Downscaling climate projections

• Information from climate projections, required for impact studies, have space and time scales much finer than those provided by climate models, either global or regional.

• Statistical downscaling relates large-scale climate variables or predictors (e.g. MSLP), to regional or local climate elements, the predictands (e.g. temperature, precipitation at weather stations).

• Once the relationship between predictors and predictand is established and validated, the large-scale output of a climate model can be used to obtain estimates of regional or local climate elements.

Methods of Statistical Downscaling (SD)
The main SD techniques can be grouped as follows:

- Weather classification schemes
- Weather generators
- Regression models

We have published under the first two methods. Here I will describe an application of the third method, specifically using Canonical Correlation Analysis (CCA).

In this application, the atmospheric large-scale forcing is represented by mean monthly sea-level pressure in the euro-atlantic region, and the local climate elements are monthly precipitation totals, and monthly means of maximum and minimum temperatures, at weather stations over continental Portugal and northwest Spain.

Validation of the CCA relationships was performed using the technique of:

Cross Validation

After monthly estimates of precipitation and temperature are obtained from climate projections of monthly MSLP, generated by a climate model, under two different SRES emission scenarios (A1B and B1), downscaling in the time domain is performed, in order to get daily and hourly estimates of the referred parameters, using the Method of Fragments.
The aim of the CCA is to obtain relationships between two samples of data with different variables.

The relationships obtained from the CCA are correlated patterns of both samples. The patterns will be linear combinations of the variables of each sample:

\[ U = a_1 X_1 + a_2 X_2 + \ldots + a_p X_p \]
\[ V = b_1 Y_1 + b_2 Y_2 + \ldots + b_q Y_q \]

These patterns have maximum correlation.

Variables from two fields (e.g. mean sea level pressure over the north Atlantic and precipitation in sites over the Iberian Peninsula)

\[ p - \text{gridpoint stations} \quad q - \text{stations} \]

Each \( X_1, \ldots, X_p \) and each \( Y_m, m = 1, \ldots, q \), are time series, which can start at the same time or not.

The canonical variables \( \tilde{u}_m \) and \( \tilde{v}_m \) are canonical vectors: \( U_m \) and \( V_m \) are canonical variables.

Each \( U_m \) and each \( V_m \) is a time series.

Assuming \( M = \min(p,q) \)

\[ U_m = \sum_{i=1}^{p} a_{mi} X_i \]
\[ V_m = \sum_{j=1}^{q} b_{mj} Y_j \quad m = 1, \ldots, M \]

Each \( \tilde{u}_m \) and \( \tilde{v}_m \) can be displayed in maps.

The canonical vectors \( \tilde{u}_m \) and \( \tilde{v}_m \) are orthogonal.

Pattern 's Correlation:

\[ U_j, V_j - \text{maximum correlatio n} \]
\[ U_j, V_j - \text{maximum correlatio n} (\leq \text{Corr}(U_j, V_j)) \]
under the condition that is not correlated with \( (U_j, V_j) \)

Each pair \( (U_m, V_m) \) represents an independent dimension in the relation between the variables \( X \) and \( Y \).

Matricial Format

\[
\begin{align*}
\hat{U} &= \hat{A} \hat{X} \quad (M \times 1) = (M \times p) (p \times 1) \\
\hat{V} &= \hat{B} \hat{Y} \quad (M \times 1) = (M \times q) (q \times 1)
\end{align*}
\]

"Prediction" with CCA

\[
\begin{align*}
V_m &= b_{0m} U_m + b_{1m} U_m \quad m = 1, \ldots, M \\
b_{0m} &= 0 \quad b_{1m} = r_{cm} \\
\hat{V} &= \hat{R} \hat{U} \\
Y' &= \hat{B}^{-1} \hat{V}
\end{align*}
\]
**KlimHist**

- Predictors – Mean Sea Level Pressure

Lat : 20ºN \& 76ºN  
Lon : 20ºE \& 60ºW  
Grid : 2º \times 2º  

Source: 20th Century Reanalysis  
NOAA-CIRES (V2)

**KlimHist**

- Predictands – Precipitation

Stations

Source:  
INAG, ECAD and AEMET

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**Downscaling da Precipitação - CCA**

- Canonical pairs and canonical correlations:

\[ U_1 = 2.2 \times 10^{-9} \cdot PC_1 + 4.2 \times 10^{-3} \cdot PC_2 + 6.6 \times 10^{-5} \cdot PC_3 \]
\[ U_2 = 2.4 \times 10^{-5} \cdot PC_1 + 8.1 \times 10^{-5} \cdot PC_2 + 8.1 \times 10^{-5} \cdot PC_3 \]
\[ U_3 = 4.4 \times 10^{-6} \cdot PC_1 - 2.4 \times 10^{-6} \cdot PC_2 - 2 \times 10^{-7} \cdot PC_3 \]
\[ U_4 = 9.5 \times 10^{-6} \cdot PC_1 + 9.5 \times 10^{-6} \cdot PC_2 - 8 \times 10^{-7} \cdot PC_3 \]
\[ U_5 = 1.1 \times 10^{-6} \cdot PC_1 - 1 \times 10^{-6} \cdot PC_2 + 1.1 \times 10^{-6} \cdot PC_3 \]
\[ U_6 = 1.2 \times 10^{-6} \cdot PC_1 - 1.2 \times 10^{-6} \cdot PC_2 + 1.2 \times 10^{-6} \cdot PC_3 \]

\[ \| U_1 \|^2 = r_1 = 89 \% \quad \| U_2 \|^2 = r_2 = 65 \% \quad \| U_3 \|^2 = r_3 = 25 \% \]

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**KlimHist**

- 51% of MSLP variance is explained by this pattern
- 66% of precipitation variance is explained by the canonical conjugate of U

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**KlimHist**

- The CCA model was developed using seasonal MSLP data and seasonal Precipitation data for the period 1951-2000.
- The Cross Validation allows to assess the predictive capacity of the CCA model.
- Using groups of ten years of the MSLP seasonal data (e.g. winter) it is possible to reconstruct the seasonal precipitation of those ten years.
- The predictivity capacity of the CCA model can be analysed through correlation coefficients and root mean square errors.

