Application of Stochastic Weather Generators in Crop Growth Modelling

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3) Sepp Eitzinger for inviting me

***** Valladolid, 27-29 June 2007 (Agridema final workshop) *****
outline

• **Met&Roll** (see my talk in Vienna 2005; available on web)
  - history / model / validation (direct, indirect /crop, hydro/)
  - applications:
    - **PERUN** [Met&Roll + WOFOST]
      - climate change impact analysis
      - probabilistic crop yield forecasting
    - **M&Rwin** [Met&Roll + (5 crop models + 2 drought indices + SAC-SMA)]
      - system with “plug-in” models
      - cc impact analysis for multiple stations / multiple models in a single batch

• Interpolation of Met&Roll generator
  - validation in terms of selected climatic characteristics and crop yields

• **GeNNeR = Generator based on Nearest Neighbours Resampling** (non-parametric)
  - comparison with Met&Roll in terms of extreme temperature and precip characteristics

• latest development: **M&Rfi** (developed for/with FAO)
  - **M&Rfi = Met&Roll flexible**
  - experiment: reproduction of variability monthly means using various time steps

• spatial simulation of wheat yields for now & future (CERES-Wheat + M&Rfi)
Met&Roll
&
related tools
(PERUN, M&Rwin)
**Met&Roll = single site 4/6-variate stochastic daily WG**

- **Met&Roll - history**
  - *1995*: first version (based on WGEN [Richardson, 1981])
  - **improvements** of the model since 1995
  - **previous applications:**
    - **crop growth modelling** (together with MUAF; in climate change impact studies, probabilistic seasonal crop yield forecasting -> **PERUN system** /2001/)
    - **hydrological modelling** (small river catchments)
    - **implemented M&Rwin system** (present and changed climate simulations for multiple stations and models in a single batch)
    - **2005: caliM&Ro project** starts (~ interpolation of Met&Roll)
    - **2006 (December): Met&Roll is used as a basis for M&Rfi generator**

- **model (present version)**
  - **PREC**: occurrence ~ Markov chain (order: 1-3; parameters: *trans.prob.*)
    - amount ~ Gamma distribution (parameters: $\alpha, \beta$ /~ shape, scale/)
  - **SRAD, TMAX, TMIN**: standardised deviations from their mean annual cycle are modelled using AR(1) model (parameters: $A, B, avg(X_i), std(X_i)$)
    - all **parameters are assumed to vary during the year**
    - daily WG is optionally linked to AR(1) based **monthly weather generator**
    - other variables may be added using a resampling algorithm

- **Met&Roll is freely available (easiest way: download PERUN system)**
PERUN = Met&Roll + WOFOST (*2001)
PERUN output: seasonal analysis
PERUN output: summary statistics
(30-year simulations; total weight of storage organs; various soils)
M&Rwin - developed within caliM&Ro project
probability of wet day occurrence

model crop yields (present climate)

M&Rwin: output (examples)
Interpolation of Met&Roll generator

= main aim of the caliM&Ro project (2005-7; 4 Czech institutes)

- Met&Roll is linked to several crop models and hydrological models to assess impacts of imperfections in WG and interpolation techniques on output from the impact models

present experiment: validation of the interpolated generator in terms of
  a) WG parameters
  b) extreme precipitation characteristics
  c) crop yields (CERES-Wheat)

project web page: www.ufa.cas.cz / dub / calimaro / calimaro.htm
- **125 Czech stations** available with data coverage greater or equal to 75% during 1961-1990: **a) circles**: “learning” set, **b) squares**: “validation” set

- **Altitude** varies from 115 to 1602 m a.s.l. (topography derived from the global digital elevation model GTOPO30 /horizontal grid spacing = 30 arc seconds/; http://edc.usgs.gov/products/elevation/gtopo30/gtopo30.html)
Experimental design

WG parameters:
- Met&Roll

Daily weather series (125 st.):
- observed series
- synthetic series

Climatic characteristics:
- climatic characteristics

Impact model (crop-growth model, hydrological model, ...)

