Assessing the impact on Agriculture from Climate Change

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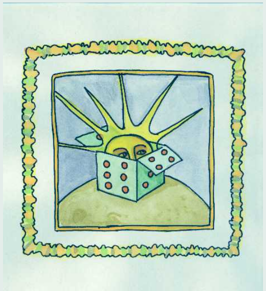
`http://www.cgd.ucar.edu/stats/`

- National Assessment
- Climate Models (PCM)
- Crop Models (CERES)
- Weather (WGEN)
- Yields for corn in NC/SC



National Center for Atmospheric Research

$\approx$ 1000 people total, several hundred PH D (physical) scientists,
half the budget ($\approx$ 60M) is a single grant from NSF-ATM

Research on nearly every aspect related to the atmosphere

Climate, Weather, the Sun, Ocean/atmosphere, Ecosystems, Economic impacts, Air quality, Instrumentation, Scientific computing and ...

Statistical methods for the geosciences

National Assessment

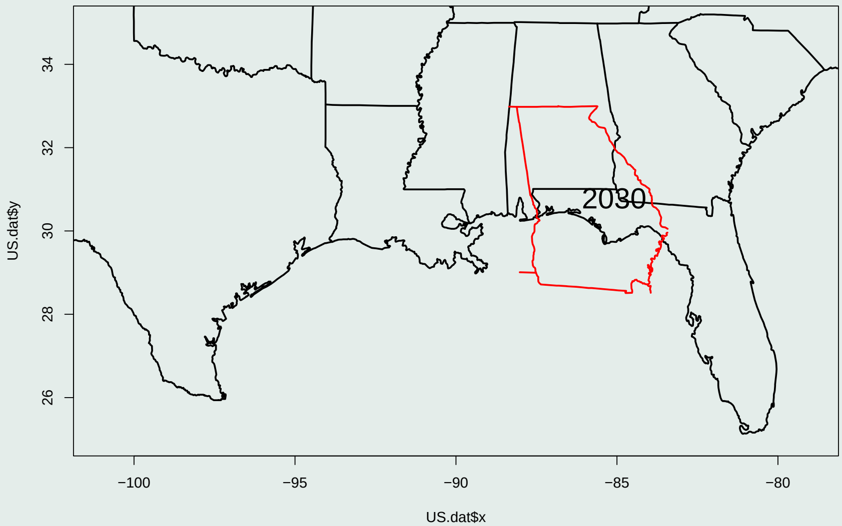
The Assessment was called for by a 1990 law.

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 formidible document, $>$ 500 pages

From one senario, the summer temperatures in Atlanta would be shifted to those more like the current Florida panhandle.



Hardly any estimates or discussion of uncertainty!

Why are we doing this?

Premise: Global warming is occurring ... and most scientists attribute some of the warming to increasing levels of greenhouse gases.

Problem: Translate geophysical predictions of climate change into terms of daily weather. How do (sometimes subtle) changes in weather effect society, the economy and the environment.

Climate are the averages of ”weather” over long time scales.

$$\text{Climate}(\mathbf{x}) = E[\text{weather}(\mathbf{x})]$$

A big change of variables problem:

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

Strategy: Build weather generators from observational data and climate change senarios. Feed generated weather to numerical, *impact* models to assess the effects of a changing climate.

e.g. To determine the impact on agricultural yields, create weather inputs and run a crop model. In this talk we present results for corn yields from the CERES model for North and South Carolina.

