# Linking Climate Prediction to Agricultural Models

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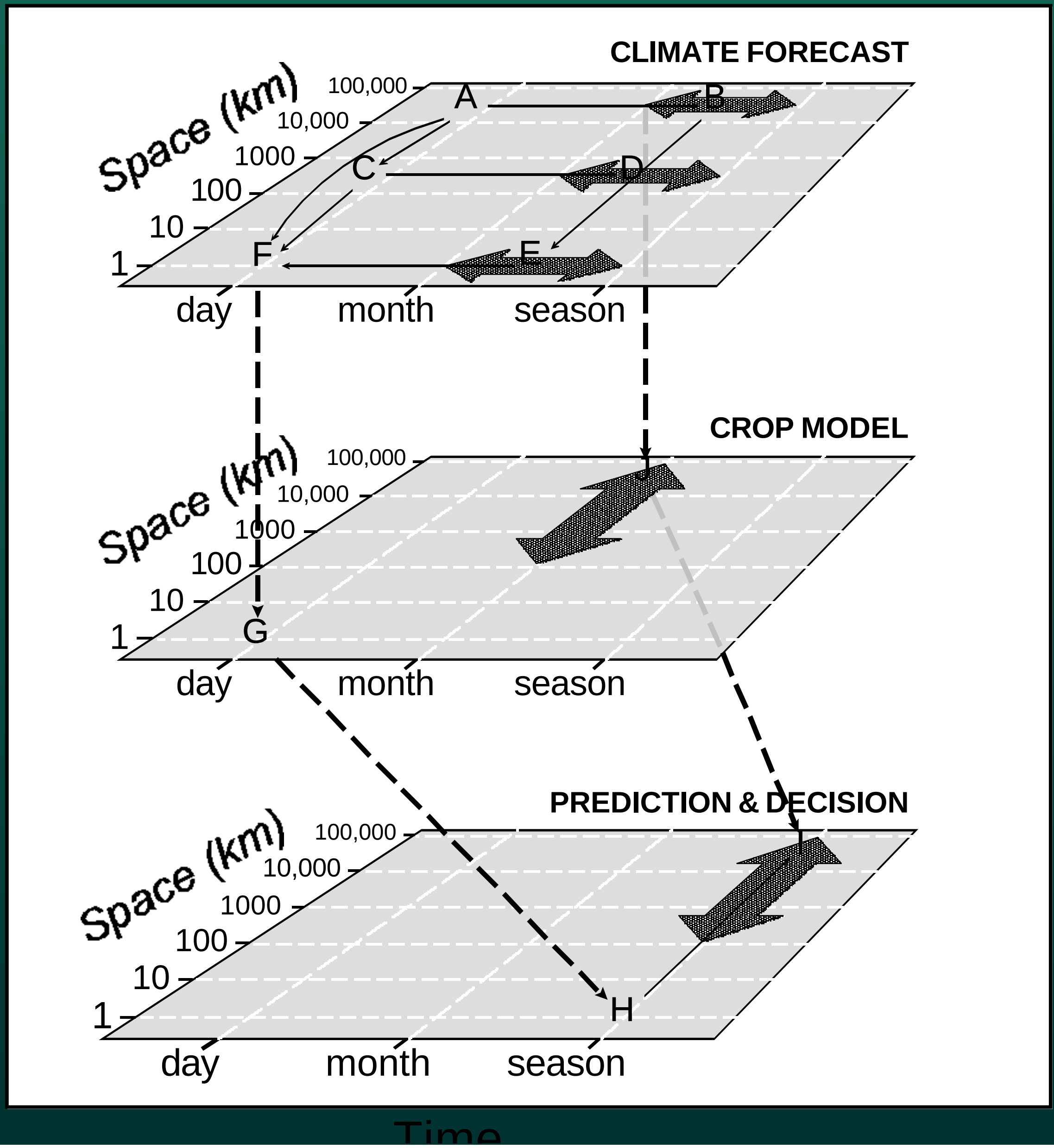
This is a crucial current research question. Intuition suggests several options. We simply have not yet evaluated what works and what doesn't.