Output from impact models:
- Crop yields, river streamflows

Parameters of site-calibrated WG
- interpolation

Parameters of interpolated WG
- A(int)

A(int) accuracy of interpolation
B(wg) ability of WG to reproduce climatic characteristics
B(int) effect of interpolation of WG on climatic characteristics in synt. series
C(wg) effects of WG inaccuracies on impact models output
C(int) effect of interpolation of WG on impact models output
interpolation methods

- implemented in GIS (ArcGIS): co-kriging was selected after many experiments

- neural networks [Multilayer Perceptron network type = 3-5-1, 29 degrees of freedom, Back Error Propagation and Conjugate Gradient Descent training algorithms used]

- weighted nearest neighbours: \( y(x,y,z) = \text{weighted average from the surrounding stations (d<100km; bell-shaped weight function) corrected for the zonal + meridional + altitudinal trends (linear relationships with } x,y,z \text{ are assumed) } \)
validation = comparison of characteristics obtained from/with
- observed weather series
- synthetic series generated by site-calibrated WG
- synthetic series generated by interpolated WG

validation has been made in terms of:

a) WG parameters (here: stress on parameters of the precipitation sub-model)
   - parameters of Gamma distribution
   - parameters of the first-order Markov chain
   - AVGs and STDs of temperature characteristics

b) extreme precipitation characteristics (mean annual max, 30year max)
   - length of dry and wet spells
   - 1day and 5day precipitation sum

c) model crop yields simulated with weather series
### Comparison of WG Parameters: Site-Calibrated vs Interpolated

<table>
<thead>
<tr>
<th>WG Parameters</th>
<th>Interpolation Methods</th>
<th>Neural Net.</th>
<th>Nearest Neigh.</th>
<th>Co-kriging</th>
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<tbody>
<tr>
<td></td>
<td>r(λ,φ,z)</td>
<td>RV [%]</td>
<td>RV [%]</td>
<td>RV [%]</td>
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<td><strong>a) Precipitation: ( \Gamma_s h ) (shape parameter of the ( \Gamma ) distribution)</strong></td>
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<tr>
<td>JAN.</td>
<td>0.19</td>
<td>-1</td>
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<td>2</td>
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<tr>
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<td>0.37</td>
<td>6</td>
<td>10</td>
<td>8</td>
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<td><strong>b) Precipitation: ( \Gamma_s h * \Gamma_s c ) (mean PREC on a wet day)</strong></td>
<td></td>
<td></td>
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<tr>
<td>JAN.</td>
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<td>53</td>
<td>42</td>
<td>52</td>
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<tr>
<td>JULY</td>
<td>0.87</td>
<td>63</td>
<td>70</td>
<td>59</td>
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<td><strong>c) Precipitation: probability of wet day occurrence</strong></td>
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<tr>
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<td>0.78</td>
<td>59</td>
<td>69</td>
<td>56</td>
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<tr>
<td>JULY</td>
<td>0.75</td>
<td>56</td>
<td>68</td>
<td>49</td>
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<tr>
<td><strong>d) Precipitation: trans. prob. of wet day occurrence (previous day was dry)</strong></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>JAN.</td>
<td>0.54</td>
<td>28</td>
<td>41</td>
<td>17</td>
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<tr>
<td>JULY</td>
<td>0.74</td>
<td>54</td>
<td>66</td>
<td>23</td>
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<tr>
<td><strong>e) Daily temperature maximum</strong></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>AVG (JAN.)</td>
<td>0.95</td>
<td>89</td>
<td>89</td>
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<td>AVG (JULY)</td>
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<td>98</td>
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<tr>
<td>STD (JAN.)</td>
<td>0.68</td>
<td>42</td>
<td>51</td>
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<td>STD (JULY)</td>
<td>0.79</td>
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<td><strong>f) Daily temperature minimum</strong></td>
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<td>AVG (JULY)</td>
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<tr>
<td>STD (JAN.)</td>
<td>0.52</td>
<td>27</td>
<td>15</td>
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<tr>
<td>STD (JULY)</td>
<td>0.68</td>
<td>44</td>
<td>52</td>
<td></td>
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</tbody>
</table>
validation in terms of $\Gamma_{sc} \times \Gamma_{sh} \text{ (Jul)}$

co-kriging: $RV = 59\%$

nearest neighbours: $RV = 70\%$

neural networks: $RV = 63\%$

- Color of the stations’ symbols relate to station-specific interpolation error
- WG parameters are mapped using GTOPO30 digital elevation map
validation in terms of Pwet (Jan.)

