Habitat suitability modeling of murine rodents in South-East Asia: use of high resolution data at a local scale

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CERoPath regional workshop, “Rodent survey: from trapping to pathogen screening”
May, 15th 2012
CERoPath project (ANR 07 BDIV 012) :

Community Ecology of Rodents and their Pathogens in South-East Asia

www.ceropath.org

→ aiming at understanding the implication of rodents in the transmission of diseases,
→ in a context of rapid environmental changes.

Photos: Herbreteau V.
Habitat suitability modeling of murine rodents in South-East Asia

• Understand the influence of spatial ecological heterogeneity on rodent communities.

• Estimate the environmental envelopes of these rodent species.

• Calculate environmental indicators of the presence of the different species.
Can we pretend to model an ecological niche?

• Niche (or ecological niche) = a term describing the relational position of a species or population in its ecosystem

→ **We should distinguish between:**
  - the *fundamental niche* = the total range of environmental conditions that are suitable for existence without the influence of interspecific competition or predation from other species;
  - the *realized niche* = the part of the fundamental niche actually occupied by the species.

→ study of “**suitable habitats**” i.e. the ecological areas where a species can live.
Different terms used for niche / habitat modeling:

- Ecological niche modeling
- Environmental niche modeling
- Habitat suitability modeling
- Resource selection/use modeling
- Climate suitability modeling
- Bio-climate modeling
- Species distribution modeling
Methods used in niche / habitat modeling:

- Relate the known occurrences of a given species to the environmental data.

- Applications are usually based on the Grinnell’s definition of ecological niches.

Source: Open Modeller (http://openmodeller.sourceforge.net)
Methods used in niche / habitat modeling:

- Increasing number of algorithms and softwares developed: MaxEnt, ENFA, BIOMOD, Openmodeller, ModEco, GARP, BIOMAPPER, CANOCO, WinBUGS, OpenBUGS, DOMAIN, SPECIES, etc.

  together with statistical models: GLM, GAM, discriminant analysis, etc.

- Usually integrating global datasets (rasters, low spatial resolution)

  → Objectives of our study:
  - model species accurately identified, described in the field and precisely located,
  - integrate high resolution spatial data.
7 study sites in 3 South-East Asian countries (Cambodia, Lao PDR, Thailand):

• Trapping in lines:
  - 30 lines of 10 traps, left 4 nights:
    - 10 in forested areas,
    - 10 in dry fields,
    - 10 in wet ricefields.
  → total of 1,200 night-traps
  - trapping during 2 season (wet / dry):
    → 2,400 night-traps per site
  → Total of 16,800 night-traps.

• Complementary trappings:
  - in villages,
  - in places with signs of rodent presence,
  - from hunters.
Rodent identification:

- Use of locally made live-traps.
- Field identification: external measurements and description.
- Genetic identification / CBGP-Montpellier
Material and Methods:

Rodent sampling

Environmental description:

• GPS localisation of each sample.

• Description of the surrounding environment: landuse, distance to main landscape features, human presence, etc.

• Pictures taken around the trap:

![Image of rodent sampling area with GPS co-ordinates and environmental information]
Material and Methods:

Global data

- Climate data:
  - **Global Precipitation Climatology Centre (GPCC):**
    - Provided by the Deutscher Wetterdienst.
    - Analyses the monthly precipitation on Earth’s landsurface based on raingauge station data.
    - 0.5° (55.5 km) spatial resolution.
  