# The Scale Mismatch Problem

- Crop simulation models operate:
  - On spatial scale of a homogeneous plot
  - On a daily time step (w.r.t. weather)
- Global climate models operate:
  - At a spatial scale of ~10,000 - 100,000 $km^2$
  - On a sub-daily time step, BUT...
    Output meaningful only at monthly to seasonal time scale
- The spatial scale problem is easier to correct than the temporal scale problem

# The Scale Mismatch Problem



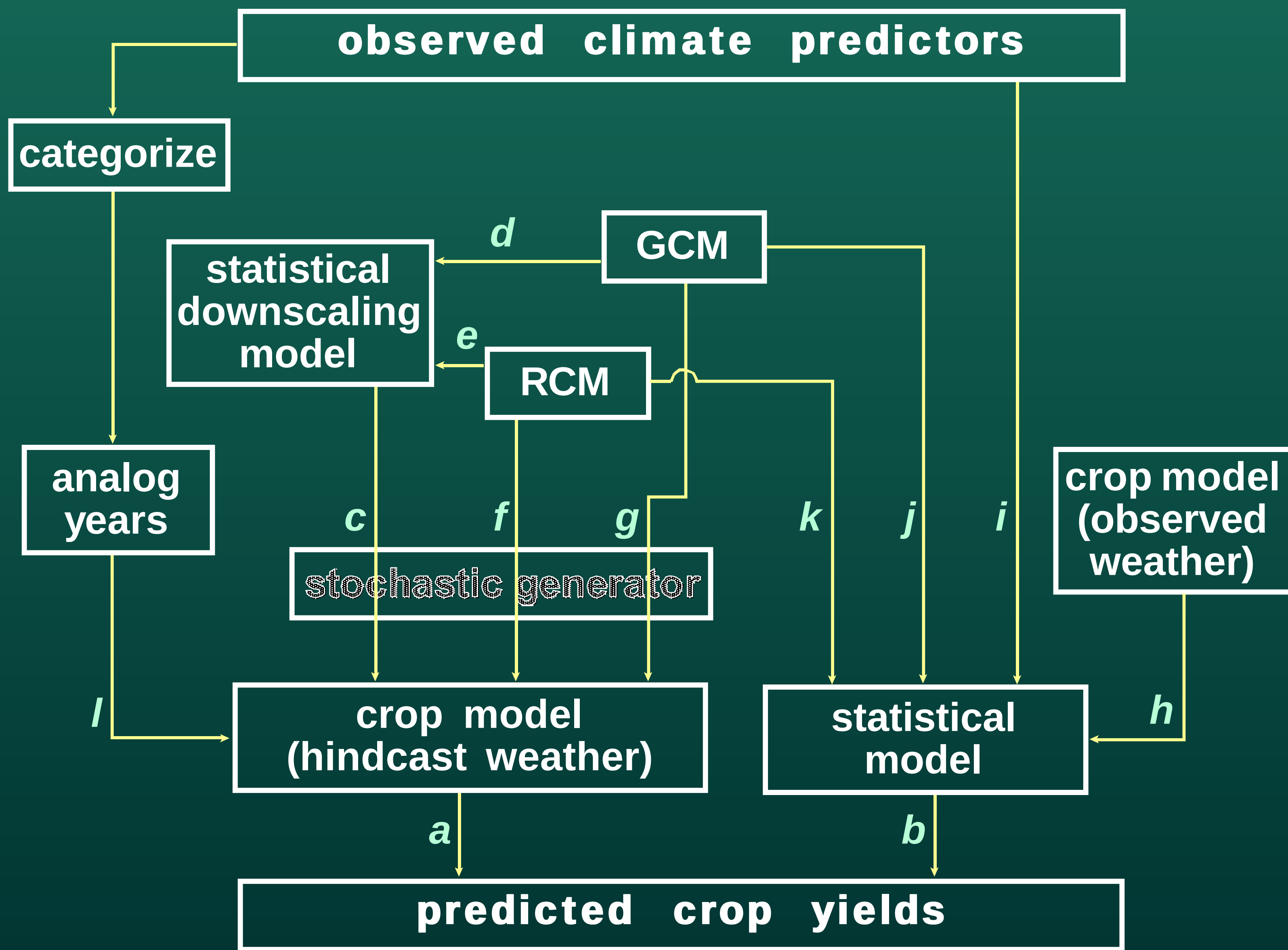
# Information Pathways

observed climate predictors

?