- Color of the stations’ symbols relate to station-specific interpolation error
- WG parameters are mapped using GTOPO30 digital elevation map
validation in terms of $P_{\text{wet|dry (Jan)}}$

cokriging: $RV = 17\%$

- Color of the stations’ symbols relate to station-specific interpolation error
- WG parameters are mapped using GTOPO30 digital elevation map
validation in terms of $\Gamma_{sh}$ (July)

- Color of the stations’ symbols relate to station-specific interpolation error
- WG parameters are mapped using GTOPO30 digital elevation map
Validation in terms of: **Annual max. length of dry spell**

- **B(int)**: WG underestimates max. length of dry spell (the fit is better if MC3 model is used)
- **B(int)**: interpolated WG performs similarly as the site-calibrated WG
- **B(wg) vs B(int)**: differences due to interpolation are lower than those due to WG imperfections
Validation in terms of: **Annual max. length of wet spell**

- WG simulates dry spell better than the dry spells
Validation in terms of: **Annual max. 1 day precipitation**

- **B(wg):** WG underestimates annual extreme precipitation
- **B(wg) vs B(int):** differences due to interpolation are lower than those due to WG imperfections
Validation in terms of: Annual max. 5-day precipitation

Similar as 1-day PREC but even more pronounced:
- \( B(wg) \): WG underestimates annual extreme precipitation
- \( B(wg) \) vs \( B(int) \): differences due to interpolation are lower than those due to WG imperfections
Annual extreme precipitation characteristics: summary

<table>
<thead>
<tr>
<th>L(dry)</th>
<th>L(wet)</th>
<th>1d-PREC</th>
<th>5d-PREC</th>
</tr>
</thead>
<tbody>
<tr>
<td>OBS</td>
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<tr>
<td>site-cal. WG</td>
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<tr>
<td>WG-int. (Neighb.)</td>
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<tr>
<td>WG-int. (Netw.)</td>
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</tbody>
</table>
30-year extreme precipitation characteristics

L(dry)  L(wet)  1d-PREC  5d-PREC

Results are similar as in the case of the annual extremes
wheat yields
[Met&Roll + CERES-Wheat; soil = cambisol typical (blue)]

A) input weather: observed series
B) input weather: site-calibrated WG
C) input weather: interpolated WG
wheat yields
[Met&Roll + CERES-Wheat; soil = haplic chernozem (brown)]
wheat yields
[Met&Roll + CERES-Wheat; soil = fluvisol (orange)]

A) input weather: observed series

B) input weather: site-calibrated WG

C) input weather: interpolated WG
interpolation of WG - conclusions

1) Comparison of 3 interpolation methods:
   - nearest neighbours provide best results (slightly better than the neural networks [But: to use the nearest neighbours, all learning data must be available during interpolation into ungauged stations (in contrast with neural network, which do not need access to learning data after being trained).
   - GIS-based co-kriging appears to provide results, which are generally slightly worse compared to the former two techniques. However, GIS was found to provide valuable help in finding other co- variates which could further improve the interpolation accuracy.

2) !!! Errors in reproducing precipitation characteristics due to interpolation of WG parameters are generally lower than those related to imperfections in WG

3) Future work: topographical characteristics (e.g. slope, variability) are planned to be used as co-variates to further improve interpolation
nearest neighbours resampling generator

GeNNeR

... and comparison with Met&Roll
(in terms of extreme TEMP and PREC characteristics)
GeNNeR: resampling generator *(under development)*

**GeNNeR** = generator based on nearest neighbours resampling

**method:** $X(t)$ is a weighted average of analogues found in “learning” data using $X(t-1), X(t-2), \ldots, X(t\text{-order})$ as a predictors

**advantages:**
- no assumption on prob. dist. function of $X$
- very flexible (various time step, various number of variables)