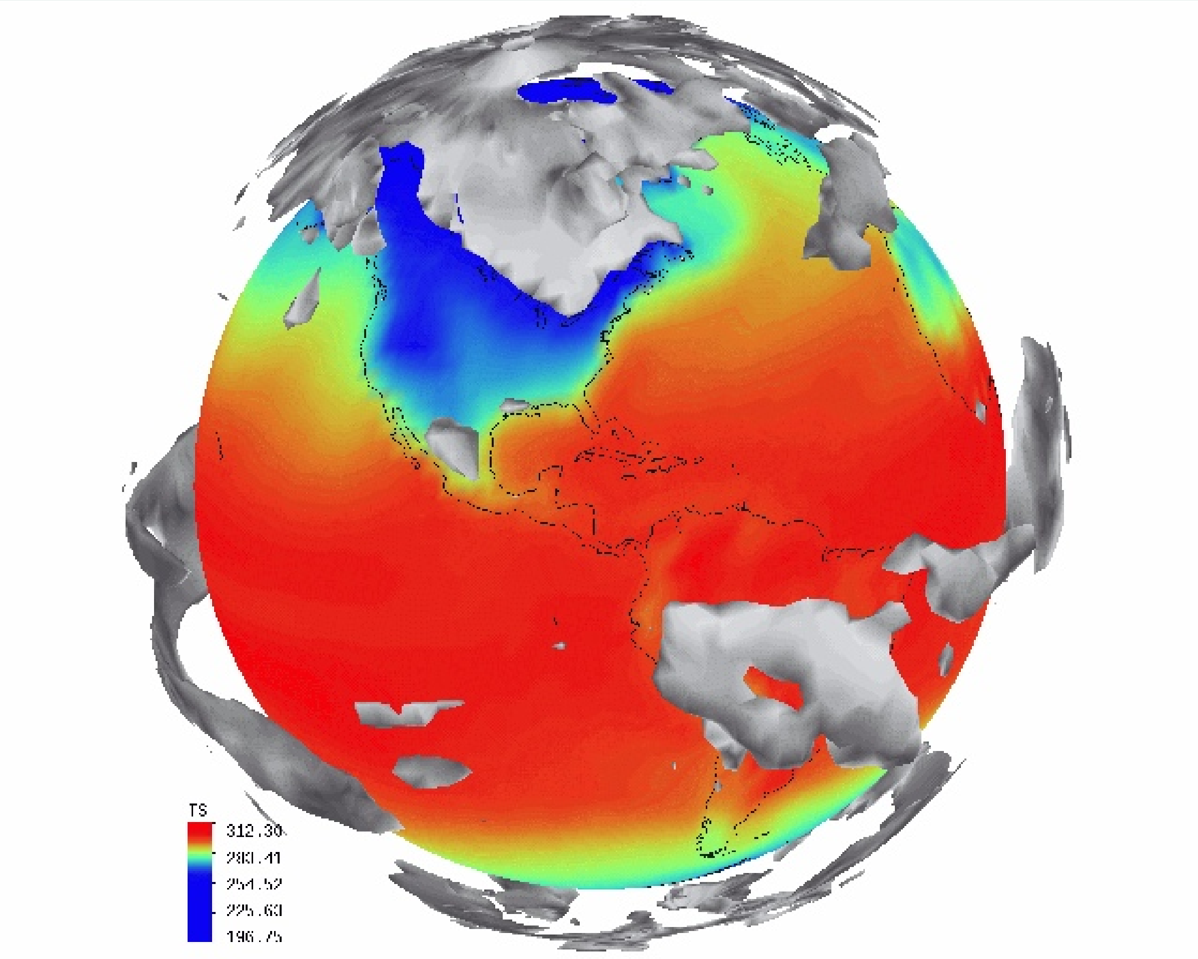
Where is the Statistics?

Statistics has a role to play in:

- Building suitable weather generators.
  Multivariate time series with (0,1) components, Spatial models for non-Gaussian fields.

- Propagating uncertainties in the models to uncertainty in the final result.
  Experimental design, Bootstrapping.

A snapshot of a climate model



How do they do it?

Modeling the atmosphere

The physical equations to describe atmospheric motion are derived from fluid mechanics and thermodynamics.
The complete state depends on:

- 3-d wind field, $\mathbf{v}$
- pressure p
- temperature T
- heating by radiation $Q_{\mathrm{r}ad}$, condensation $Q_{\mathrm{c}on}$
- evaporation E and condensation C from clouds
- D_H D_M and D_q are diffusion terms.

Primitive Equations

$$
\begin{aligned}
\frac{\partial \mathbf{v}}{\partial t} &= -\mathbf{v} \, . \, \nabla \mathbf{v} - \omega \frac{\partial \mathbf{v}}{\partial p} + f \mathbf{k} \times \mathbf{v} - \nabla \Phi + \mathbf{D}_M \\
\frac{\partial T}{\partial t} &= -\mathbf{v} \, . \, \nabla T + \omega \left(\frac{\kappa T}{p} - \frac{\partial T}{\partial p} \right) + \frac{Q_{\mathrm{r}ad}}{c_p} + \frac{Q_{\mathrm{c}on}}{c_p} + D_H \\
\frac{\partial q}{\partial t} &= -\mathbf{v} \, . \, \nabla q - \omega \frac{\partial q}{\partial p} + E - C + D_q \\
\frac{\partial \omega}{\partial p} &= -\nabla \, . \, \mathbf{v} \\
\frac{\partial \Phi}{\partial p} &= -\frac{RT}{p}
\end{aligned}
$$

where Φ geopotential (height) and $\omega = \frac{dp}{dt}$.
Despite the precision of this physical description, the radiative and cloud terms involve complicated additional physics.
see Berliner (2001)

Climate System Model (CSM)

General Circulation Model (GCM): A deterministic numerical model that describes the circulation of the atmosphere by solving the primitive equations in a discretized form.

- Conceptually based on grid boxes (for the NCAR climate system model: there are $128 \times 64 \times 17 \approx 141K$) and the state of the atmosphere is the average quantities for each box ($\approx 1M$ real numbers).
- Each grid cell is large (for NCAR CSM/PCM $\approx$ 300km $\times$ 300km) in area and so important processes that affect large scale flow are not resolved by the grid.
- GCM must be stepped on the order of minutes, even for a 200+ year numerical experiment!