predicted crop yields

# Information Pathways



# Options

- Classification and selection of historic analogs
- Direct use of daily dynamic climate model output
- Stochastic temporal disaggregation of (sub-)seasonal forecasts
- Direct statistical prediction
- Weighted historic analogs

# Classification & Historic Analogs

- Divide predictor state space into categories (“phases,” “composites”)
- Treat all years within category as equally-weighted analogs
- Many agricultural application efforts use either “ENSO phases” (3) or “SOI phases” (5).
- Most quantitative studies of seasonal forecast value for agricultural decisions have used this approach. Most have ignored cross-validation.

# Classification & Historic Analogs

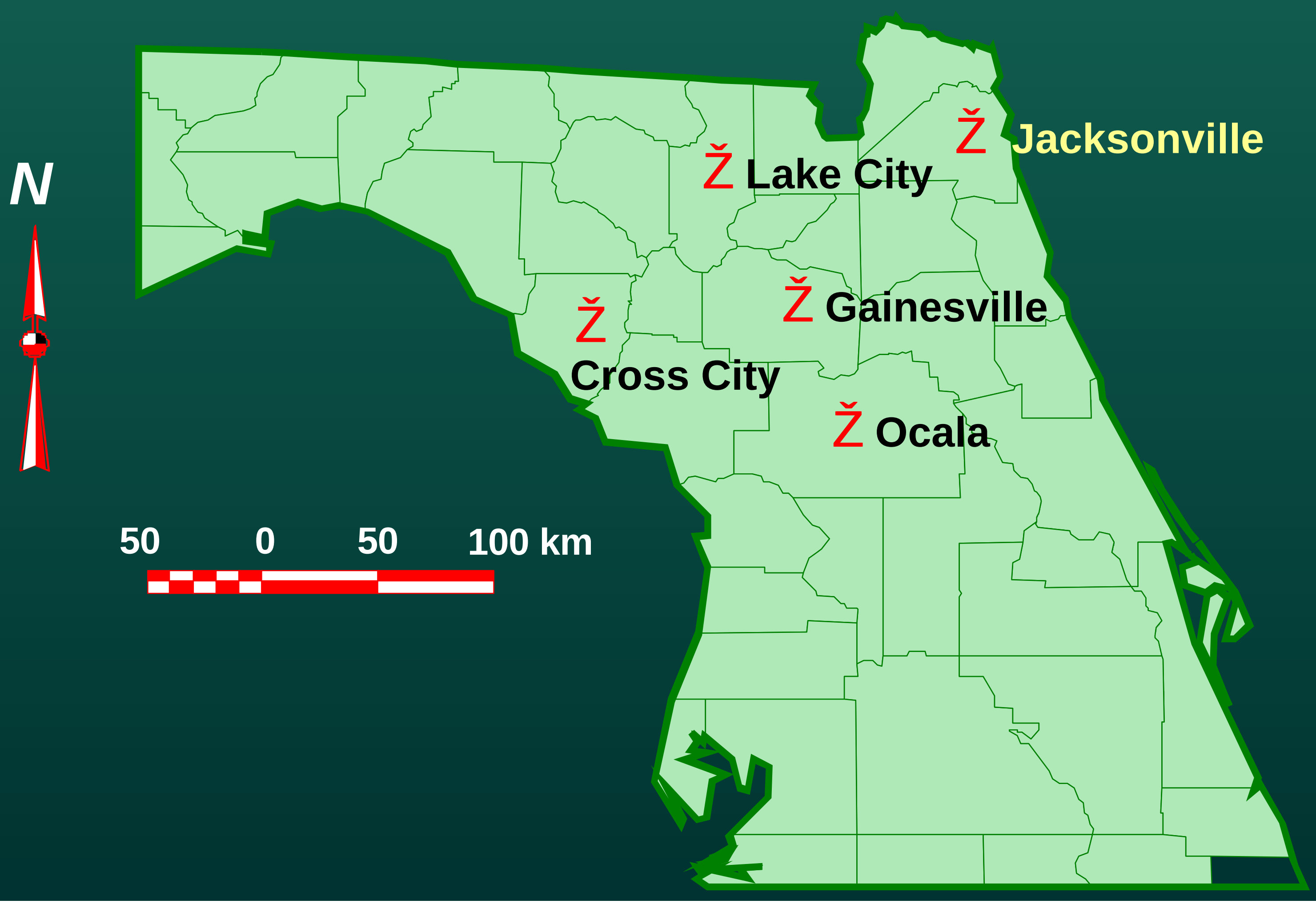
- Strengths:
  - Spatial and temporal scale constrained only by data availability
  - Retains any information about within-season variability
  - Intuitive probabilistic interpretation
- Weaknesses:
  - Sample size within categories
  - Neglecting cross-validation inflates skill and value
  - Extension to multivariate or dynamic prediction not straightforward