**disadvantages:**
- generator cannot “extrapolate” beyond the learning data
- access to the learning data is required during generation *(instead of the set of parameters in Met&Roll)*
- problems in applying climate change scenario
- How to interpolate???
GeNNeR vs. Met&Roll
reproducing extreme temperature and precipitation characteristics

**experiment:** reproduction of extreme temp. and prec. characteristics by Met&Roll (various settings) vs. GeNNeR (various settings)

**data:** 8 European stations (taken from EC&D project)

**GeNNeR’s settings:**
- precipitation is considered either binary or continuous variable
- other variables are conditioned/not-conditioned on precipitation (only terms with the same precipitation status on the previous day are considered as potential analogues)
- inclusion of the randomisation term

**Met&Roll settings:**
- inclusion of the annual cycle of lag-0 and lag-1 correlations among SRAD, TMAX and TMIN (values = Yes / No)
- order of the Markov chain (values = 1 or 3)
- linking daily WG with monthly WG (values = Yes / No)

[presented at ECAC2006]
GeNNeR vs. Met&Roll

**experiment:**  
1) For each station, 10x30-years series generated using 8 versions of Met&Roll and 36 versions of GeNNeR  
2) Characteristics from the synthetic series compared with those derived from the observed series

**a) temperature characteristics (annual and 30-year extremes):**
- \( \text{max}(T_{\text{MAX}}) \) = annual/30-year **maximum** \( T_{\text{MAX}} \)  
- \( \text{min}(T_{\text{MIN}}) \) = annual/30-year **minimum** \( T_{\text{MIN}} \)  
- \( \text{Lmax(Heat)} \) = annual/30-year **maximum length of heat spell***  
- \( \text{Lmax(Cold)} \) = annual/30-year **maximum length of cold spell***  

**b) precipitation characteristics:**
- \( \text{max}(\text{PREC}) \) = annual/30-year **maximum** of \( \text{PREC} \)  
- \( \text{max}(5\text{-day PREC}) \) = annual/30-year **maximum of 5- day precipitation**  
- \( \text{Lmax(Dry)} \) = annual/30-year **maximum length of dry spell***  
- \( \text{Lmax(Wet)} \) = annual/30-year **maximum length of wet spell***  

• **heat spell** = continuous period with \( T_{\text{MAX}} > \text{avg}(T_{\text{MAX}}) + 1.645 \times \text{std}(T_{\text{MAX}}) \)  
• **cold spell** = continuous period with \( T_{\text{MIN}} < \text{avg}(T_{\text{MIN}}) - 1.645 \times \text{std}(T_{\text{MIN}}) \)  
  \( \text{avg}(*) \) and \( \text{std}(*) \) are climatological means and std’s for a given day of the year  
• **dry spell** = continuous period with \( \text{PREC} < 0.1 \text{ mm} \)  
• **wet spell** = continuous period with \( \text{PREC} \geq 0.1 \text{ mm} \)
GeNNeR vs. Met&Roll: annual and 30-year max of TMAX

Legend:

annual max: avg±std from 30 years (OBS) or 300 years (synthetic)

30-year max: avg±std from ten 30y series (only synthetic series)

M* = Met&Roll
OBS = observed
A*, BB, CB, D* = GeNNeR)
Legend:

**annual max:** avg±std from 30 years (OBS) or 300 years (synthetic)

**30-year max:** avg±std from ten 30y series (only synthetic series)

M*= Met&Roll
OBS = observed
A*, BB, CB, D* = GeNNeR
**Legend:**

**annual max:**
avg±std from 30 years (OBS) or 300 years (synthetic)

**30-year max:**
avg±std from ten 30y series (only synthetic series)

*M* = Met&Roll  
OBS = observed  
A*, BB, CB, D* = GeNNeR
**GeNNeR vs Met&Roll:** annual and 30-y max of L(Cold spell)

**Legend:**

- **annual max:** avg±std from 30 years (OBS) or 300 years (synthetic)
- **30-year max:** avg±std from ten 30y series (only synthetic series)
- **M* = Met&Roll**
- **OBS = observed**
- **A*, BB, CB, D* = GeNNeR**
**Legend:**