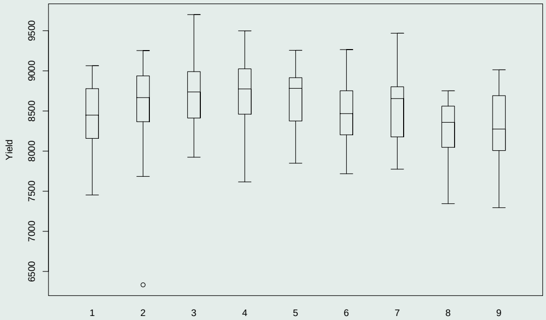
Climate System A GCM coupled to models for the ocean, ice , land, chemistry, etc. to model the entire climate system. Coupling these components without overt flux adjustments is a recent achievement of the modeling commmunity.

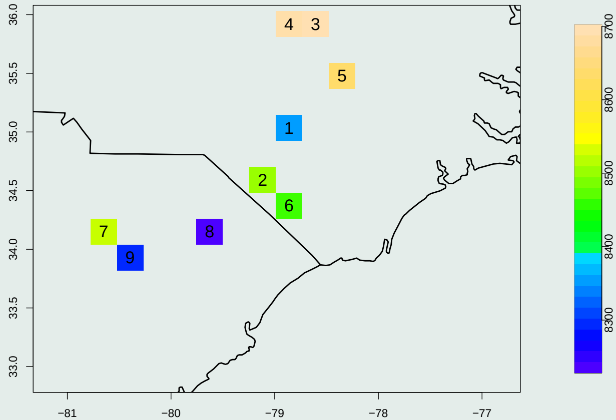
Crop models

CERES corn model: A numerical model that simluates the daily growth of a corn crop based on

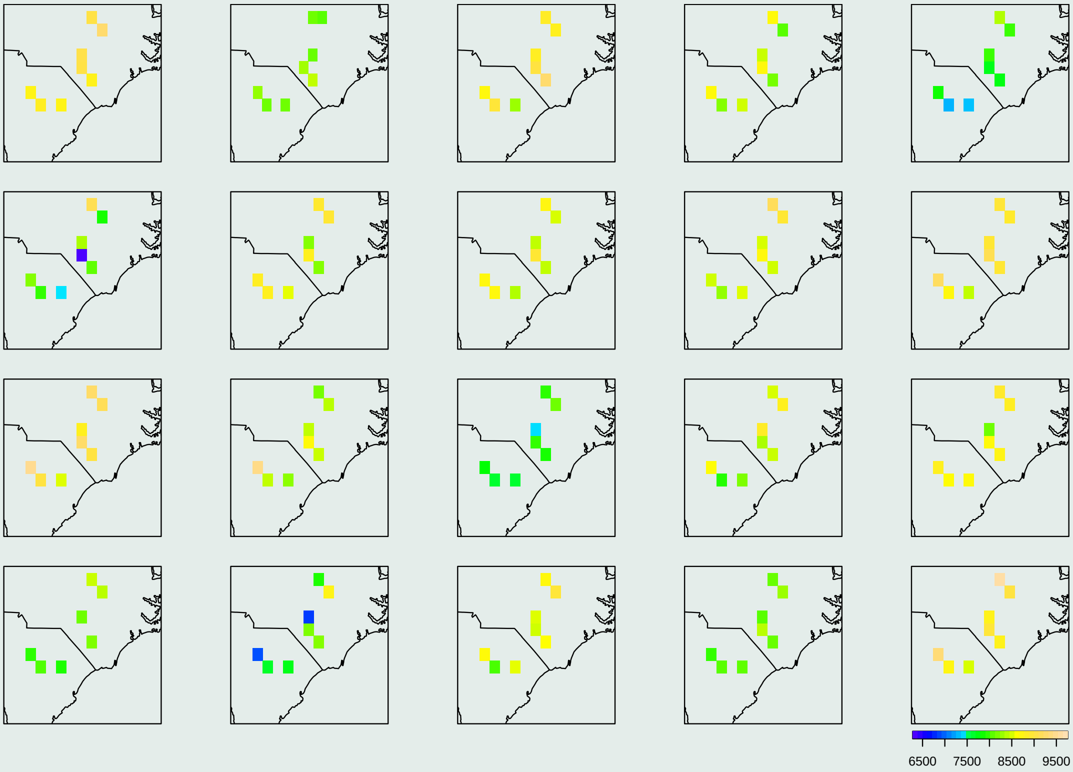
- Soil type/layers, Latitude
- Cultivar
- Farming practice
- Daily weather: max/min temperature, solar radiation,
- Initial conditions precipitation

Average corn yield (Kg/Ha) using observed daily weather 1965-1984





Spatial sequence of yields



Statistical problem (again)

How can we simulate spatial and temporal patterns of yeilds under a senario of climate change? How can we simluate yields for locations where observational data is not available?.

Weather

A climate model has limited spatial resolution and possible biases. The goal is to simulate daily weather consistent for a particular location but use the climate model to inform these simulated values.

Some approaches:

- Feed GCM results into a finer resolution regional model that uses the GCM values as boundary conditions. (e.g. RegCSM from MM4).
- Build a weather generator, a multivariate timeseries model based on observational data but modified by statistics from the GCM results.

