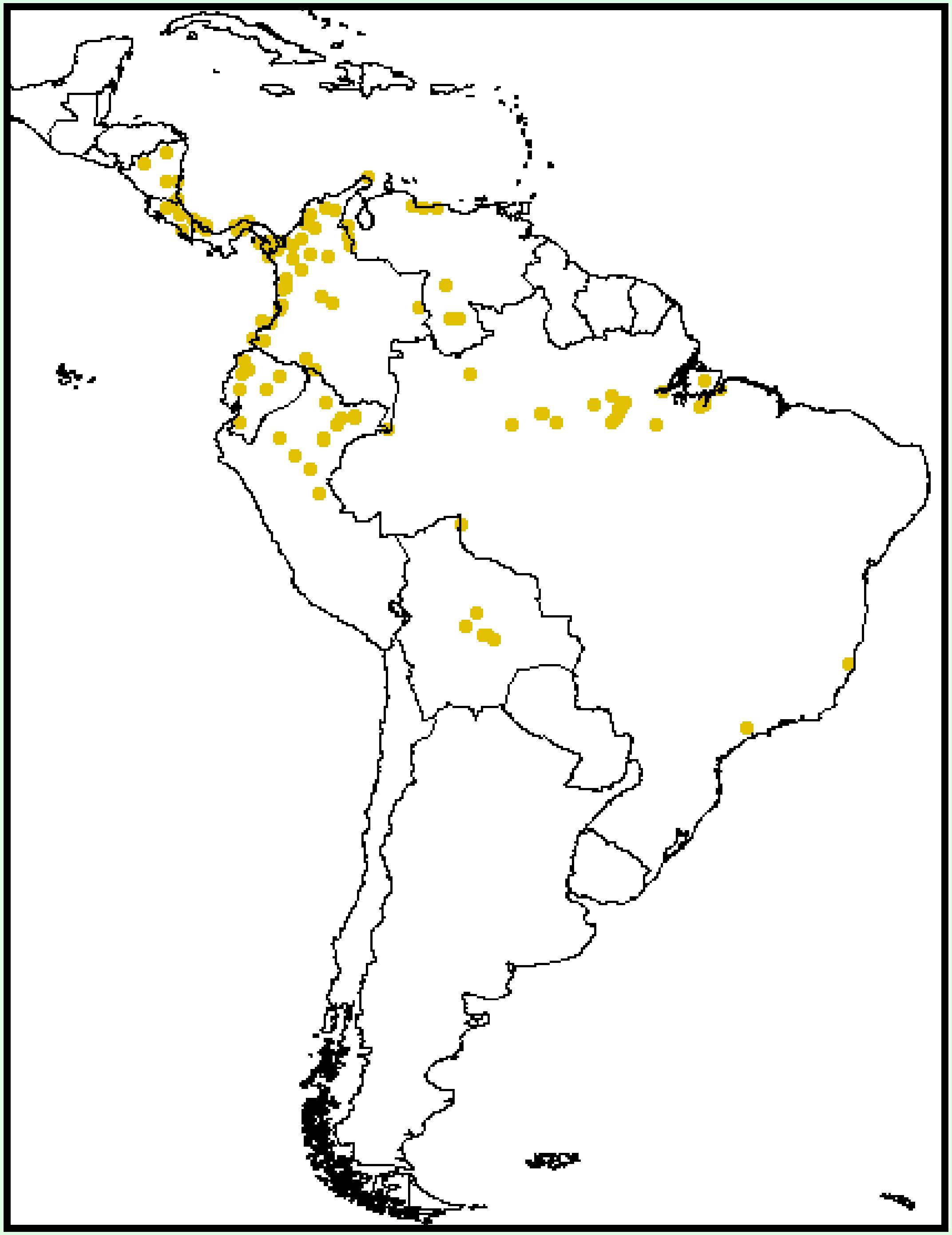
“logistic” probability is probability that the environment is suitable (or probability of occurrence if distribution is at equilibrium with environment)