# Daily Climate Model Output

- Dynamic climate models operate on a sub-daily time step
- They tend to:
  - distort daily variability
  - generate too many rainy days
  - generate too little rain on rainy days
- High-resolution regional models might help, but do not eliminate the problem

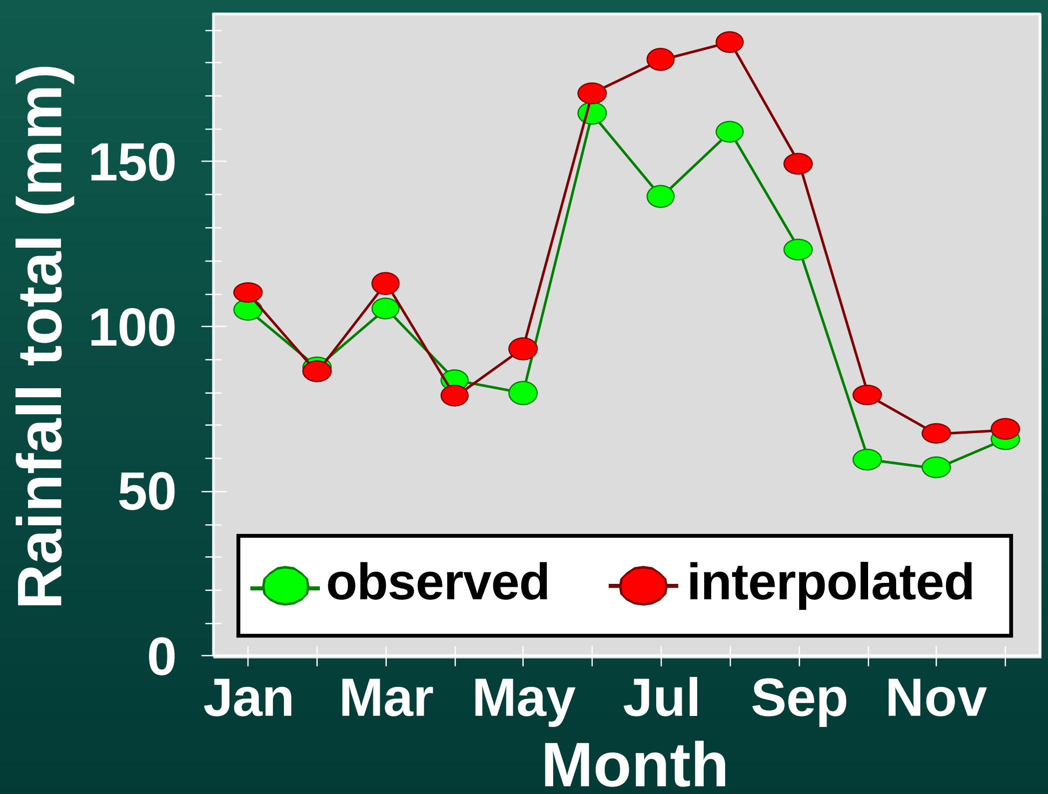
# Daily Climate Model Output

## Illustration: Spatial Weather Averaging



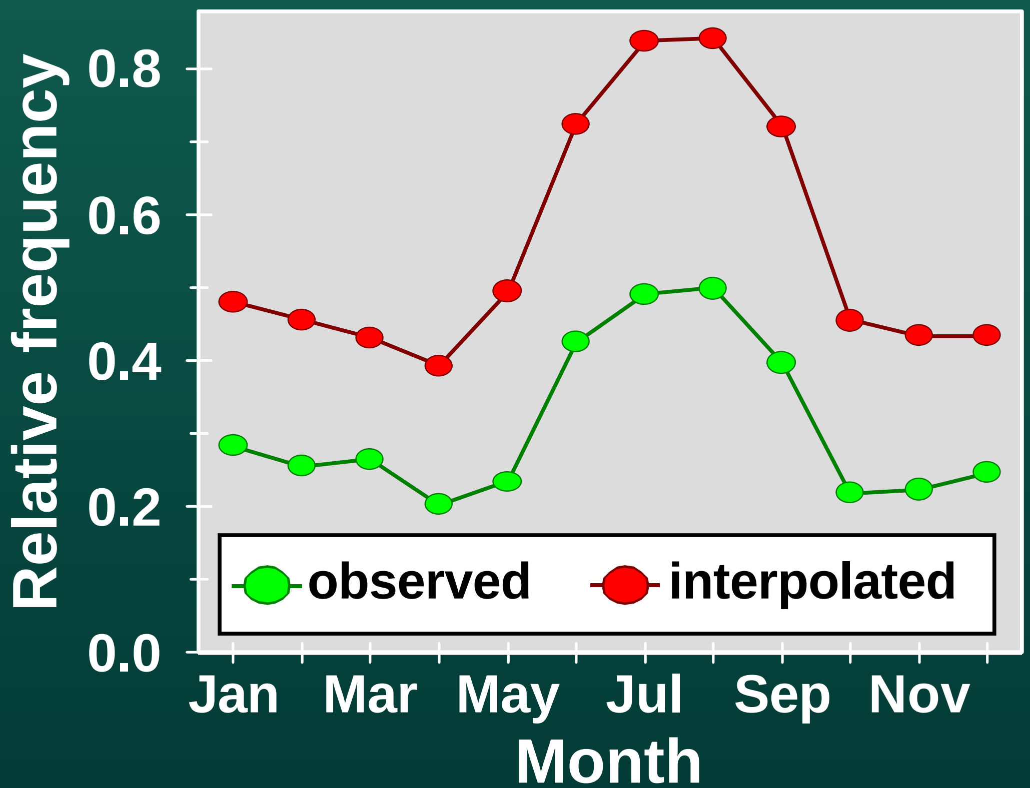
# Daily Climate Model Output

## Rainfall Total



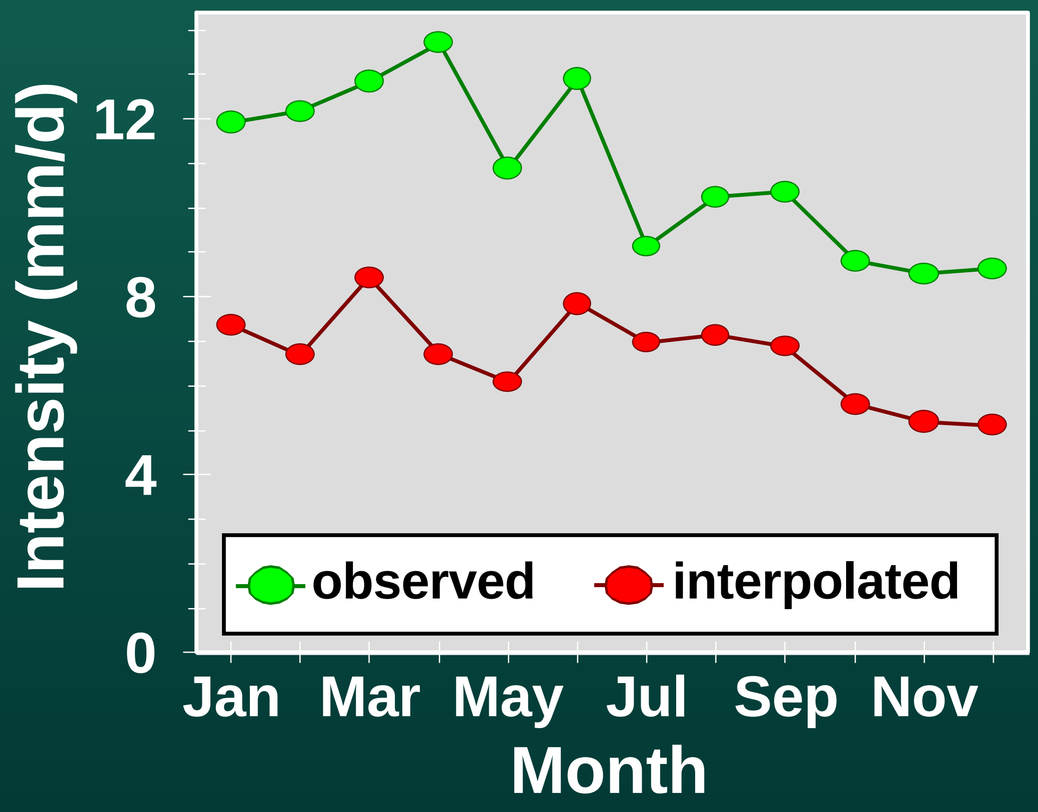
