Downscaling Applications

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Summary

• Why bother?
• Recap of Downscaling Methods
• Incorporating uncertainty
• Using downscaling for societally relevant questions
  – *Statistical Downscaling Applications*
    • Weather generators
    • Minimal step approach
    • Extreme value theory (EVT)
  – *Hybrid statistical-dynamical applications for decisions*
    • Combining model output with EVT
    • Incorporating in impact models
    • Using large-scale atmospheric signals
Society demands climate information at local levels BUT all climate models have biases and these have highest impact at small scales.
Why Bother?

• Individual components of models (e.g. parameterization) contain errors that are situation and model dependent

• Dynamical downscaling is computer expensive and there is tentative evidence that going below, say, 20 km may not provide a benefit corresponding to the cost

• Much high-impact weather is truncated by achievable resolutions

• Adaptation to high impact weather requires reasonable estimates of the probability of failure, at the local level

• Societal and Ecological modules demonstrably can benefit from a statistical interface between them and the dynamical predictions.
Downscaling Approaches (recap)

- **Statistical downscaling**
  - *Apply empirical relationships*
  - *Weather generators*

- **Dynamical downscaling via RCM**
  - *High resolution atmospheric global models*
  - *Variable resolution grid models*

- **Ensembles of models to quantify uncertainty**

- **Hybrid statistical-dynamical downscaling**

- **Apply corrections:**
  - *At the boundary conditions prior to driving RCM*
  - *To the regional model outputs*
INCORPORATING (SOME) UNCERTAINTY
Example: The Cyclone Genesis Index

\[ CGI = \left( \frac{PI}{70} \right)^{3} \left( 1 + 0.1(V_{shear} + a) \right)^{-2} \]

(Bruyere et al 2012)
Quantifying uncertainty

% change from 1995-2005 mean

-250 -150 -50 50 150 250 350 450

Year

1940 1960 1980 2000 2020 2040 2060 2080 2100

- CCSM-CGI ens. mean
- CCSM-CGI A1B ens. mean
- CCSM-CGI A2 ens. mean
- CCSM-CGI
- NRCM TC 11-year mean
STATISTICAL DOWNSCALING APPROACHES
Weather Generators

• Stochastic series generated from observed weather characteristics at a specific location for decision tools e.g. agricultural models, run-off generation

• Classical 3-part structure defined from observations:
  – Precipitation occurrence
  – Precipitation intensity
  – Daily temperature maxima and minima

• Model can be dependent on a large scale index (e.g. ENSO, SST) so can be used to many realisations of possible future weather
Minimal Step Approach

• Most societal impacts go via an extended path, e.g.

*Model Prediction*....*Statistical Downscaling*.....*Impacts Model*

• The extra steps introduce additional errors
• If possible a single-step approach will almost always be better

Go directly to the societal application!
Example: Cyclone Damage Potential

\[ CDP = 4 \frac{\left( \frac{v_m}{65} \right)^3 + 5 \left( \frac{R_h}{50} \right)}{v_t}, \]

For \( v_m > 65 \); if \( v_t < 5 \), set \( v_t = 5 \);
if \( CDP > 10 \) set \( CDP = 10 \).

- Will require scaling to accommodate varying structures and engineering design levels for explicit damage assessment.
- We are developing the CDP to work directly from proportion of insured loss compared to the total portfolio. This removes difficulties with assessing direct absolute damage.

(Holland and Done AGU 2011)
Damage Potential Paths
Historical Tropical Cyclones

(Done 2011)
## Potential Future Changes: Gulf of Mexico

<table>
<thead>
<tr>
<th></th>
<th>1995-2005</th>
<th>2020-2030</th>
<th>2045-2055</th>
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</thead>
<tbody>
<tr>
<td># Tropical Cyclones</td>
<td>16</td>
<td>13</td>
<td>11</td>
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<tr>
<td># 6-hourly data points</td>
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<td>Average $V_m$ (kt)</td>
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<td>63</td>
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<td>Max $V_m$ (kt)</td>
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<td>Average $R_{max}$ (nm)</td>
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<tr>
<td>Average $V_t$ (kt)</td>
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<tr>
<td>Average CDP</td>
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<tr>
<td>Max CDP</td>
<td>7.7</td>
<td>8.1</td>
<td>5.0</td>
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</table>

(Done et al 2011)
Distributional Approach

• Create PDF of the field of interest for current climate
  – e.g. hurricane intensity, daily rainfall, daily maximum temperatures

• Fit an appropriate distribution to this
  – e.g. GEV, GPD, gamma, weibull etc.