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**annual max:**
avg±std from 30 years (OBS) or 300 years (synthetic)

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- **30-year max:** avg±std from ten 30y series (only synthetic series)
- **M** = Met&Roll
- **OBS** = observed
- **A**, **BB**, **CB**, **D** = GeNNeR

**GeNNeR vs. Met&Roll: annual and 30-y max of PREC**
**Legend:**

- **annual max:** avg±std from 30 years (OBS) or 300 years (synthetic)
- **30-year max:** avg±std from ten 30y series (only synthetic series)
- **M* = Met&Roll**
- **OBS = observed**
- **A*, BB, CB, D* = GeNNeR**

**GeNNeR vs Met&Roll: annual and 30-y max of 5d PREC**
GeNNeR vs. Met&Roll: Conclusion

a) most of the extreme characteristics analysed here are reproduced better by GeNNeR (best version) than by Met&Roll (best version)

b) GeNNeR

- precipitation extremes (both 1-day and 5-day) are best reproduced by version (not shown in the figures), which employs the random term and uses precipitation amount as a predictor

- inclusion of the random term has not so definite effect on reproduction of the other extreme climatic characteristics; better specification of the random term will hopefully help

- conditioning the search for the neighbours on precipitation occurrence or using the precipitation amount as a predictor perform similarly well

c) Met&Roll

- effects of the three modifications (with respect to the basic version of Met&Roll) on reproduction of most extreme characteristics [e.g. max(TMAX) and min(TMIN)] is only slight.

- 3rd order Markov chain improves reproduction of the dry spells (but not the wet spells)

- inclusion of the monthly generator significantly affects precipitation. It improves reproduction of the 5-day PREC extremes, but the effect on extreme 1day PREC is not so definite
new parametric weather generator

M&Rfi

- based on Met&Roll
- developed for FAO

www.ufa.cas.cz/dub/wg/marfi/marfi.htm
M&Rfi - introduction

M&Rfi = Met&Roll flexible (or Met&Roll generalised and enhanced; Met&Roll may be considered to be a special case of M&Rfi)

important features:

- optional number of variables (<=8) [typically 3 or 4: (PREC, SRAD, (TMAX + TMIN) or (TAVG + DTR) or TAVG)
- optional time step (1d, 3d, 5d, 1w, 10d*, 2w, ½m, 1m)
- 1 variable (precip) is optionally “the conditioning variable”
- transformation of variables (including time-aggregation)
- estimation of solar radiation from cloudiness or sunshine
- estimation of evapotranspiration using Penman-Monteith equation
- run via command line [-M&R]
- all WG parameters stored in a single file, more stations may be stored in a single file
- the synthetic weather series may be “forced” to fit [-M&R]
  - weather forecast for a forthcoming period (following days, month or whole season)
  - climate change scenario (including changes in variability)
    - through modifying WG parameters
    - through direct modification of input weather series

!!! freely available from web: demo batch files + user’s guide !!!
M&Rfi – model

- (optional!) conditioning variable is modelled:
  - two state Markov chain for precip occurrence
  - Gamma distribution for precip amount

- variables (all except for the conditional variable) are modelled by First-order autoregressive model
  - standardised deviations from the mean annual cycle are modelled by AR(1) model; annual cycle of AVG and STD (used for standardisation/destandardisation) are smoothed by robust locally weighted regression (only in case of daily generator)
  - conditioning: it is specified for each variable separately, whether it is conditioned or not. If it is conditioned, the AVG and STD values are used different for wet and dry days. If the variable is not conditioned, AVG and STD values are the same for both wet and dry days.
experiment: **variability of monthly means using M&Rfi run at different time-steps**