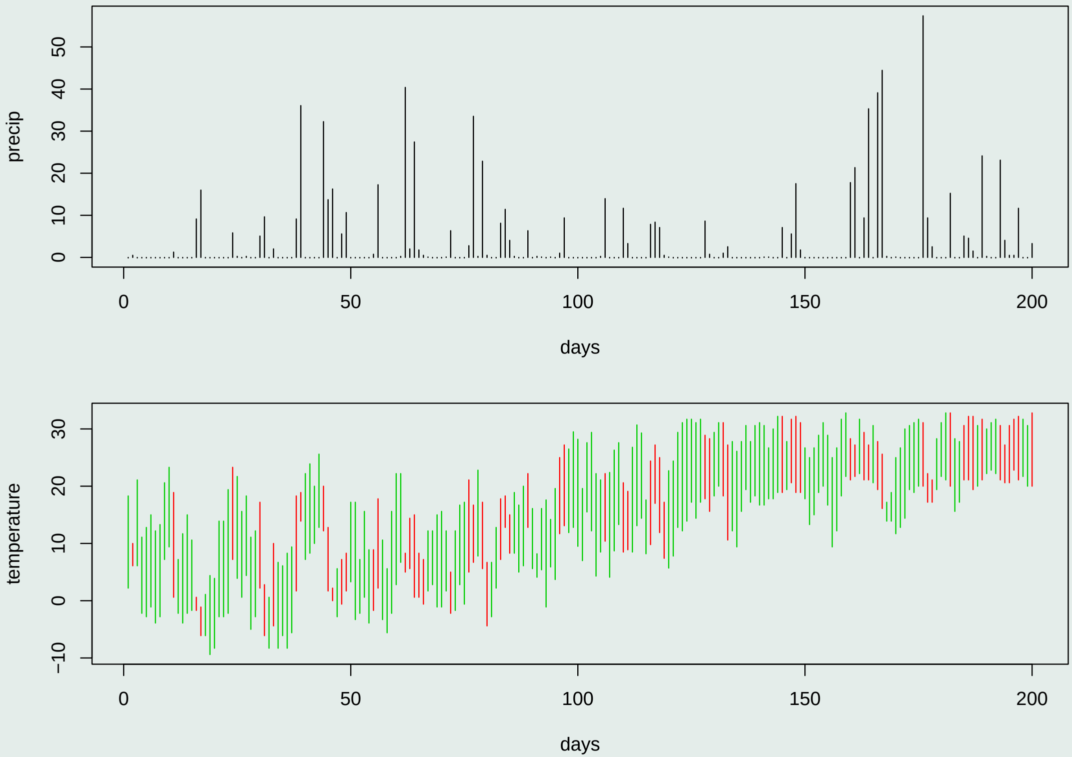
Weather generators

WGEN Richardson (1981), Parlange and Katz (1999)
Set $\mathbf{Z}_t$ to be the daily weather variables. Essentially a multivariate time series model for

- Precipitation: occurrence, amount
  This talk will concentrate on occurrence.
- Solar Radiation
- Daily average temperature and range
- Humidity and Wind speed

The key is to *separate the model into dry and wet days*.

Weather for first 200 days for station 1 conditioned by occurrence



A model for precipitation occurence

Occurence $Y_t =$ (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:

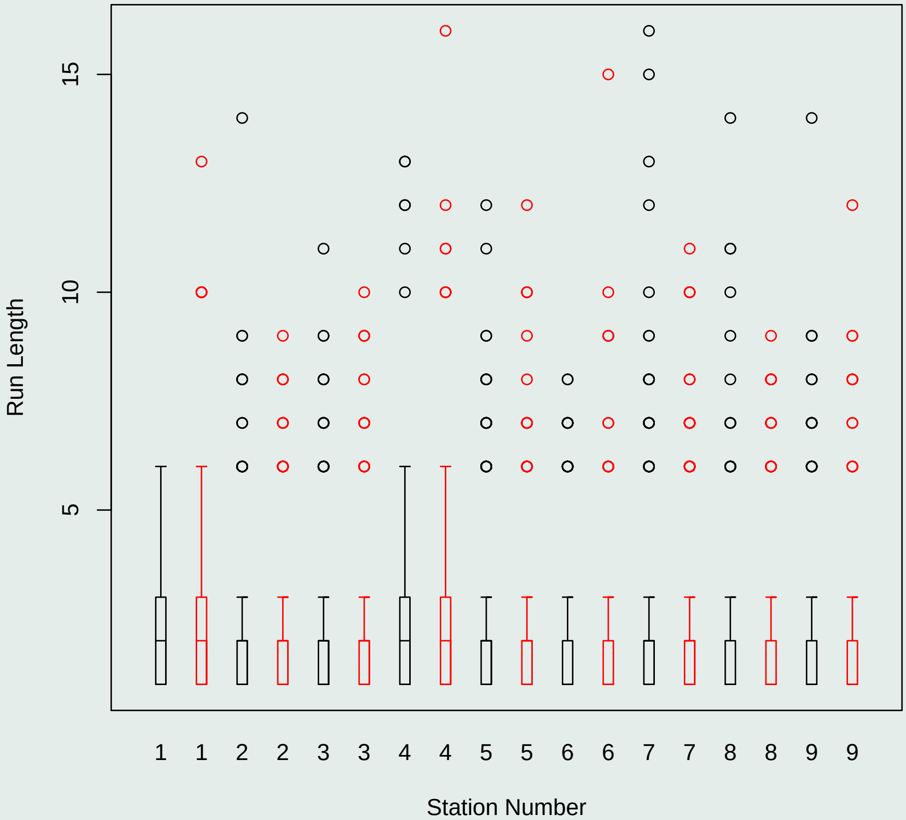
logit transformation $p_t = e^{\theta_t}/(1 + e^{\theta_t})$

