AgMIP The Agricultural Model Intercomparison and Improvement Project

Incorporating Climate Scenarios for Studies of Pest and Disease Impacts

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Thanks to AgMIP Climate co-Leader: Sonali McDermid, NYU

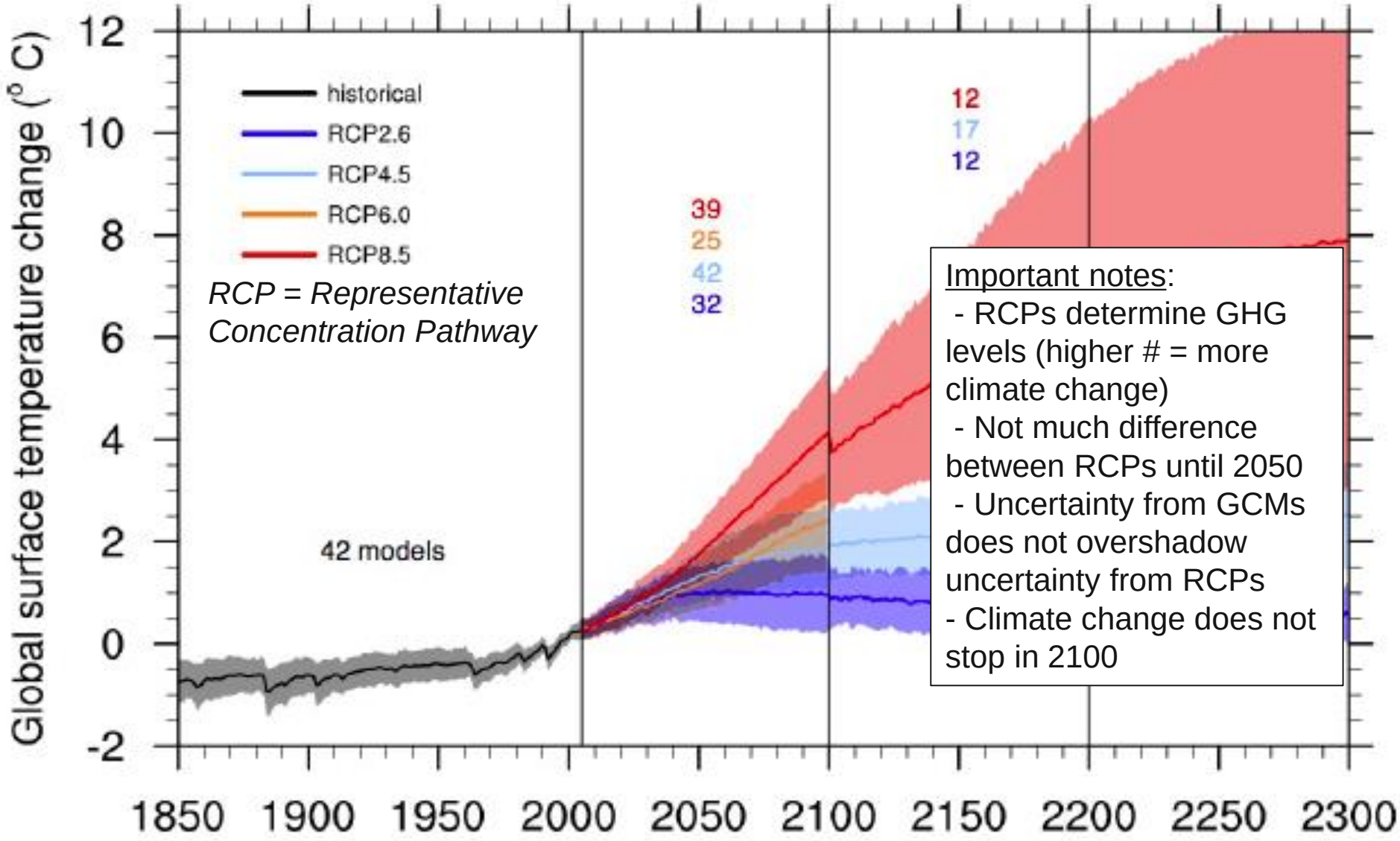
Overview

The AgMIP Climate Team is eager to help you deliver the climate data and scenarios needed for climate impact applications of crop, pest, and disease models.

- **Quick background on climate change and key uncertainties**
- **Focus on climate variables of particular interest for pests and diseases modeling**
- **Climate change scenarios for impacts assessment**
- **AgMIP climate data and scenario approaches**

Climate Change Background

Climate Change Uncertainty



Important notes:
- RCPs determine GHG levels (higher # = more climate change)
- Not much difference between RCPs until 2050
- Uncertainty from GCMs does not overshadow uncertainty from RCPs
- Climate change does not stop in 2100

Figure: Results from CMIP5 Global Climate Models; Adapted from Figure 12.5 in IPCC, 2013