Ranges from 0 to 1


Maximum Entropy Species Distribution Modeling
Samples
File samples/trainLocalities.csv
Browse
bradypus_variegatus
bradypus_variegatus_1
bradypus_variegatus_2
bradypus_variegatus_3
bradypus_variegatus_4
bradypus_variegatus_5
bradypus_variegatus_6
bradypus_variegatus_7
bradypus_variegatus_8
bradypus_variegatus_9
Environmental layers
Directory coverages
Browse
cld6190_ann.asc Continuous
dtr6190_ann.asc Continuous
ecoreg.asc Categorical
frs6190_ann.asc Continuous
h_dem.asc Continuous
pre6190_ann.asc Continuous
pre6190_l1.asc Continuous
pre6190_l10.asc Continuous
pre6190_l4.asc Continuous
pre6190_l7.asc Continuous
Linear features
Quadratic features
Product features
Convergence threshold 1.0E-5
Maximum iterations 1000
Regularization value 1.0E-4
Output format Cumulative
Output directory outputs
Browse
Projection directory
Browse
Run
Help

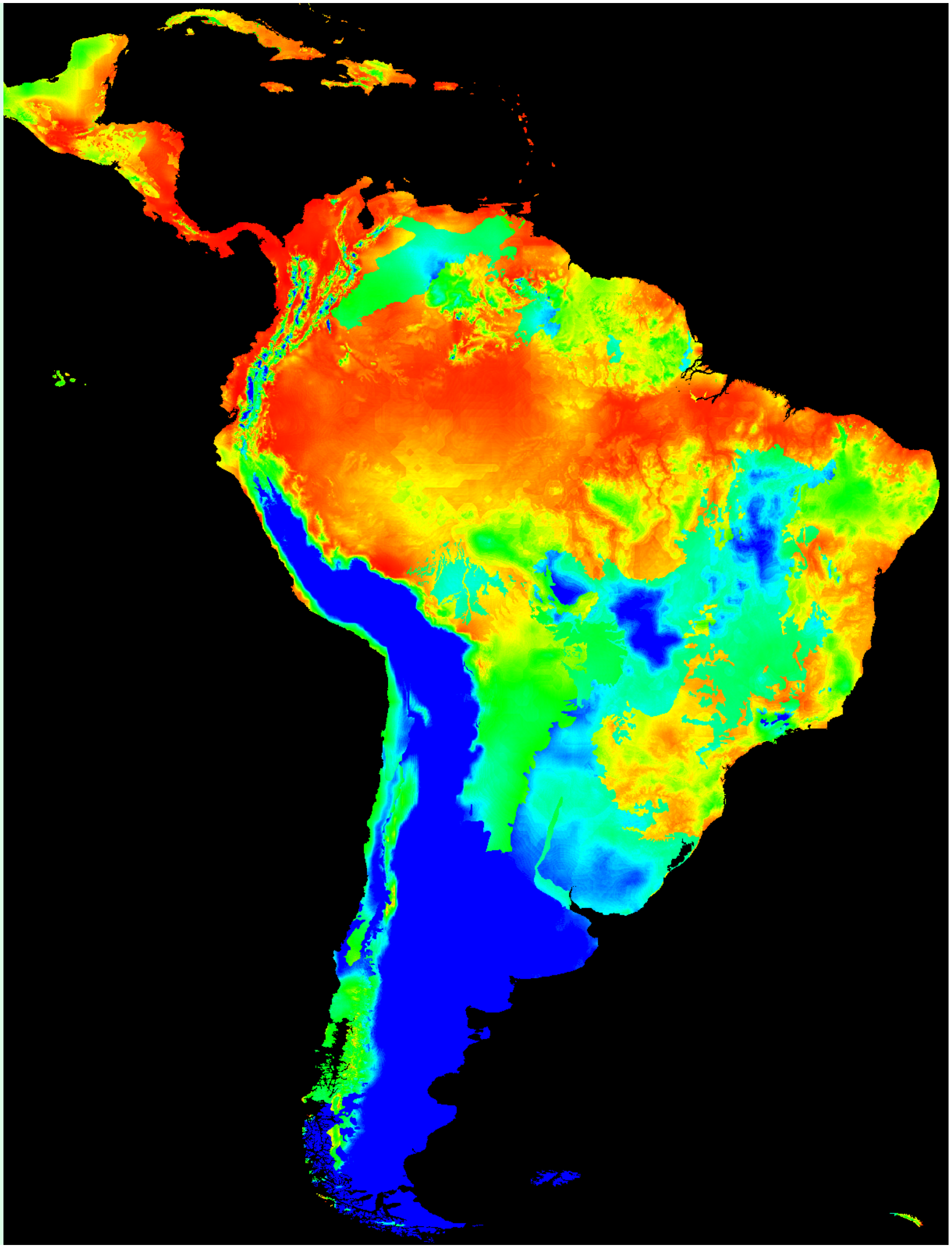
Bradypus variegatus

Localities from Anderson and Handley (2001)