# Daily Climate Model Output

## Wet-day Frequency



# Daily Climate Model Output

## Wet-day Intensity



# Daily Climate Model Output

## Simulated Yields

| Source | $\bar{Y}$ | $s$ | $CV$ |
|---|---|---|---|
| | (- $Mg\ ha^{-1}$ -) | | |
| Ocala (OC) | 7.49 | 1.81 | 24.2% |
| Lake City (LC) | 7.61 | 1.35 | 17.7% |
| Cross City (CC) | 7.38 | 1.90 | 25.8% |
| Jacksonville (JA) | 5.76 | 2.10 | 36.4% |
| Gainesville (GA) | 6.71 | 1.89 | 28.2% |
| Interpolated weather | 8.19 | 0.95 | 11.6% |

# Daily Climate Model Output

## Enhancements

- SDSM (Wilby et al., 2002)
  - Statistical downscaling of daily climate model output (perfect prognosis)
  - Separate statistical estimation of precipitation ocurrence and intensity to preserve mean wet-day frequency
  - “Variance inflation” – adds a stochastic process to correct underprediction of daily-to-day variability.
    - a “hybrid” method

# Stochastic Disaggregation

P Disaggregate seasonal or monthly mean forecasts to obtain daily sequences:

< High-frequency (i.e., day-to-day) variability matches the historic daily record

< Low-frequency variations match forecast variations

P Use a stochastic weather generator

P Two approaches:

< Condition parameters on the forecasts

< Condition the output on the forecasts

# Stochastic Disaggregation

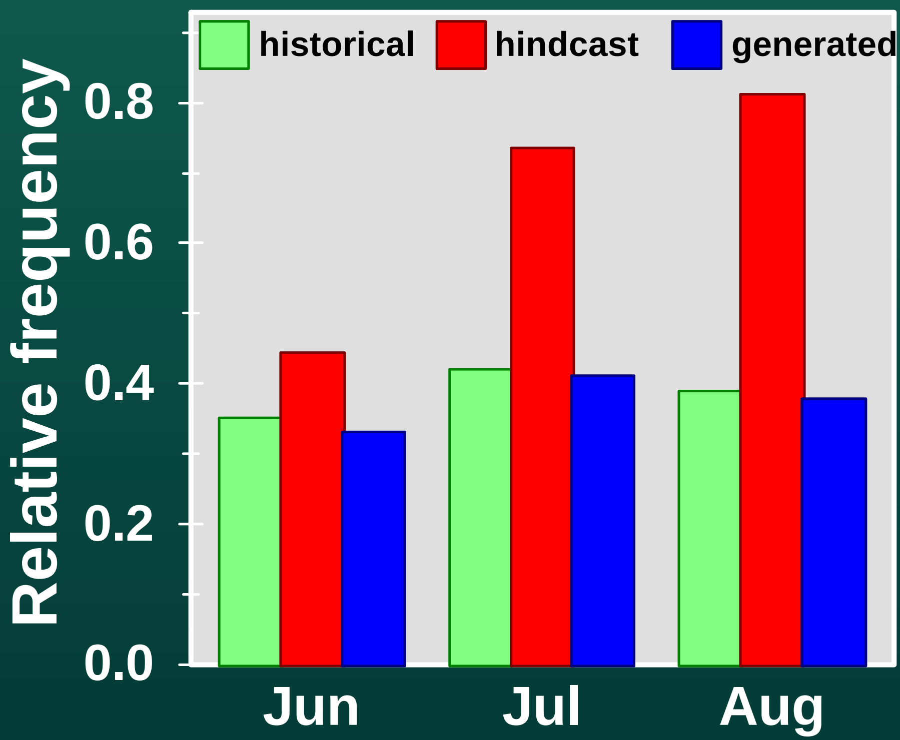
- A series (e.g., month) of *n* generated daily values **y** with mean *Y* can be rescaled to match target mean $Y_T$ by adding series $\Delta y(t)$ such that

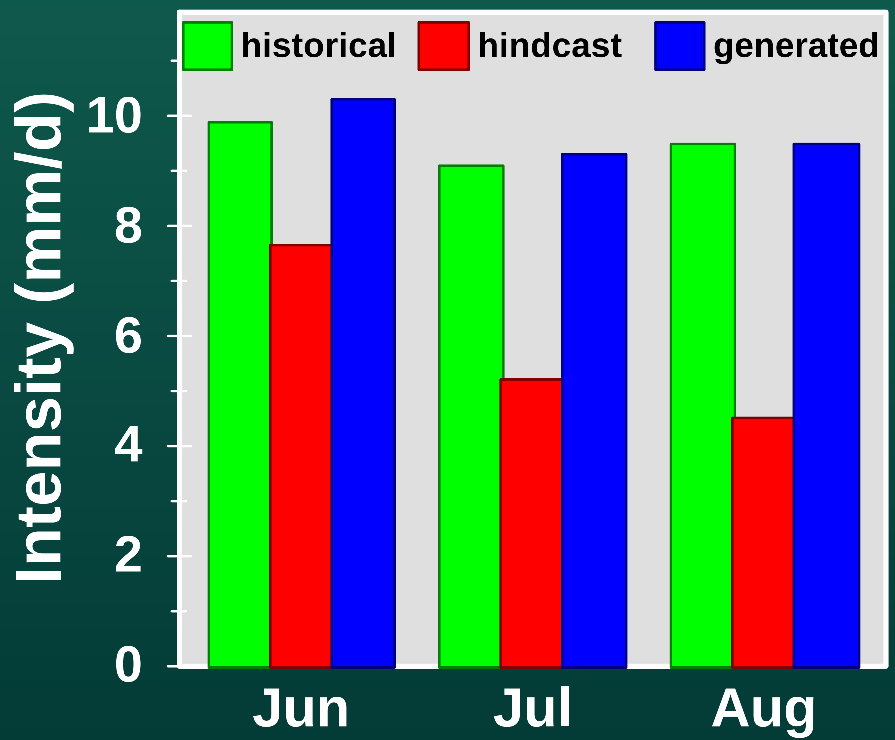
$$\sum_{t=1}^{n} \Delta y(t) = n\,Y_T$$

- Multiplicative adjustment would preserve sequence of dry days, but could produce unrealistic combinations of frequencies and amounts if target $R_T$ is very different from generated total $R_G$.
- *A solution*: Generate rain for given month repeatedly until $R_G$ is close (within 5%) to forecast $R_T$.
- Then obtain exact target total by multiplying daily