• Estimate the changes to the distribution parameters from the climate simulations

• Derive new estimates of the fitting parameters

• Voila!
Example: Weibull Distribution

We utilize the Weibull distribution for which the CDF and PDF are:

\[
CDF = f(x) = 1 - e^{-\left(\frac{x}{\alpha}\right)^\beta}
\]

\[
PDF = f'(x) = \frac{\beta}{\alpha} \left(\frac{x}{\alpha}\right)^{\beta-1} e^{-\left(\frac{x}{\alpha}\right)^\beta}
\]

Where parameters \( \alpha \) and \( \beta \) determine the scale and the shape, respectively.
Histograms of wind speeds and superimposed best Weibull fits

- Very different distributions for model simulations than observed
- Weibull distributions provide good fits to all high wind speeds
Two approaches to transform model output

- Apply differences between control model and observations to get future
- Weibull distributions provide good fits to all high wind speeds
Estimate the changes

Transform the distribution parameters:

Parameter Transformations

Shape:
\[
\beta_{X'} = \frac{\beta_x \beta_y}{\beta_y}
\]

Scale (CF):
\[
\alpha_{X'} = \alpha_y \left( \frac{\alpha_x}{\alpha_y} \right)^{\beta_y/\beta_x}
\]

Scale (BC):
\[
\alpha_{X'} = \alpha_x \left( \frac{\alpha_y}{\alpha_y} \right)^{\beta_y/\beta_x}
\]

Estimate new probability of exceeding a threshold

\[
P \left( E \{ x' > c \} \right) = 1 - f(c) = e^{-\left( \frac{c}{\alpha} \right)\beta}
\]
Probability densities for observed future wind speeds ($X'$)

Use new parameter estimates to calculate “future” distributions.
Estimating Extremes

- Use extreme value theory to estimate likely return frequency of high impact events
- Easily applied in R with \{extRemes\}
- Compare current and future distributions

\[
P(S) = \exp\left\{- \left[ 1 + \frac{x}{\xi} \left( \frac{S - \mu}{\sigma} \right) \right]^{-1/\xi} \right\}
\]

Distribution is fit to historic maximum values of interest (S)
Estimating Extremes

\[ P(S) = \exp\left\{ -\left[ 1 + \frac{\xi}{\sigma} \left( \frac{S - \mu}{\sigma} \right) \right]^{-1/\xi} \right\} \]

3 Model parameters
Location parameter: \( \mu \) (where distribution is centered)
Scale parameter: \( \sigma > 0 \) (spread of the distribution)
Shape parameter: \( \xi \) (behavior of distribution tail)
GEV Parameters
HYBRID STATISTICAL-DYNAMICAL DOWNSCALING APPLICATIONS
1. Allowing for non-stationarity

Take the “stationary” annual maxima and fit GEV
Allowing for Non-stationarity

Introduce covariates to allow for time varying processes

\[
\mu_i = \beta_0 + \beta_1 \text{(covariates)}
\]

\[
P_i(S) = \exp \left\{ - \left[ 1 + \xi \left( \frac{S - \mu_i}{\sigma} \right) \right]^{-\frac{1}{\xi}} \right\}
\]
Conditional GEV shifts with climate covariates

(Towler et al., 2010)
Derive Relevant Future Climate Response

Use climate change projections as covariates in the non-stationary GEV

Historic (USGS)
36 model runs
36 model average

Increasing maximum streamflow anomalies
(Towler et al. 2010)
Combine EVT with Dynamics

- Atmospheric Blocking is a known driver of European heat waves
- Sustained, quasi-stationary, high-pressure systems that disrupt the prevailing westerly circumpolar flow

Sillmann, 2009
Use with EVT to estimate impacts
Estimate likely impacts

1:10 year

1:25 year

1:50 year

(Photiadou et al. in review)
2 Combine Projections with Impacts

Climate model provides maximum temperatures

NRCM shows 3 degree increase in daily maximum temperature
2 Combine Projections with Impacts

Ecological Impact Assessment from
Lewis Woodpecker Nest Survival Impact Model

Impact

Daily maximum temperature (°C)

Climate

Erin Towler

Aspen Woodlands (Photos courtesy of Vicki Saab, RMRS)
Use climate info in conjunction with impact model to quantify outcome

Climate + Impact Model = Nest survival

Current 2045–2055
Use climate info in conjunction with impact model to quantify outcome

\[ \text{Climate} + \text{Impact Model} = \text{Outcome} \]

(Towler et al. 2012)
Nest survival is more relevant to management decisions than raw temperature information.

- Nest survival is more relevant to management decisions than raw temperature information.
USING LARGE SCALE DYNAMICS WITH STATISTICAL MODELS
Investigate large-scale features that are associated with climate impacts of interest

Example: SSTs correlated with Oklahoma drought index

Erin Towler, Debasish PaiMazumder
Derive relationships between dynamics and response

Dynamical (High-frequency variability) + Statistical (Expected “mean” value) = Hybrid

Erin Towler, Debasish PaiMazumder
Conclusions

• Decision makers require local information but high-resolution modelling is computationally expensive so we need to downscale.

• Downscaled outputs need to be relevant for decision making, direct climate parameters may not be appropriate.

• Many different approaches used including “reshaping” distributions and weather generators.

• Hybrid Statistical-Dynamical Approaches are an essential component of any regional climate application.