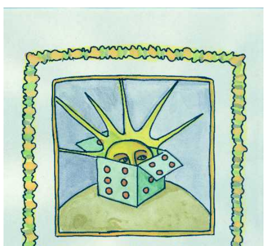
Weather generators for studying climate change

Douglas Nychka, Sarah Streett

Geophysical Statistics Project,
National Center for Atmospheric Research
`http://www.cgd.ucar.edu/stats/`

and Steve Sain
University of Colorado-Denver

- Assessing climate impacts
- Generating Weather (WGEN)
- Conditional models for precip
- Observation driven models for binary sequences



National Assessment

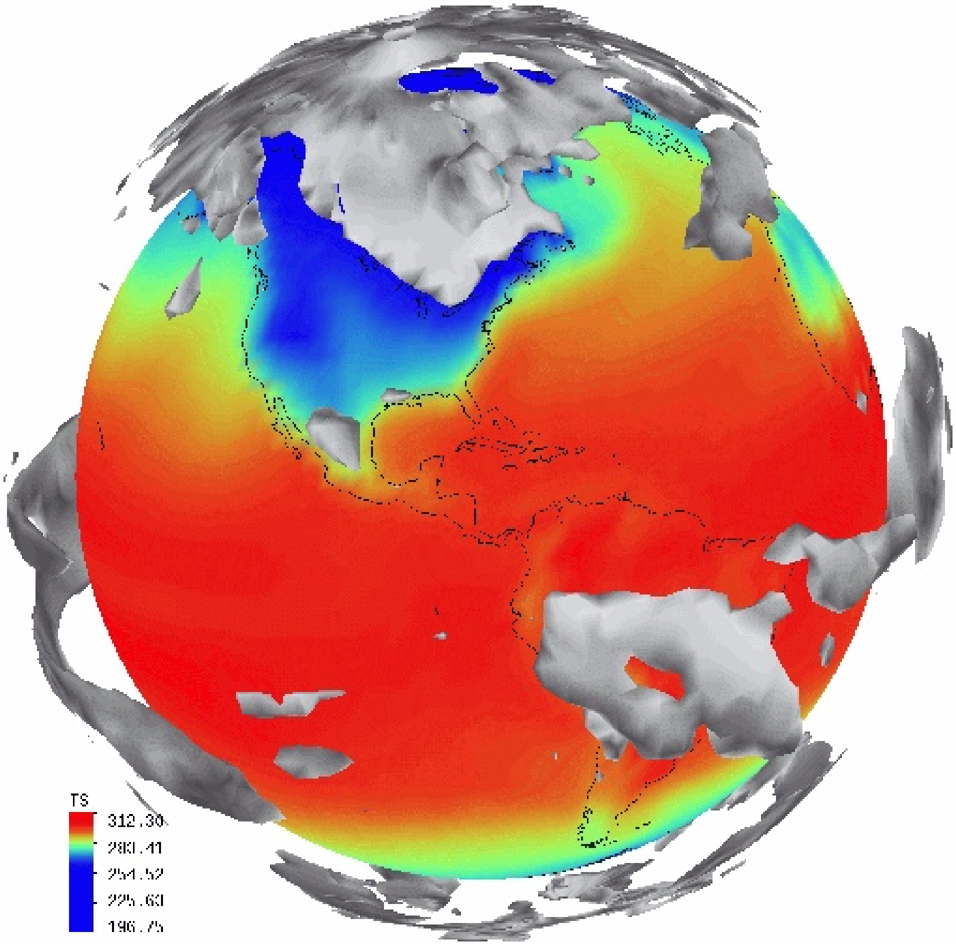
The Assessment was called for by a 1990 law.

Purpose:
“ to synthesize, evaluate, and report on what we presently know about the potential consequences of climate variability and change for the US in the 21^{st} century. ”

Report of the National Assessment Synthesis Team:
Climate Change Impacts on the United States (2001)

A formidable document, $>$ 500 pages

A snapshot of a climate model



Weather generators

Despite the complexity of current climate system simulations, the results are coarse in resolution and may not accurately reproduce short term weather. The strategy is to blend models for weather based on observed data with adjustments suggested by climate models.

WGEN Richardson (1981), Parlange and Katz (1999) stochastic simulation of meteorology at a point location.