  - **WorldClim:**
    - compiled from different dataset and provided by: http://www.worldclim.org/.
    - 1/6° (approx. 18.5 km) spatial resolution.
    - 1950-2000 temperature and rainfall data.
Material and Methods:

Global data

- Climate data:
- Topographic data:
  - Shuttle Radar Topography Mission (SRTM):
    - Provided by USGS - NASA (http://srtm.usgs.gov/)
    - Digital Elevation Model with a 3 arc-second (approx. 90 meters) spatial resolution.
  - ASTER Global Digital Elevation Model (GDEM):
    - Provided by USGS - Japan’s Ministry of Economy, Trade and Industry (http://www.ersdac.or.jp/GDEM/E/)
    - Digital Elevation Model with a 1 arc-second (approx. 30 meters) spatial resolution.
    - Serious artifacts.
Material and Methods:

Global data

- Climate data:
- Topographic data:
- Land cover data
  - **GlobCover 2.2:**
    - Provided by POSTEL (Pôle d’Observation des Surfaces Terrestres aux Echelles Larges) (http://medias.obsmip.fr/postel/)
    - Land cover map (2005-2006) derived from ENVISAT – MERIS satellite images (300 m spatial resolution).
  - **Global Land Cover Facility (GLCF):**
    - Provided by University of Maryland Dpt of Geography (http://www.landcover.org/)
    - Land cover map (1981-1994) derived from AVHRR satellite images (1 km spatial res.).
High resolution information can be gained through remote sensing:

- Acquisition of high resolution SPOT V images.

  SPOT data was provided via the ISIS program operated by the French Space Agency, CNES.

  → Difficulties to get high quality images from optical sensors in tropical areas
High resolution information can be gained through remote sensing:

- Acquisition of high resolution SPOT V images.

<table>
<thead>
<tr>
<th>Study site</th>
<th>Date</th>
<th>Satellite / sensor</th>
<th>Image type / Spatial resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cambodia - Mondolkiri</td>
<td>16/03/2008</td>
<td>SPOT 5 HRG 1</td>
<td>Pan / 5 . MS / 10</td>
</tr>
<tr>
<td>Cambodia - Veal Renh</td>
<td>19/12/2006</td>
<td>SPOT 5 HRG 1</td>
<td>Pan / 2,5 . MS / 10</td>
</tr>
<tr>
<td></td>
<td>22/03/2007</td>
<td>SPOT 5 HRG 1</td>
<td>MS / 10</td>
</tr>
<tr>
<td>Lao PDR - Luang Prabang</td>
<td>31/10/2006</td>
<td>SPOT 5 HRG 2</td>
<td>Pan / 2,5 . MS / 10</td>
</tr>
<tr>
<td></td>
<td>03/01/2007</td>
<td>SPOT 5 HRG 1</td>
<td>MS / 10</td>
</tr>
<tr>
<td>Lao PDR - Pakse</td>
<td>13/12/2007</td>
<td>SPOT 5 HRG 1</td>
<td>Pan / 2,5 . MS / 10</td>
</tr>
<tr>
<td>Thailand - Buriram</td>
<td>11/11/2006</td>
<td>SPOT 5 HRG 2</td>
<td>MS / 10</td>
</tr>
<tr>
<td></td>
<td>17/01/2008</td>
<td>SPOT 5 HRG 2</td>
<td>Pan / 2,5 . MS / 10</td>
</tr>
<tr>
<td>Thailand - Loei</td>
<td>13/01/2007</td>
<td>SPOT 5 HRG 1</td>
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</tr>
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<td>19/04/2008</td>
<td>SPOT 5 HRG 2</td>
<td>MS / 10</td>
</tr>
<tr>
<td>Thailand - Nan</td>
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<tr>
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</tr>
</tbody>
</table>
Use of Object-Based Image Analysis methods (OBIA):

Different approaches of land-cover classification:

Pixel-based classification

Each pixel is classified according to its spectral signature.

Contextual techniques for classification

Response and class of 2 spatially neighbouring pixels are highly related: pixels are classified according to their context.
Different steps:

1. Image pre-processing
2. Image segmentation
3. Image classification
4. Change detection
5. Landscape analysis
1- **Satellite image pre-processing:**

→ with ERDAS Imagine 2010®

- Radiometric calibrations (to make different images comparable):
  1. Conversion of digital numbers (recorded by sensors) to spectral radiance (i.e. total light emitted by the objects), according to the gain and bias of the sensor.
  2. Conversion of spectral radiance to exoatmospheric reflectance (because spectral radiance depends on the degree of illumination of the object, that varies with time of day, season, latitude).