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**KlimHist**


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**Downscaling da Precipitação - CCA**

- Map of MSLP in the first canonical pair:

\[ U_1 = 2.2 \times 10^{-9} \cdot EOF_1 + 4.2 \times 10^{-3} \cdot EOF_2 + 6.6 \times 10^{-5} \cdot EOF_3 \]

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27-05-2013
KlimHist

- Correlation coefficient given by the Cross Validation of the CCA model (winter) for each group of ten years.

<table>
<thead>
<tr>
<th></th>
<th>Cor</th>
<th>S. C.</th>
<th>Sar</th>
<th>Brdc</th>
<th>Barc</th>
<th>Cam</th>
<th>Coi</th>
<th>C.B.</th>
<th>Lisb</th>
<th>Evo</th>
<th>Beja</th>
<th>Tau</th>
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</thead>
<tbody>
<tr>
<td>51/60</td>
<td>0.60</td>
<td>0.51</td>
<td>0.56</td>
<td>0.42</td>
<td>0.37</td>
<td>0.57</td>
<td>0.49</td>
<td>0.13</td>
<td>0.24</td>
<td>0.20</td>
<td>0.18</td>
<td>0.11</td>
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<tr>
<td>61/70</td>
<td>0.28</td>
<td>0.17</td>
<td>0.14</td>
<td>0.19</td>
<td>0.12</td>
<td>0.10</td>
<td>0.10</td>
<td>0.46</td>
<td>0.47</td>
<td>0.29</td>
<td>0.44</td>
<td>0.48</td>
</tr>
<tr>
<td>71/80</td>
<td>0.66</td>
<td>0.69</td>
<td>0.65</td>
<td>0.49</td>
<td>0.62</td>
<td>0.62</td>
<td>0.50</td>
<td>0.26</td>
<td>0.20</td>
<td>0.20</td>
<td>0.07</td>
<td>-0.13</td>
</tr>
<tr>
<td>81/90</td>
<td>0.47</td>
<td>0.55</td>
<td>0.45</td>
<td>0.00</td>
<td>0.43</td>
<td>0.34</td>
<td>0.29</td>
<td>0.14</td>
<td>0.21</td>
<td>0.02</td>
<td>-0.36</td>
<td>-0.71</td>
</tr>
<tr>
<td>Avg</td>
<td>0.34</td>
<td>0.39</td>
<td>0.45</td>
<td>0.71</td>
<td>0.62</td>
<td>0.64</td>
<td>0.67</td>
<td>0.36</td>
<td>0.64</td>
<td>0.55</td>
<td>0.53</td>
<td>0.28</td>
</tr>
</tbody>
</table>

- RMSE (mm) given by the Cross Validation of the CCA model (winter) for each group of ten years.

<table>
<thead>
<tr>
<th></th>
<th>Cor</th>
<th>S. C.</th>
<th>Sar</th>
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<th>Lisb</th>
<th>Evo</th>
<th>Beja</th>
<th>Tau</th>
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<tbody>
<tr>
<td>51/60</td>
<td>119.4</td>
<td>333.2</td>
<td>189.0</td>
<td>111.1</td>
<td>240.7</td>
<td>137.3</td>
<td>127.2</td>
<td>121.7</td>
<td>129.5</td>
<td>97.4</td>
<td>123.5</td>
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<tr>
<td>61/70</td>
<td>159.2</td>
<td>428.9</td>
<td>308.6</td>
<td>181.7</td>
<td>359.2</td>
<td>300.8</td>
<td>207.7</td>
<td>301.7</td>
<td>152.5</td>
<td>143.9</td>
<td>112.8</td>
<td>164.9</td>
</tr>
<tr>
<td>71/80</td>
<td>153.3</td>
<td>295.8</td>
<td>295.3</td>
<td>159.1</td>
<td>304.6</td>
<td>409.3</td>
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<td>166.9</td>
<td>136.2</td>
<td>119.0</td>
<td>168.6</td>
</tr>
<tr>
<td>81/90</td>
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<td>392.3</td>
<td>195.0</td>
<td>168.8</td>
<td>312.7</td>
<td>492.3</td>
<td>167.3</td>
<td>126.9</td>
<td>220.2</td>
<td>160.5</td>
<td>160.5</td>
<td>218.7</td>
</tr>
<tr>
<td>Avg</td>
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<td>274.5</td>
<td>171.7</td>
<td>112.9</td>
<td>187.2</td>
<td>264.5</td>
<td>105.6</td>
<td>156.1</td>
<td>128.6</td>
<td>129.3</td>
<td>272.8</td>
<td></td>
</tr>
</tbody>
</table>

- For future downscaling data from ECHAM5 was used.

- ECHAM5 is a AOGCM developed in the Max Planck Institute, Hamburg.

- For future downscaling, predictors were obtained from the difference of MSLP data simulated by ECHAM5, for the period 2071 – 2100 and the control period (1971 – 2000).

Thank you!

João Corte-Real
Sandro Veiga
http://www.icaam.uevora.pt

Pólo Rural da Universidade de Évora

Suporte Técnico: Regina Corte-Real