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

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

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

Evaluate the occurence model by checking the distribution of “wet spells” against the observed station data. (black= model red= data)



Generating Precip Amount, Solar radiation, temperature, etc.

Given that it has rained, the rainamounts 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.

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

Adding spatial structure

Spatial dependence

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

Precipitation occurrence:

$$P(Y_t(\mathbf{x}) = 1) = P(U_t(\mathbf{x}) > p_t) = P(\Omega_t(\mathbf{x}) > F^{-1}(p_t))$$

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

We assume that $\Omega_t(\mathbf{x}) = F^{-1}(U_t(\mathbf{x}))$ a Gaussian spatial process $F \sim \mathrm{N}(0, 1)$.

AR 1 innovations:
Assume that $\mathbf{e}_t(\mathbf{x})$ is a multivariate Gaussian spatial process.

Extrapolating parameters

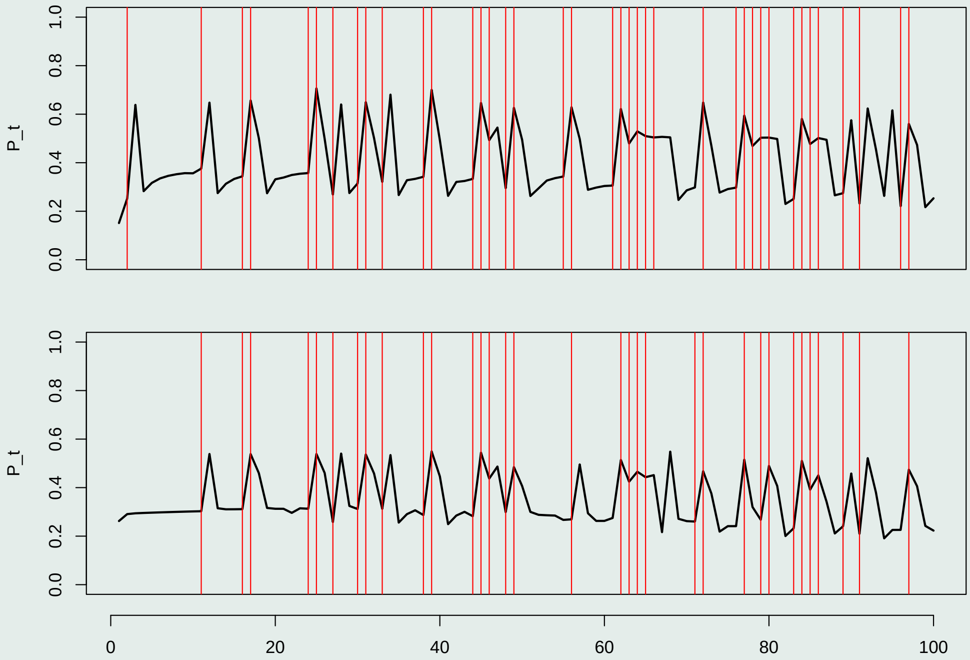
Smooth or interpolate weather generator parameters over space, using functional data methods for the transformations.