- Resampling the 10 m Multispectral images to 2.5 m resolution of the Panchromatic images.
2- Image segmentation
(subdivision into homogeneous regions)

→ with eCognition Developer 8®

• Use of a “Multiresolution segmentation” algorithm.

• Applied on the most recent scene.

• Same segmentation parameters for all sites (scale factor, shape and compactness values).

• Two levels of segmentation.

Segmentation of SPOT image from Loei province, Thailand
Material and Methods: Satellite images analysis

3- Image classification

Preliminary calculations:

• **Texture indices**: contrast and dissimilarity indices derived from Panchromatic images.

• **Topographic index**: slope derived from DEMs.
3- Image classification

Classification using membership functions:

- Objects intrinsic characteristics:
  - Reflectance values
  - Shape
  - Texture indices
  - Vegetation indices
  - Water indices
  - Slope

- Same characteristics and membership functions parameters for all sites

*Level 1 - Classification of SPOT image from Loei province, Thailand*
3- Image classification

Supervised nearest neighbour classification

• Selection of training samples from field observations:
  – Different wooded and agricultural classes
  – e.g. rice fields, rubber tree or teak plantations

• Site-dependent process

Level 2 - Classification of SPOT image from Loei province, Thailand
4- Change detection

Object-based classification of older scenes:

- Merging objects to allow inter-site comparison:
  - Water
  - Wooded areas
  - Cultivated areas
  - Built-up areas

- Segmentation:
  - Based on the 4 classes limits.

- Classification:
  - Intrinsic properties.
  - Topologic characteristics (relations to neighboring objects).
  - Contextual characteristics (semantic relationships).

Land-cover changes, Loei province, Thailand
### Material and Methods: Landscape analysis

#### Increasing fragmentation

<table>
<thead>
<tr>
<th>Occupation</th>
<th>Area (ha)</th>
<th>Continuous landscape</th>
<th>Fragmented landscape</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forested area</td>
<td>30</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agricultural area</td>
<td>64</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Water body</td>
<td>6</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Patch density (patches / ha)</th>
<th>0.03</th>
<th>0.08</th>
</tr>
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<tbody>
<tr>
<td>Edge density (m / ha)</td>
<td>0.76</td>
<td>1.24</td>
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Patch density = \( \frac{\text{Number of patches}}{\text{Total area (ha)}} \)

Edge density = \( \frac{\text{Total edge (m)}}{\text{Total area (ha)}} \)
## Material and Methods: Landscape analysis

### Increasing fragmentation

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### Material and Methods: Landscape analysis

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<td>1.35</td>
</tr>
<tr>
<td>Shannon Diversity Index</td>
<td>0.82</td>
<td>0.82</td>
<td>0.82</td>
</tr>
</tbody>
</table>

\[
\text{SHDI} = -\sum_{i=1}^{m} (P_i \times \ln P_i)
\]

With \( P_i \) = proportion of area covered by land cover class \( l \)

\( m \) = number of patch types
### Material and Methods: Landscape Analysis

#### Patch density (patches / ha)
- 0.03
- 0.03
- 0.03

#### Edge density (m / ha)
- 0.76
- 0.76
- 0.90

#### Shannon Diversity Index
- 0.82
- 0.65
- 1.10

\[
\text{SHDI} = \sum_{i=1}^{m} (P_i \times \ln(P_i)) \\
\text{with: } P_i = \text{proportion of area covered by land cover class } i \\
\text{and: } m = \text{number of patch types}
\]

→ **SHDI increases:**
- with the number of classes,
- as the proportion of each class becomes equal.
### Material and Methods: Landscape Analysis