- **3 versions of M&Rfi** are employed in the test. All of them are **3-variate** generators (variables: $TMAX$, $TMIN$, $PREC$). The three versions differ in (i) the time step, (ii) a way in which the precipitation is involved:
  - **M&Rfi-daily**: daily weather generator. Precipitation occurrence is modelled by Markov chain (1st order), precipitation amount by Gamma distribution. $TMAX$ and $TMIN$ are modelled by bivariate 1st-order AR (*this generator is equivalent with Met&Roll except for not employing solar radiation*)
  - **M&Rfi-10day**: time step = 10 days; all three variables (including precipitation) are modelled by the 3-variate 1st-order autoregressive model
  - **M&Rfi-monthly**: time step = 1 m; all other settings are the same as in M&Rfi-10day

- **For each station** (see the Table for the list):
  - (i) **estimating parameters** of M&Rfi-daily, M&Rfi-10day and M&Rfi-monthly from 30-y observed series
  - (ii) **generation** of 30×30-year synthetic series with all three WGs
  - (iii) **analysis** of the synthetic series for selected characteristics.

*(presented in EGU-2007)
**experiment:** variability of monthly means using M&Rfi run at different time-steps

- **data:** 8 stations from Europe (ECA&D database) + 11 U.S. stations

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<thead>
<tr>
<th>acronym</th>
<th>station</th>
<th>state</th>
<th>LAT</th>
<th>LONG</th>
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M&Rfi - reproduction of variability of monthly means: PREC

**Summer**

**Winter**
M&Rfi - reproduction of variability of monthly means: TMAX

- **Summer**

- **Winter**
M&Rfi - reproduction of variability of monthly means: TMIN

summer

winter
• **The results** shown in the figures show, that the best performance in reproducing monthly variability is obtained by monthly generator *(not surprising, but useful to know!)*

• **to be tested:** transformation of some variables (especially PREC, SRAD and DTR) might help
Spatial crop model simulations for Czechia:

present climate and changed climate (cc scenario = HadCM3-2050-high)
Spatial crop model simulations for Czechia

- **crop model** = CERES-Wheat (*Mirek Trnka’s words: “very carefully calibrated”*)
- **weather generator** = M&Rfi [daily, 4-variate (*PREC, SRAD, TMAX, TMIN*); ~Met&Roll]
- **data:**
  - 0.5x0.5 km soil map (394 soil types) produced by MUAF
  - 125 weather stations (provided by CHMI)

- **spatial analysis** (for given climate scenario):
  - **step 1:** the model is used to simulate crop growth for all 49250 possible combination of [weather station, soil type]
    - each simulation: 99-year crop model run with synthetic weather series
    - present climate: WG is calibrated using station daily weather series
    - changed climate: WG parameters modified according to CC scenario
  - **step 2:** crop yields are interpolated into 0.5x0.5km soil grid map. For each grid box, the yield is interpolated from the 125 simulations made for a given grid-specific soil type
    - interpolation method = nearest neighbours with accounting for the x-y-z trends
Spatial crop model simulations for Czechia - soil types

Rendzina, pararendzina, regozem, fluvizem

Černosol - černozem a černice

Kambizem typická
Interpolated model wheat yields for now and 2050
(data: 125 weather stations X 394 soil types; HadCM3/SRES-A2-high scenario)

2050: only changed weather effect

2050: combined effect of CO2+weather changes:
CC impact on wheat yields - arable lands
(2050 - HadCM3/SRES-A2-high scenario)

a) only changed weather effect

b) combined effect of CO₂+weather changes:

c) difference: combined effect minus weather effect
(= CO₂ fertilisation effect under changed climate)
conclusions

• Met&Roll:
  - old but still useful (available from PERUN)
  - I do not assume further improvements

• GeNNeR (non-parametric WG): results are promising but:
  - not yet ready for operational use
  - limitations in usage

• M&Rfi (more flexible follower of Met&Roll):
  - 1st version already available on web
  - improvements will hopefully follow

• use weather generators!
  \[(more \ users \ > \ more \ improvements \ in \ WG)\]
References (related to Met&Roll)


• Trnka M., Dubrovsky M., Semeradova D., Zalud Z., 2004: Projections of uncertainties in climate change scenarios into expected winter wheat yields. *Theoretical and Applied Climatology*, 77, 229-249


papers and presentations are found at: [www.ufa.cas.cz / dub / dub.htm](http://www.ufa.cas.cz / dub / dub.htm)
END