A digression: Details for spatial precipitation occurrence

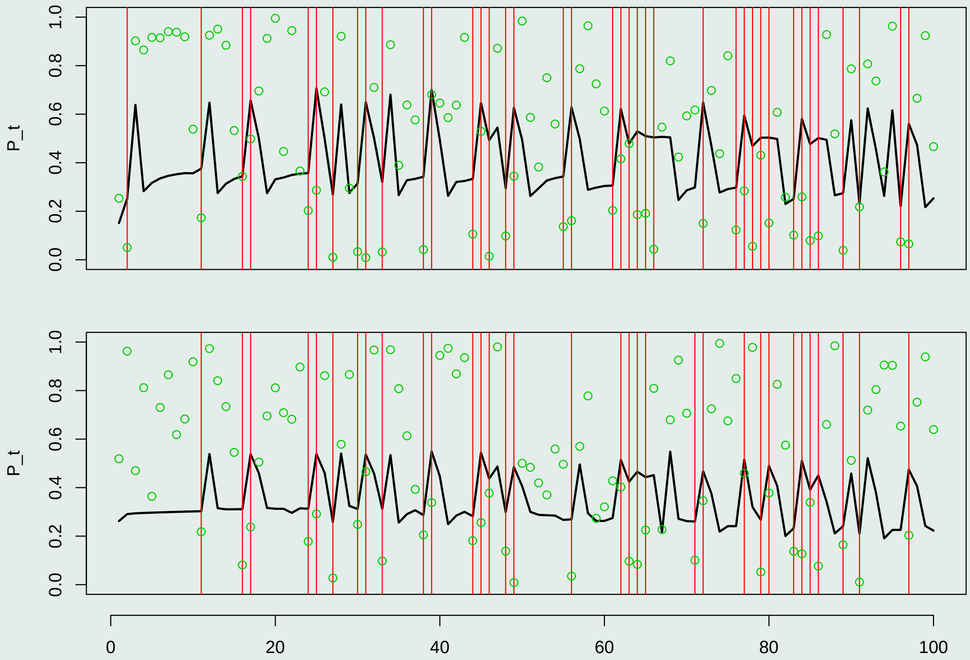
Recall that given a p_t we would generate precip according to whether a uniform R.V. is less than p_t. We want to look at the dependence among these (latent) uniforms for the different stations.

The useful idea is to simulate uniforms for each day and station consistent with the estimated probablity and also the actual data.

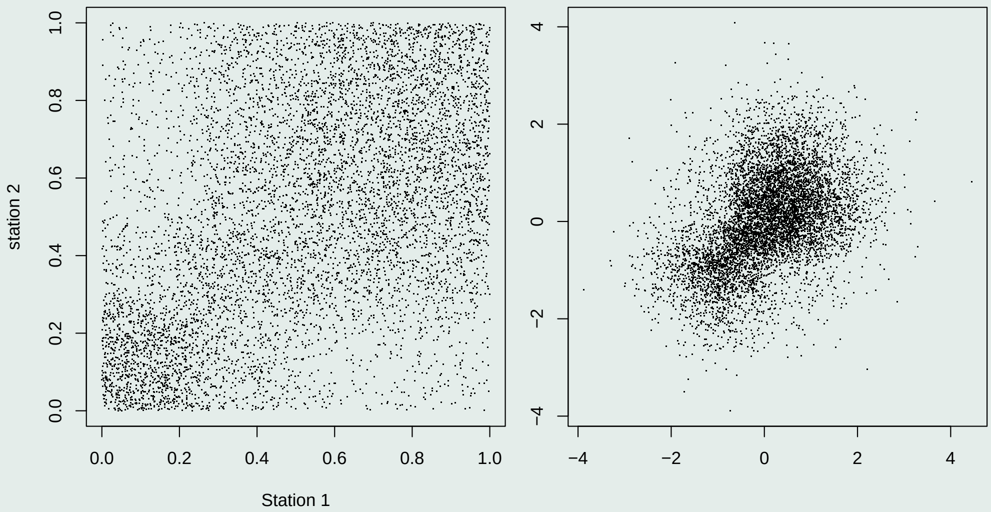
Observed occurences and p_t for stations 1 and 2



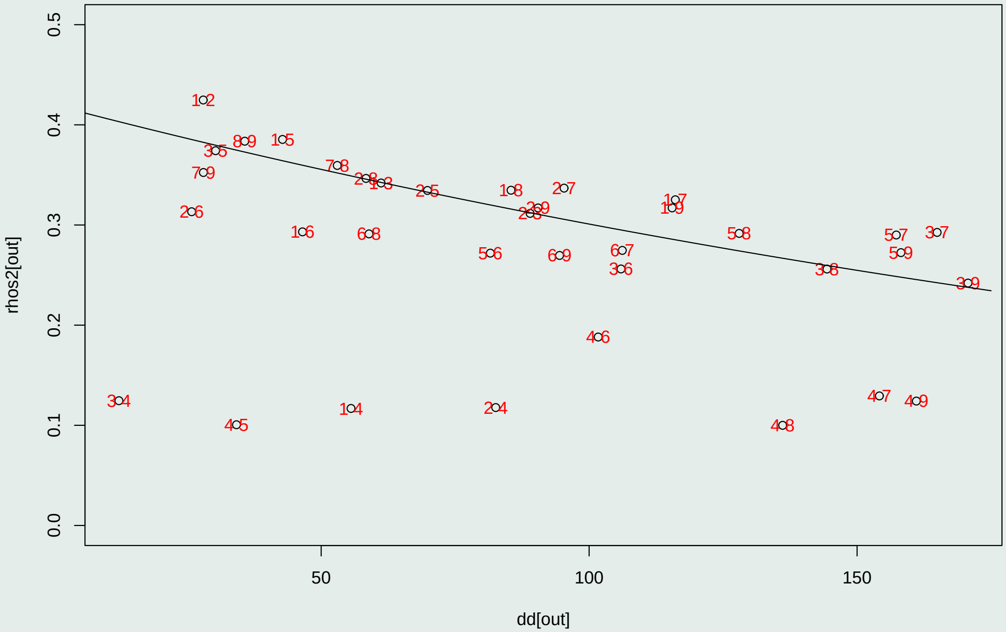
Observed occurences and p_t for stations 1 and 2