**Patch density (patches / ha)**

<table>
<thead>
<tr>
<th></th>
<th>0.03</th>
<th>0.03</th>
<th>0.03</th>
</tr>
</thead>
</table>

**Edge density (m / ha)**

<table>
<thead>
<tr>
<th></th>
<th>0.76</th>
<th>0.76</th>
<th>0.90</th>
</tr>
</thead>
</table>

**Shannon Diversity Index**

<table>
<thead>
<tr>
<th></th>
<th>0.82</th>
<th>0.65</th>
<th>1.10</th>
</tr>
</thead>
</table>

**Shannon Evenness Index**

<table>
<thead>
<tr>
<th></th>
<th>0.74</th>
<th>0.94</th>
<th>1.00</th>
</tr>
</thead>
</table>

\[
\text{SHEI} = \frac{\text{SHDI}}{\ln m} = -\frac{\sum_{i=1}^{m} (P_i \ln P_i)}{\ln m} \quad 0 \leq \text{SHEI} \leq 1
\]
### Material and Methods:

**Landscape analysis**

<table>
<thead>
<tr>
<th></th>
<th>Value 1</th>
<th>Value 2</th>
<th>Value 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patch density (patches / ha)</td>
<td>0.03</td>
<td>0.02</td>
<td>0.03</td>
</tr>
<tr>
<td>Edge density (m / ha)</td>
<td>0.76</td>
<td>0.76</td>
<td>0.90</td>
</tr>
<tr>
<td>Shannon Diversity Index</td>
<td>0.82</td>
<td>0.65</td>
<td>1.10</td>
</tr>
<tr>
<td>Shannon Evenness Index</td>
<td>0.74</td>
<td>0.94</td>
<td>1.00</td>
</tr>
<tr>
<td>Simpson Diversity Index</td>
<td>0.50</td>
<td>0.46</td>
<td>0.67</td>
</tr>
</tbody>
</table>

\[
\text{SIDI} = 1 - \sum_{i=1}^{m} P_i^2 \\
0 \leq \text{SHEI} \leq 1
\]
Various landscapes

- 2 sites largely covered by wooded areas (Luang Prabang, Lao PDR, and Mondolkiri, Cambodia)
- 1 site with limited forested areas (Buriram, Thailand)
- Differences in size of forested patches

Photos: Morand S.
Land use / land cover classification in Loei province, in 1987
Land use / land cover classification in Loei province, in 1996
Land use / land cover classification in Loei province, in 2007
Land use / land cover classification in Mondolkiri province, in 1988
Results:

Land use / cover changes

Land use / land cover classification in Mondolkiri province, in 1998
Results:
Land use / cover changes

Land use / land cover classification in Mondolkiri province, in 2008
Results:

Land use / cover changes

Proportion of each land use / land cover class

Loei province

1987
1996
2007

Mondolkiri province

1988
1998
2008

- Agricultural areas
- Clouds and shadows
- Forested areas
- Built-up
- Water
Results: Land use / cover changes

- **Patches density (nb/ha)**
  - Loel
  - Mondolkiri

- **Edge density (m/ha)**
  - Loel
  - Mondolkiri

- **Simpson’s Diversity Index**
  - Loel
  - Mondolkiri

- **Shannon’s Diversity Index**
  - Loel
  - Mondolkiri
Diminution of forested areas

- All sites

- Estimation of annual deforestation rates: from 0.65% (Buriram, Thailand) to 1.84% (Mondolkiri, Cambodia)

- Major cause: conversion of forest to agricultural land
Increase of all landscape indices

- All sites

- Increase of habitat fragmentation and landscape heterogeneity

- Different dynamics between the three countries
  - Fragmentation higher in Thailand and lower in Cambodia

In blue: Thai study sites
In green: Lao study sites
In maroon: Cambodian study sites
- Total of 2,136 murine rodents
- 27 different species (incl. 10 species with less than 10 individuals)
• Total of 2,136 murine rodents
• 27 different species (incl. 10 species with less than 10 individuals)
• Based on global data (DEM, climate):