WGEN is essentially a nonGaussian, multivariate time series model for

- Precipitation: occurrence and amount
- Solar Radiation
- Daily average temperature and range
- Humidity and Wind speed

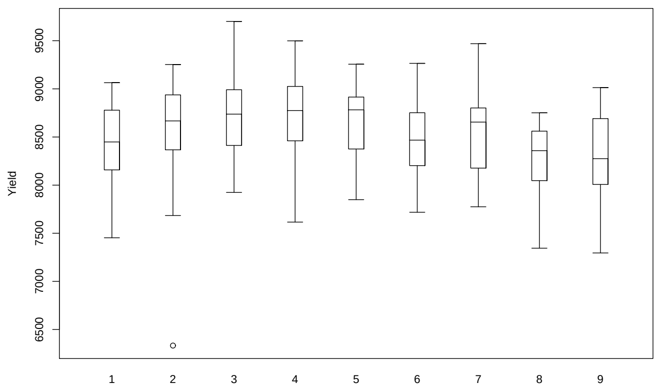
Goal is to model this process based on observational data.
A new area is to extend point WGEN models to a spatial domain.

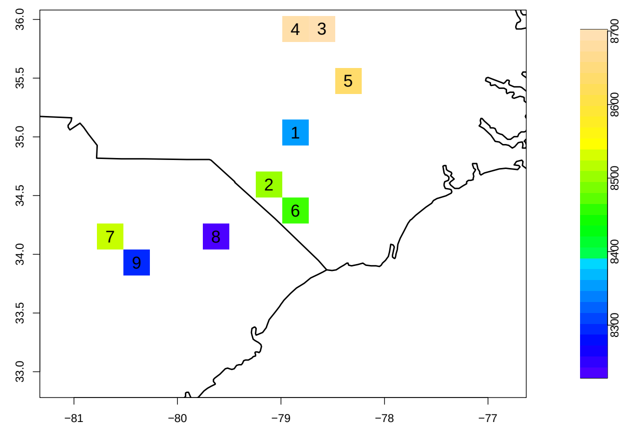
Projects using weather generators

Agricultural impacts: Given the (multivariate) distribution of weather at a location determine the distribution of the impact model outputs.

Build weather generators from observational data and *alter* them based on possible climate change.
Use the generated weather to force numerical, impact models, such as crop models to the effects of a changing climate on yields.

Average corn yield (Kg/Ha) using observed daily weather 1965-1984, CERES crop model.





Climate model resolution: The land component of a climate model responds in a nonlinear manner to precipitation. Thus the average response over a grid box is not simply a function of the spatially averaged precipitation.

How does a land model respond to different levels of resolution?

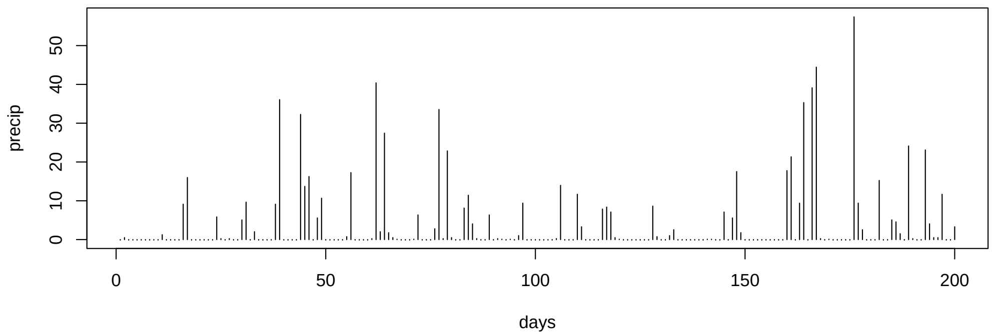
Use a spatial weather generator with high resolution to create a "true" field. Evaluate the land model on different levels of spatial aggregation and compare to the results using the "truth".

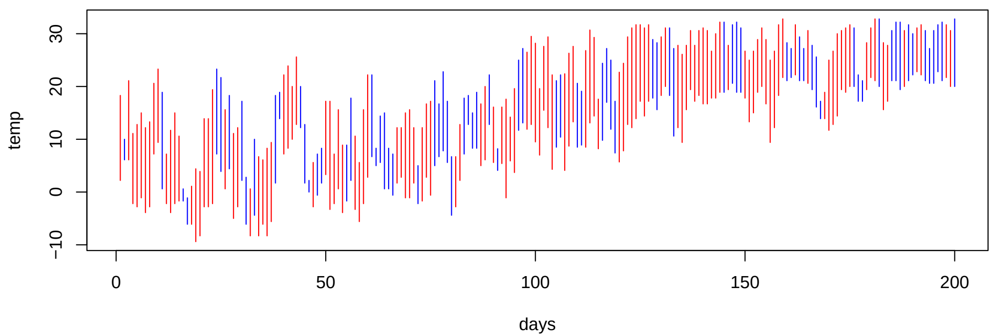
Main feature of model

Get the precipitation occurrence right!

The rest of the model is conditioned on this variable.

Weather for first 200 days for station 1 conditioned by occurrence





A temporal model for precipitation occurrence

Occurrence $Y_t =$ (0 or 1) follows an observation driven model:

$$P(Y_t = 1) = p_t$$

where p_t depends on past values of Y and seasonality.