Bivarate relationship between latent variables

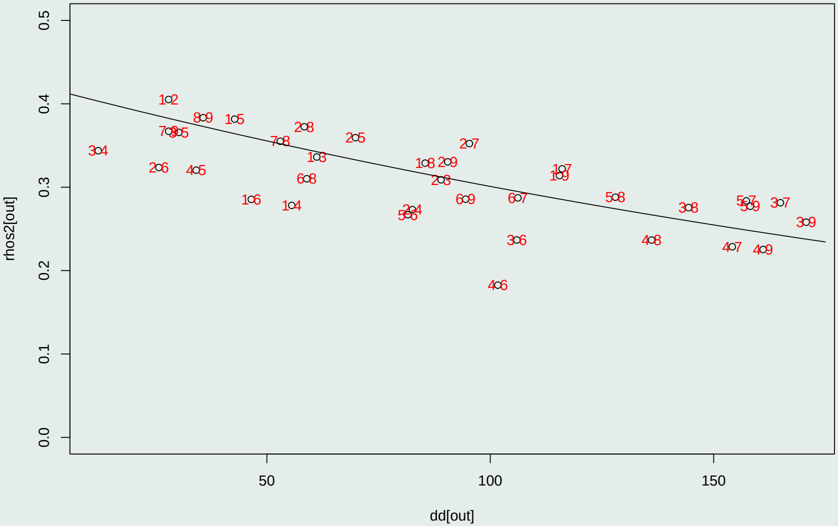


Correlations among all stations against distance



You can see a lot just by looking ...

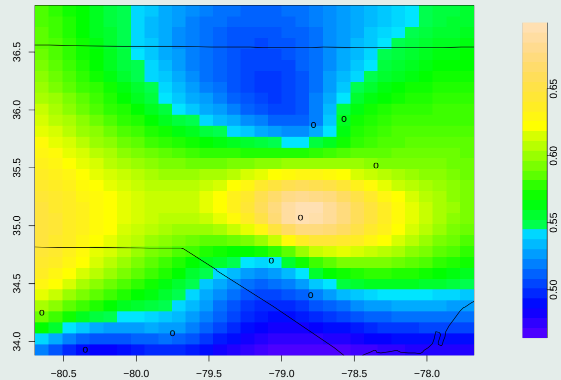
Shifting station 4 record by one day.

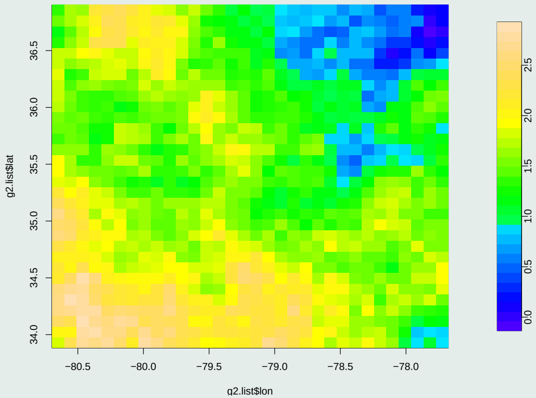


Correlation model: $COR(\mathbf{x}, \mathbf{x}') = .42e^{-(\|\mathbf{x}-\mathbf{x}'\|/300)}$

What does this process look like?

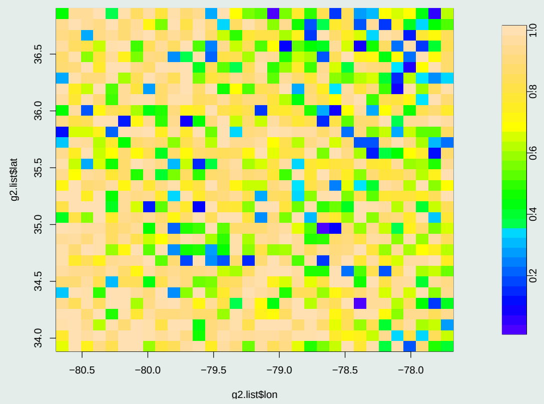
A simulated example, p_t surface (25-jan-1961) and the random surface