Example: Range of elevation per species

<table>
<thead>
<tr>
<th>Species</th>
<th>Number</th>
<th>Average elevation</th>
<th>Minimum elevation</th>
<th>Maximum elevation</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandicota indica</td>
<td>97</td>
<td>254,7</td>
<td>113</td>
<td>558</td>
<td>445</td>
</tr>
<tr>
<td>Bandicota savilei</td>
<td>49</td>
<td>171,1</td>
<td>115</td>
<td>379</td>
<td>264</td>
</tr>
<tr>
<td>Berylmys berdmorei</td>
<td>27</td>
<td>221,8</td>
<td>8</td>
<td>358</td>
<td>350</td>
</tr>
<tr>
<td>Berylmys bowersi</td>
<td>15</td>
<td>391,9</td>
<td>253</td>
<td>587</td>
<td>334</td>
</tr>
<tr>
<td>Maxomys surifer</td>
<td>86</td>
<td>133,0</td>
<td>11</td>
<td>379</td>
<td>368</td>
</tr>
<tr>
<td>Mus caroli</td>
<td>91</td>
<td>298,5</td>
<td>163</td>
<td>594</td>
<td>431</td>
</tr>
<tr>
<td>Mus cervicolor</td>
<td>126</td>
<td>220,4</td>
<td>154</td>
<td>358</td>
<td>204</td>
</tr>
<tr>
<td>Mus cookii</td>
<td>125</td>
<td>402,3</td>
<td>206</td>
<td>878</td>
<td>672</td>
</tr>
<tr>
<td>Niviventer fulvescens</td>
<td>63</td>
<td>276,6</td>
<td>20</td>
<td>379</td>
<td>359</td>
</tr>
<tr>
<td>Rattus argentiventer</td>
<td>37</td>
<td>30,8</td>
<td>2</td>
<td>190</td>
<td>188</td>
</tr>
<tr>
<td>Rattus exulans</td>
<td>494</td>
<td>159,8</td>
<td>2</td>
<td>379</td>
<td>377</td>
</tr>
<tr>
<td>Rattus losea</td>
<td>85</td>
<td>288,6</td>
<td>162</td>
<td>379</td>
<td>217</td>
</tr>
<tr>
<td>Rattus phylogenetic R3</td>
<td>133</td>
<td>76,4</td>
<td>1</td>
<td>316</td>
<td>315</td>
</tr>
<tr>
<td>Rattus tanezumi</td>
<td>181</td>
<td>329,2</td>
<td>4</td>
<td>587</td>
<td>583</td>
</tr>
<tr>
<td>Suncus murinus</td>
<td>42</td>
<td>5,6</td>
<td>2</td>
<td>32</td>
<td>30</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>1651</strong></td>
<td><strong>217,4</strong></td>
<td><strong>1</strong></td>
<td><strong>878</strong></td>
<td><strong>877</strong></td>
</tr>
</tbody>
</table>
• Based on global data (DEM, climate):

Example: Range of average temperatures per species

→ Ranges are depending on the study sites
→ Further samplings will enhance the knowledge of each species’ ecological ranges.
• Application of Maxent for HSM:

Based on global data (landcover, DEM, climate
Example of *Rattus exulans*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Percent contribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Globcover</td>
<td>67.3</td>
</tr>
<tr>
<td>Mean temperature during the coolest month</td>
<td>24.1</td>
</tr>
<tr>
<td>Mean daily precipitation during the warmest month</td>
<td>4.1</td>
</tr>
<tr>
<td>Elevation (SRTM)</td>
<td>3</td>
</tr>
<tr>
<td>Mean temperature during the warmest month</td>
<td>1.5</td>
</tr>
<tr>
<td>Mean daily precipitation during the wettest month</td>
<td>0</td>
</tr>
</tbody>
</table>
• Selection of 6 species and samples with an accurate knowledge of the sampling location:

<table>
<thead>
<tr>
<th>Site</th>
<th>Bandicota indica</th>
<th>Maxomys surifer</th>
<th>Mus cookii</th>
<th>Rattus exulans</th>
<th>Rattus phylogenetic R3</th>
<th>Rattus tanezumi</th>
<th>Total</th>
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<tbody>
<tr>
<td>Lao PDR - Luang Prabang</td>
<td>-</td>
<td>-</td>
<td>37</td>
<td>-</td>
<td>-</td>
<td>1</td>
<td>38</td>
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<td>Thailand - Nan</td>
<td>5</td>
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<td>4</td>
<td>22</td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>31</td>
</tr>
<tr>
<td>Lao PDR - Champasak</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>17</td>
<td>3</td>
<td>2</td>
<td>22</td>
</tr>
<tr>
<td>Thailand - Buriram</td>
<td>-</td>
<td>-</td>
<td>1</td>
<td>58</td>
<td>22</td>
<td>3</td>
<td>84</td>
</tr>
<tr>
<td>Cambodia - Mondolkiri</td>
<td>1</td>
<td>29</td>
<td>38</td>
<td>26</td>
<td>4</td>
<td>98</td>
<td></td>
</tr>
<tr>
<td>Cambodia - Preah Sihanouk</td>
<td>-</td>
<td>37</td>
<td>-</td>
<td>59</td>
<td>53</td>
<td>1</td>
<td>150</td>
</tr>
<tr>
<td>Total</td>
<td>6</td>
<td>70</td>
<td>80</td>
<td>175</td>
<td>105</td>
<td>22</td>
<td>458</td>
</tr>
</tbody>
</table>
• Selection of 6 species:

- Bandicota indica
- Maxomys surifer
- Mus cookii
- Rattus exulans
- Rattus R3
- Rattus tanezumi

Photos: Herbreteau V.
• Shortest distance to each class:
• Shortest distance to each class:

- *Bandicota indica*

- *Maxomys surifer*

- *Mus cookii*

- *Rattus exulans*

- *Rattus tanezumi*

- *Rattus phylogenetic R3*
Results:

Landscape metrics

- Buffer analysis

→ Calculation of the proportion of each class around sampling locations
→ Calculation of landscape metrics: PD, ED, SHDI, SHEI, SIDI.
Discriminant analysis (forward stepwise):

19 available variables:

- Longitude, latitude,
- Elevation,
- Proportion of 5 classes inside the buffer: Water, Agricultural area-flat, Agricultural area-steep, Roads-villages, Forested areas,
- Landscape metrics: PD, ED, SHDI, SHEI, SIDI,
- 6 climatic variables: Rainfall of the driest month, of the wettest month, Annual rainfall, Minimum temperature of the coldest month, Maximum temperature of the warmest month, Average temperature.
• Discriminant analysis (forward stepwise):
  • 19 available variables.
  • The best model can predict 74.5% of the 5 species:

<table>
<thead>
<tr>
<th></th>
<th>Wilks’ - Lambda</th>
<th>Partial - Lambda</th>
<th>p-level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Latitude</td>
<td>0.165954</td>
<td>0.702933</td>
<td>0.000000</td>
</tr>
<tr>
<td>Elevation</td>
<td>0.138322</td>
<td>0.843352</td>
<td>0.000000</td>
</tr>
<tr>
<td>Annual rainfall</td>
<td>0.137007</td>
<td>0.851449</td>
<td>0.000000</td>
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<tr>
<td>Prop. Forested areas</td>
<td>0.129674</td>
<td>0.899598</td>
<td>0.000010</td>
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<tr>
<td>Rainfall wettest month</td>
<td>0.132332</td>
<td>0.881530</td>
<td>0.000001</td>
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<tr>
<td>Average temp.</td>
<td>0.123372</td>
<td>0.945547</td>
<td>0.004464</td>
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<tr>
<td>Shannon Div. Index</td>
<td>0.125543</td>
<td>0.929200</td>
<td>0.000541</td>
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<tr>
<td>Edge density</td>
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<td>0.007912</td>
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<tr>
<td>Prop. Artificial areas</td>
<td>0.120147</td>
<td>0.970927</td>
<td>0.092838</td>
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</tbody>
</table>
• Discriminant analysis (forward stepwise):
  • 19 available variables.
  • The best model can predict 74.5% of the 5 species:

<table>
<thead>
<tr>
<th>Species</th>
<th>% of correct prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandicota indica</td>
<td>63.6</td>
</tr>
<tr>
<td>Maxomys surifer</td>
<td>71.8</td>
</tr>
<tr>
<td>Mus cookii</td>
<td>89.2</td>
</tr>
<tr>
<td>Rattus R3</td>
<td>79.6</td>
</tr>
<tr>
<td>Rattus tanezumi</td>
<td>13.0</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>74.1</strong></td>
</tr>
</tbody>
</table>
Results:
Species prediction

- Discriminant analysis (forward stepwise):
  - using only landscape metrics and distances to classes
  - 6 species can be predicted:

<table>
<thead>
<tr>
<th>Species</th>
<th>% of correct prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Bandicota indica</em></td>
<td>94.5</td>
</tr>
<tr>
<td><em>Mus cookii</em></td>
<td>88.7</td>
</tr>
<tr>
<td><em>Maxomys surifer</em></td>
<td>78.1</td>
</tr>
<tr>
<td><em>Rattus argentiventer</em></td>
<td>76.5</td>
</tr>
<tr>
<td><em>Mus cervicolor</em></td>
<td>51.6</td>
</tr>
<tr>
<td><em>Rattus losea</em></td>
<td>43.5</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>75.9</strong></td>
</tr>
</tbody>
</table>
Discussion: How to extrapolate local results?

- High resolution data (i.e. land cover classification) not available over the distribution of the species.

→ Possibility to calculate similar landscape metrics with GlobCover

<table>
<thead>
<tr>
<th>GlobCover</th>
<th>Reclassification</th>
<th>Focal statistics (sum)</th>
<th>Extraction for each class</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 2 5</td>
<td>10 10 10000</td>
<td>00011220 . . . . . .</td>
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<tr>
<td>4 3 3</td>
<td>1000 100 100</td>
<td>00024000 . . . . . .</td>
<td>. . . . . . . . . . . .</td>
</tr>
</tbody>
</table>

Number of pixels classified as agriculture in a 3*3 window
Number of pixels classified as forests in a 3*3 window
Calculation for *Maxomys surifer*:
2 < nb pixels forests < 6
2 < nb pixels agriculture < 5
Built up = 0

Sum of calculations for each species
A limited approach in time:

- Animal samples / land cover are described at a given date
- Environmental changes can be very fast:
Discussion:

Limitations of the use of high resolution data

- A limited approach in time:
  - Animal samples / land cover are described at a given date
  - Environmental changes can be very fast:
    → Need to process images regularly.
    → Higher temporal resolution of remote sensing data is required for a proper land-cover changes monitoring.
    → Potential of medium resolution satellite images (Landsat), and automated classifications (as a future perspective).
• A limited approach in time:
  - Animal samples / land cover are described at a given date
  - Environmental changes can be very fast:

• Difficulties to integrate the human activities impacting land use and rodents dynamics:
  Agricultural shifts, hunting, introduction of species, etc.

Perspectives:

• Socio-economic investigation on land uses to identify underlying driving factors.

• Study of the impact of environmental changes on biodiversity of rodent and pathogens communities.
Acknowledgements

CERoPath project (Dir. Serge Morand)

Colleagues: Stéphane Dupuy, Tristan Feyfant and Annelise Tran

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