Reduced Overdispersion in Stochastic Weather Generators for Statistical Downscaling of Seasonal Forecasts and Climate Change Scenarios

Yongku Kim

Institute for Mathematics Applied to Geosciences
National Center for Atmospheric Research

Joint work with R. W. Katz, B. Rajagopalan and G. Podestá

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Outline

• Challenge/Motivation

• GLM Stochastic Weather Generator
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  – Overdispersion Phenomenon

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  – Downscaling Climate Change Scenarios

• Possible Extensions
Utility of Weather Generators
Challenge/Motivation

• Weather generation in the Pampas region of Argentina

• A wet season in the Southern Hemisphere summer impact to crop models.

• Interactions between changing climate and technological innovations in agricultural decision making.

Study Region
GLM Stochastic Weather Generator

- Richardson stochastic weather generator (e.g., Richardson WRR 1981).
  - Precipitation Occurrence: chain-dependent process (i.e. Markov chain for occurrence).
  - Precipitation Intensity: independent, identically distributed conditional on occurrence.
  - Min. and Max. temperature: bivariate first-order autoregressive process.
  - Dependence between temperature and precipitation.
  - Overdispersion phenomenon.
  - Computationally intense and unwieldy to modify it to downscaling.
GLM Stochastic Weather Generator

- Furrer & Katz (Clim. Res. 2007).
  - Introduction of covariates such as a seasonal cycle and/or an atmospheric index.
  - e.g., The probability that it rains on a specific day is modeled depending on the day of the year and the ENSO.
  - A separate model fit for each month of the year and/or for each ENSO category.
  - All glm model selection via likelihood ratio test, AIC or BIC.
  - A limitation of parametric stochastic weather generators: A marked tendency to underestimate the observed interannual variance of seasonally aggregated variables (e.g., Katz and Parlange (1998)).
  - Webpage: Generalized linear model (GLM) weather generator, see http://www.image.ucar.edu/~eva/GLMwgen/.
GLM Stochastic Weather Generator

Downscaling of Seasonally Aggregated Climate

- To reduce overdispersion phenomenon, incorporate time series of seasonal total precipitation and seasonal mean minimum and maximum temperature in the GLM weather generator as covariates (Summer: October-March, Winter: April-September).

- These seasonal time series are smoothed using locally weighted scatterplot smoothing (LOESS) to avoid introducing underdispersion.
GLM Stochastic Weather Generator

Precipitation occurrence: Logistic GLM for \( p_t = Pr\{J_t = 1\} \),

\[
\ln[p_t/(1 - p_t)] = \beta_0 + \beta_1 J_{t-1} + \beta_2 \cos t + \beta_3 \sin t + \beta_4 J_{t-1} \cos t + \beta_5 J_{t-1} \sin t + \beta_6 I_t S_t + \beta_7 (1 - I_t) W_t
\]

homogeneous Markov chain
parallel sine waves
separate sine waves
summer total precip. \((I_t = 1)\)
winter total precip. \((I_t = 0)\)

Treats both transition probabilities \( P_{01} \) and \( P_{11} \) simultaneously, incorporating common and separate signals.

Precipitation intensity: Gamma GLM for mean precipitation intensity

\[
\ln \mu_t = \gamma_0 + \gamma_1 \cos t + \gamma_2 \sin t + \gamma_3 I_t S_t + \gamma_4 (I_t - 1) W_t.
\]
GLM Stochastic Weather Generator

**Temperature:** Coupled univariate models for minimum \((X_t)\) and maximum \((Y_t)\) daily temperature, essentially equivalent to bivariate AR(1)

\[
X_t = \alpha_0 + \alpha_1 J_t + \alpha_2 X_{t-1} + \alpha_3 Y_{t-1} + \alpha_4 \cos t + \alpha_5 \sin t + \alpha_6 I_t S_t + \alpha_7 (I_t - 1) W_t + \varepsilon_t(X)
\]

- dependence on precipitation
- autoregressive / crosscorrelation term
- seasonal cycle
- seasonal mean minimum temp., error

\[
Y_t = \lambda_0 + \lambda_1 J_t + \lambda_2 Y_{t-1} + \lambda_3 X_t + \lambda_4 \cos t + \lambda_5 \sin t + \lambda_6 I_t S_t + \lambda_7 (I_t - 1) W_t + \varepsilon_t(Y)
\]

- dependence on precipitation
- autoregressive / crosscorrelation term
- seasonal cycle
- seasonal mean maximum temp., error

The normally distributed error terms \(\varepsilon_t(X)\) and \(\varepsilon_t(Y)\) are uncorrelated, the two models are fit separately.
GLM Stochastic Weather Generator

Overdispersion Phenomenon

boxplots of the inter-annual SDs for precipitation
(red lines: observed inter-annual SDs)
boxplots of the inter-annual SDs for minimum temperature
(red lines: observed inter-annual SDs)
boxplots of the inter-annual SDs for maximum temperature
(red lines: observed inter-annual SDs)
Applications

Downscaling Seasonal Forecasts

- Seasonal climate forecasts based on multiple global climate models (e.g., IRI: upto 6-9 months in 3-month moving windows).

- Historical years are classified into three categories (wet/normal/dry) based on the terciles of the smoothed historical seasonal precipitation.

- The years are resampled with replacement with the probabilistic forecast as the weight metric (e.g., 40(wet):35(normal):25(dry) forecast).

- The smoothed seasonal precipitation values of the resampled years are plugged in the GLM weather generator as covariates.
Applications

Pilar region based on IRI seasonal forecast 2003 (dry year)
Pilar region based on IRI seasonal forecast 2000 (wet year)
Applications

Downscaling Climate Change Scenarios

- Climate change projections for the 21st century are only reliably available at monthly time scale and for a spatial scale given by the model grid-size based on an ensemble of global climate change models (IPCC AR4).

- Our approach can also be used for downscaling short term (i.e., decadal) projections. To demonstrate this, we select an earlier dry epoch (1931-1955).

- The smoothed precipitation and temperature for each year of these epochs were used as covariates to the GLM weather generator to produce daily weather sequences consistent with the decadal variability of these epochs.
Simulated means and 95th projection band during earlier dry epoch (1931-1955) for Pergamino region
Pergamino region during earlier dry epoch (1931-1955)
Possible Extensions

- Multisite: consider a spatial structure in the GLM.

- Weather variability: variance and autocorrelation constrained to be constant. Could be addressed by introducing winter/summer differences.

- Extremes: high precipitation amounts are not sufficiently reproduced by the model. Apply extreme value technique using, for example, the stretched exponential distribution.

- Hidden Markov modeling approach: Consider a hidden regime for each GLM stochastic process.

- Uncertainty analysis: assess and report uncertainty of the generated weather.