Let U, be a uniform R.V. on $[0, 1]$:
if $U > p_t$ *no rain*, if $U \leq p_t$ *rain*

Modeling Hierarchy:

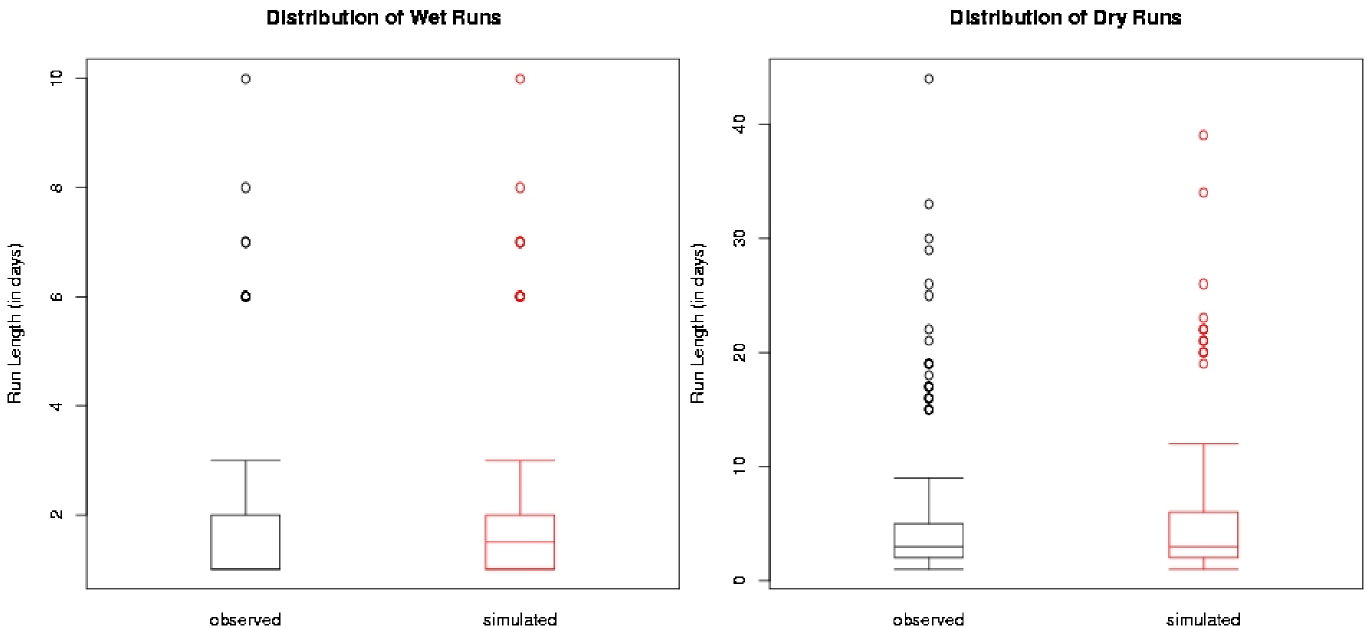
logit transformation $p_t = e^{\theta_t}/(1 + e^{\theta_t})$

seasonality and memory $\theta_t = \mathbf{x}_t\beta + \epsilon_t$

means depend on past $\epsilon_t = \alpha(Y_{t-1}, Y_{t-2}) + \delta V_{t-1}$

innovations depend on past $V_{t-1} = (Y_{t-1} - p_{t-1})/\sqrt{p_{t-1}(1 - p_{t-1})}$

Fit of model to run length distribution



Generating Precip Amount, Solar radiation, temperature, etc.

Given that it has rained, the rain amounts are assumed to follow a Gamma distribution where the gamma parameters vary over season.

Condition on occurrence, find (seasonal) transformations of the variables to standard normals. $\mathbf{u}_t = \Gamma_t(\mathbf{Z}_t)$.
Γ based on best fitting Gamma distribution followed by a (nonparametric) spline transformation.

$\mathbf{u}_t$ evolves according to a (seasonal) AR 1.

$$\mathbf{u}_t = A_t \mathbf{u}_{t-1} + \mathbf{e}_t$$

Spatial dependence

How does one add stochastic structure that is coherent over space?

Precipitation occurrence:

$$P(Y_t(\mathbf{x}) = 1) = P(U_t(\mathbf{x}) < p_t(\mathbf{x}))$$

with U_t a correlated spatial process with marginals that are uniform.