Bradypus variegatus

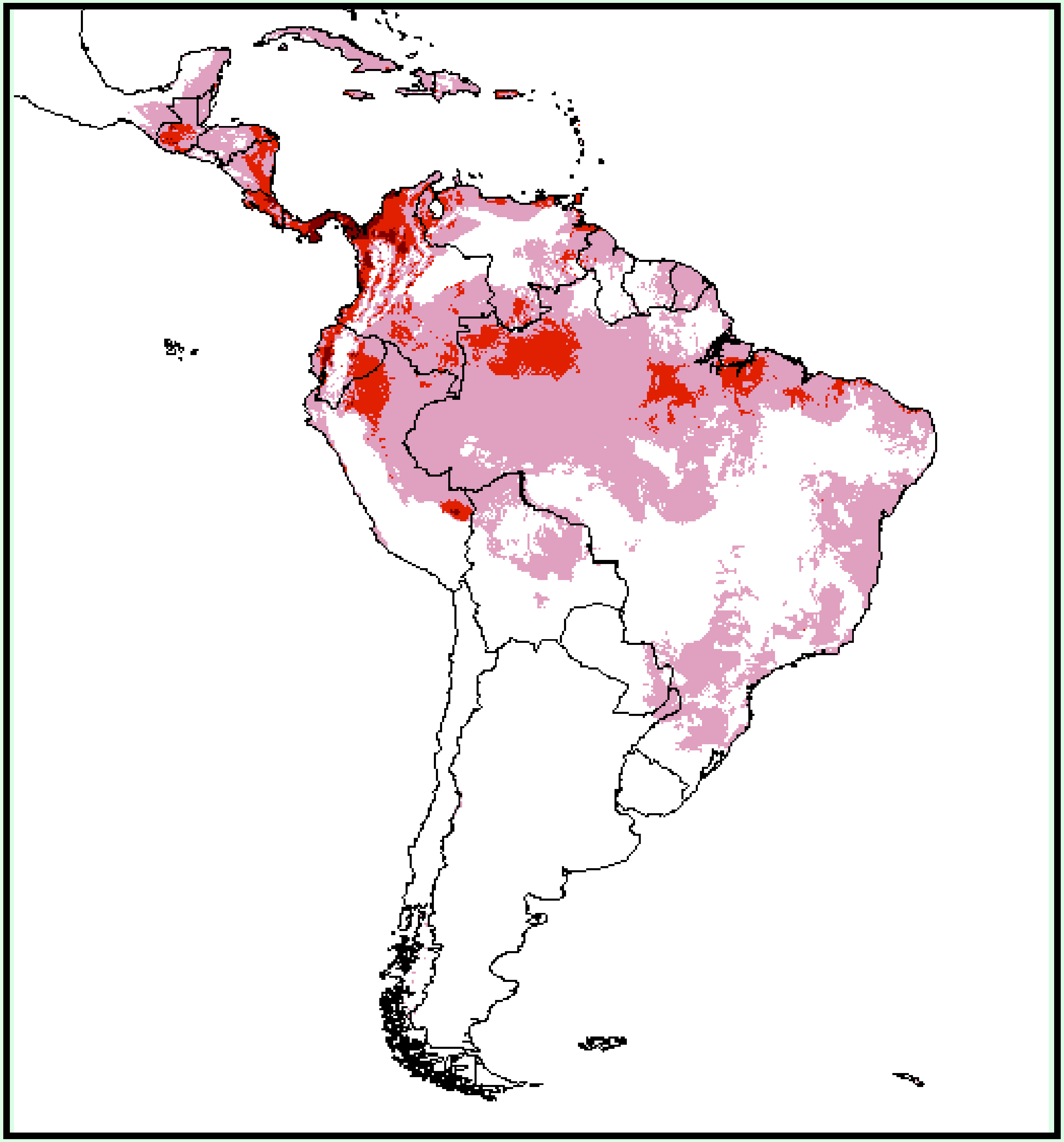
Climatic, topographic, and vegetational variables



Bradypus variegatus

Climatic, topographic, and vegetational variables

3 thresholds applied



Thank you

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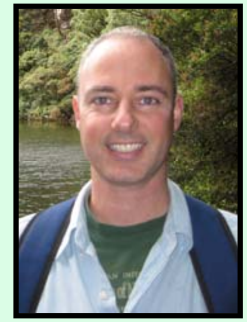

http://web.sci.ccny.cuny.edu/~anderson