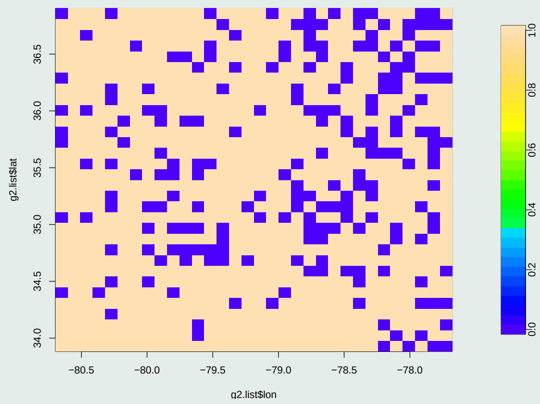




Implied occurrence field

With nugget and transformed to Uniform, the occurrence surface

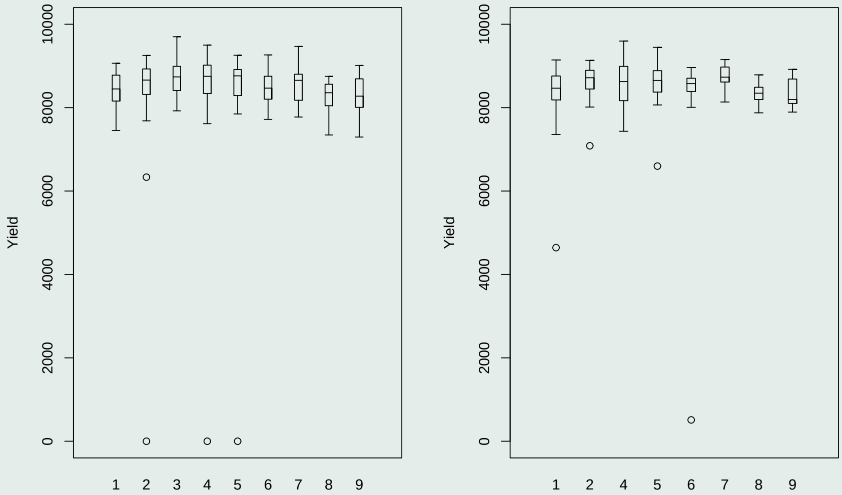




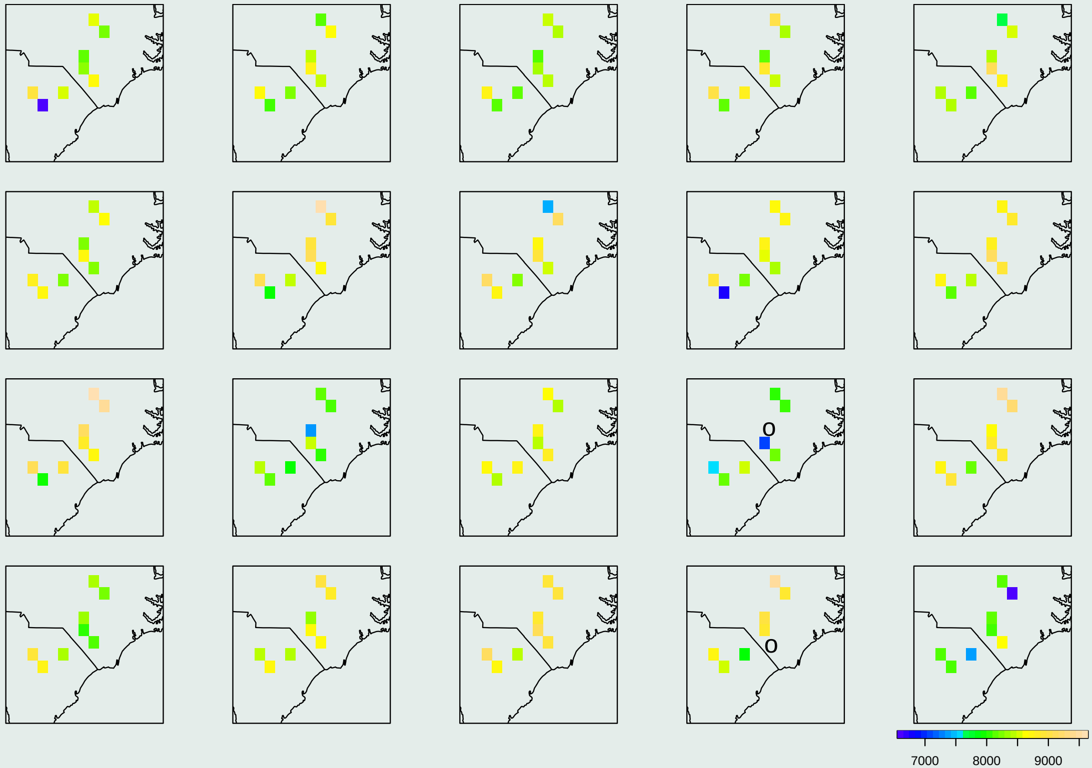
Results from forcing corn models

Distribution of yields (1965-1984): True, simulated

Using the weather generator fit to the observed data, a realization of crop yeilds over time and space. (These are preliminary!)



Spatial distribution from simulated weather



Discussion

- The seemly straightforward exercise of building a weather generator poses new statistical models.
  e.g. *functional data*, *NonGaussian*, *Space-time Processes*
- Useful to find statistical properties of yields and agregated over counties.
- Incorporate hidden Markov models for large scale structure in precip. (Bellone, Guttorp, Hughes)
- Important to extend analysis to (crop) model uncertainty and uncertainty in the soils.
- Developing and posting WGEN in *R* or *S* will make it more accessible.
- This is really fun!