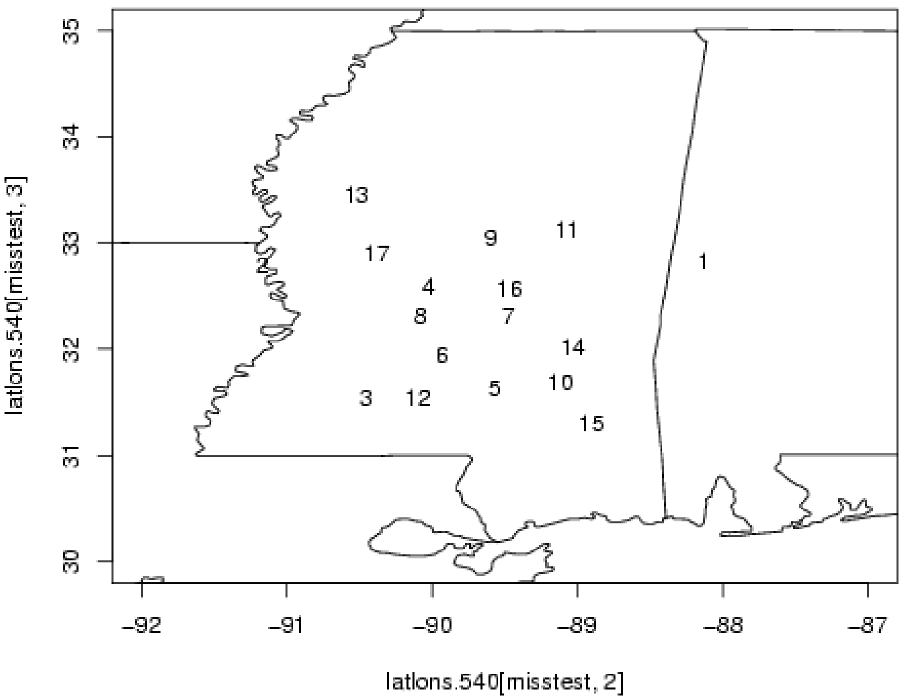
A Continuous latent process:
We assume

$$U_t(\mathbf{x}) = F(\Omega_t(\mathbf{x}))$$

$\Omega_t(\mathbf{x})$ a *Gaussian* spatial process with marginals $N(0,1)$ and F its CDF.

Note that this is not a simple threshold of a continuous spatial field because p_t depends on time and past values of precip.

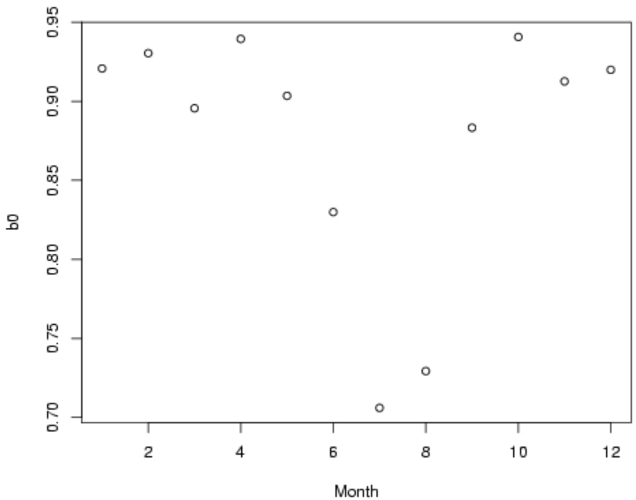
Correlations for Mid-Alabama by month

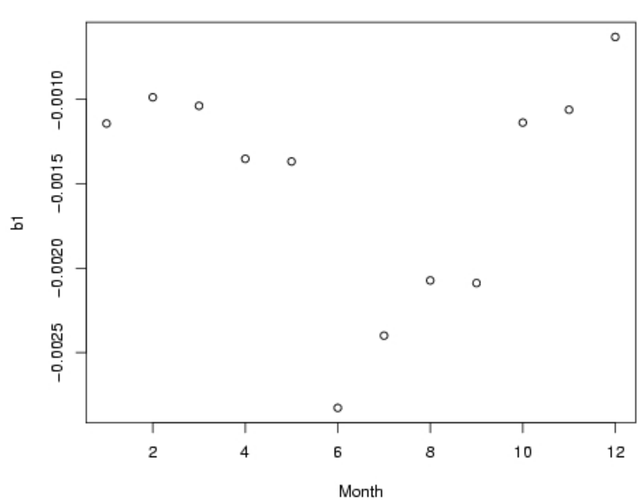


Dependence on month

Correlation model for latent Gaussian field:

$$COR(\mathbf{x}, \mathbf{x}') = b_0 + b_1 \|\mathbf{x} - \mathbf{x}'\|$$





Discussion

It is an open question how the observation driven temporal model will behave when it is coupled spatially.

How should more complex parts of the WGEN model e.g. transformations be extrapolated spatially.

A challenge is to estimate the covariance of the latent Gaussian process and test its validity in representing actual precipitation spatial patterns.

How should a WGEN model be modified by coarse scale climate model output.