# Stochastic Disaggregation

## EACHAM 3.6 Rain, Plains, GA, 1971-96



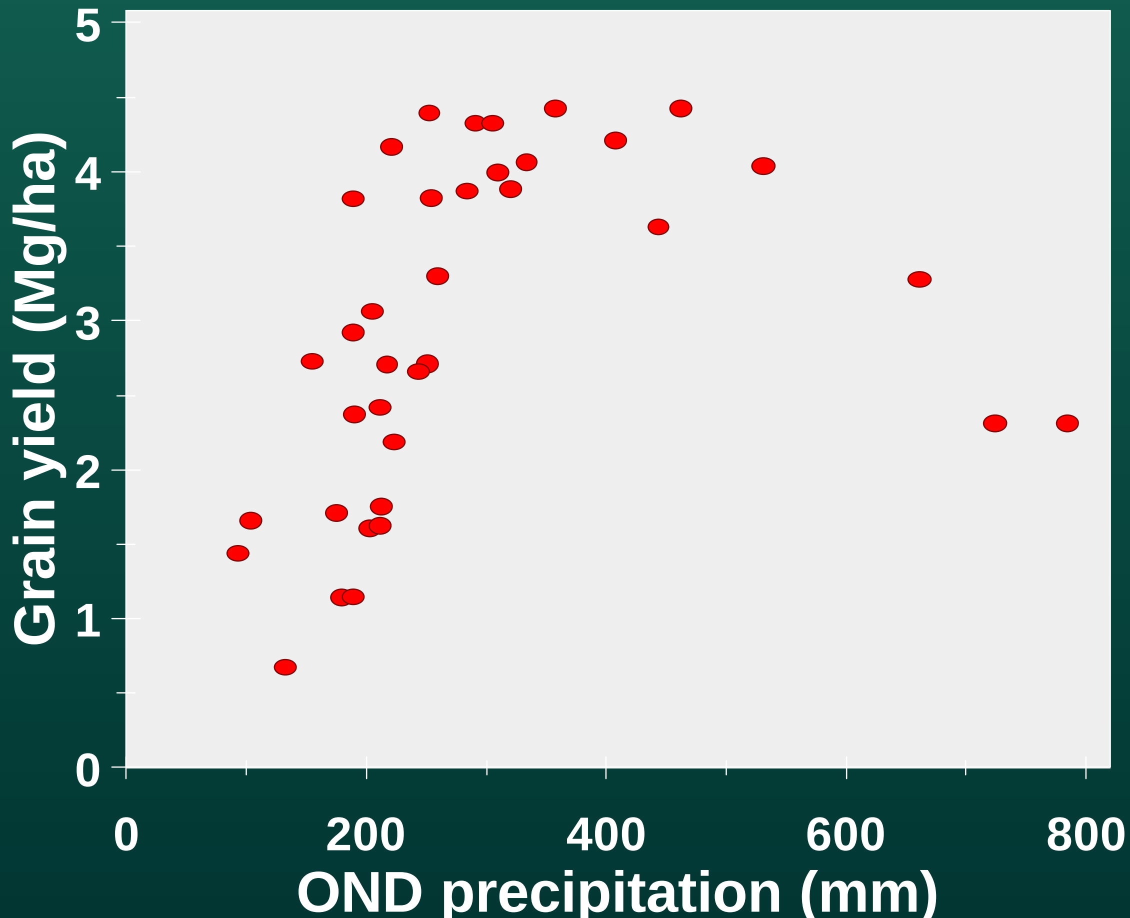



# Direct Statistical Prediction

- Assume predictors of meterological determinants of production should be predictors of production
- Treat e.g., crop yields simulated with historic weather data as the predictand
- Use predictors (observed or climate model output) of relevant climate variables and periods
- Avoids the need for daily weather intermediary

# Direct Statistical Prediction

- Challenge of non-linear, non-monotonic crop response to, e.g., rainfall



# Weighted Historic Analogs