Climate Change Projections

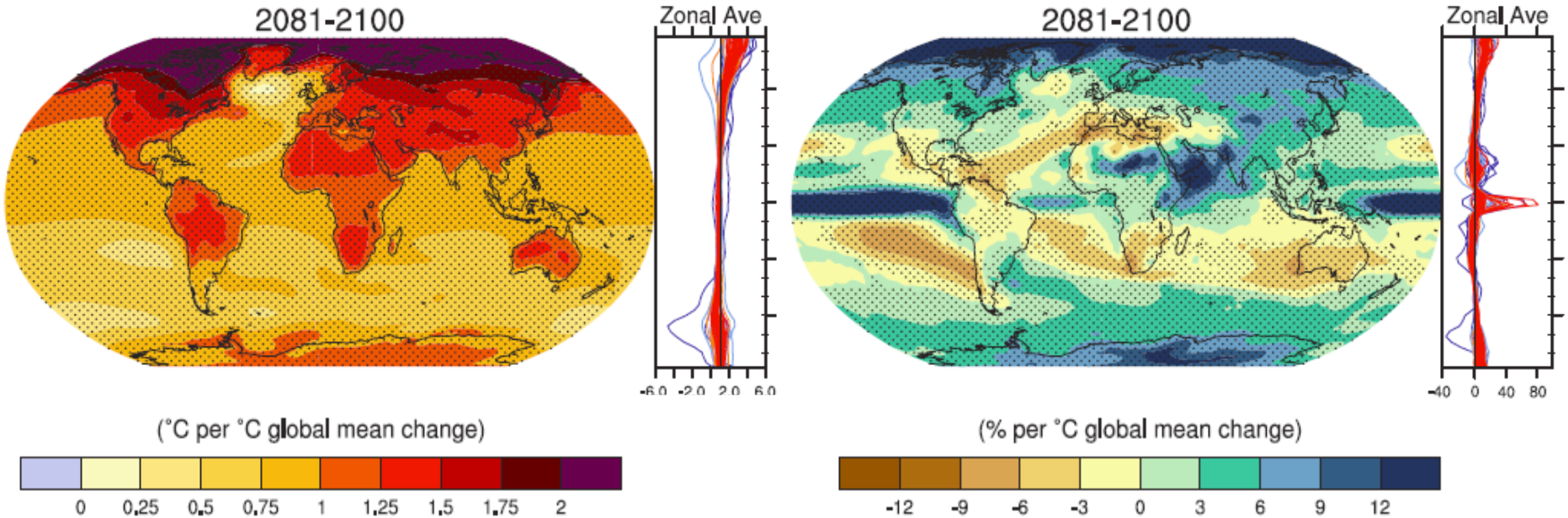
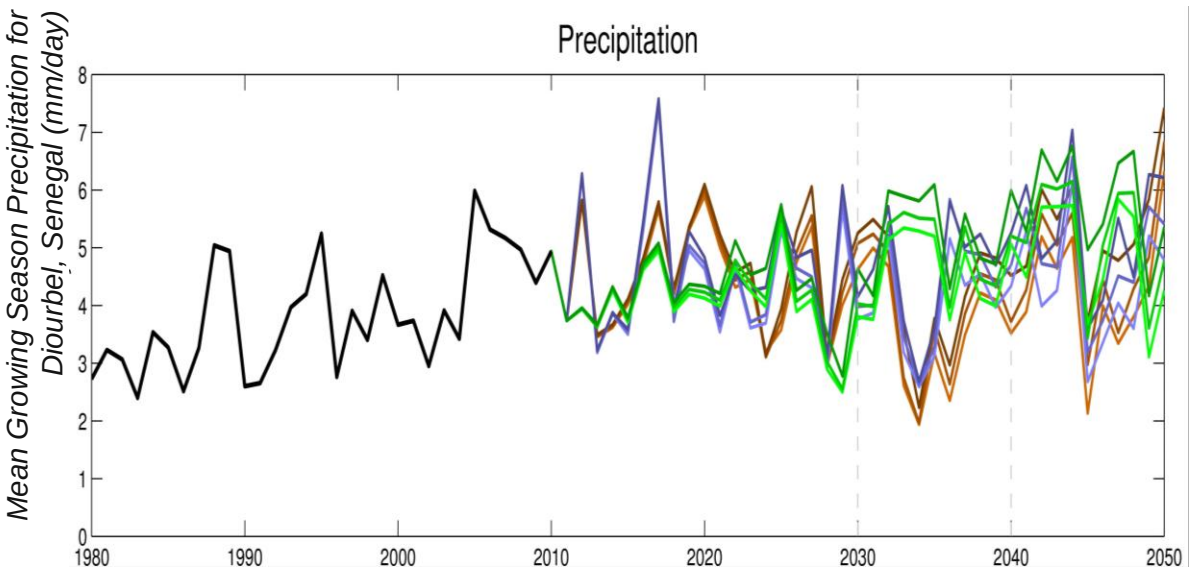


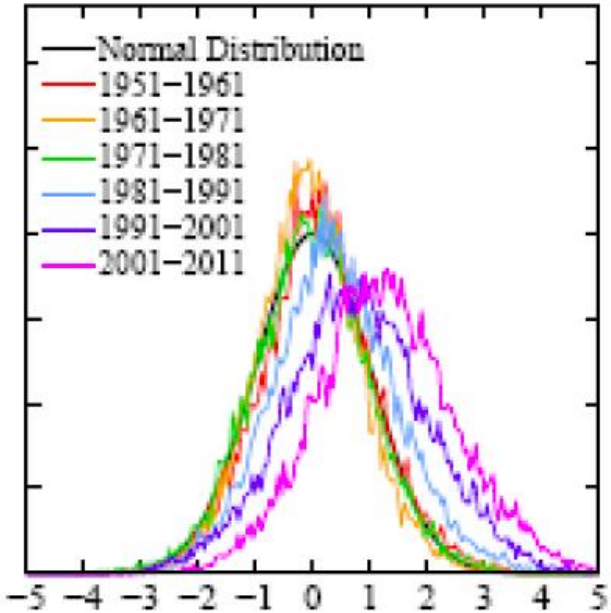
Figure: Results from CMIP5 Global Climate Models; Adapted from Figure 12.10 in IPCC, 2013

- Climate change is projected to increase temperatures and shift patterns of precipitation.
- Temperature increase is not uniform, with land areas and high-latitudes warming at a greater rate than the global average
- "*Rich get richer, poor get poorer*": more rain where it already is wet, less where it is dry (Trenberth et al., 2011)

Climate Change amidst Variability



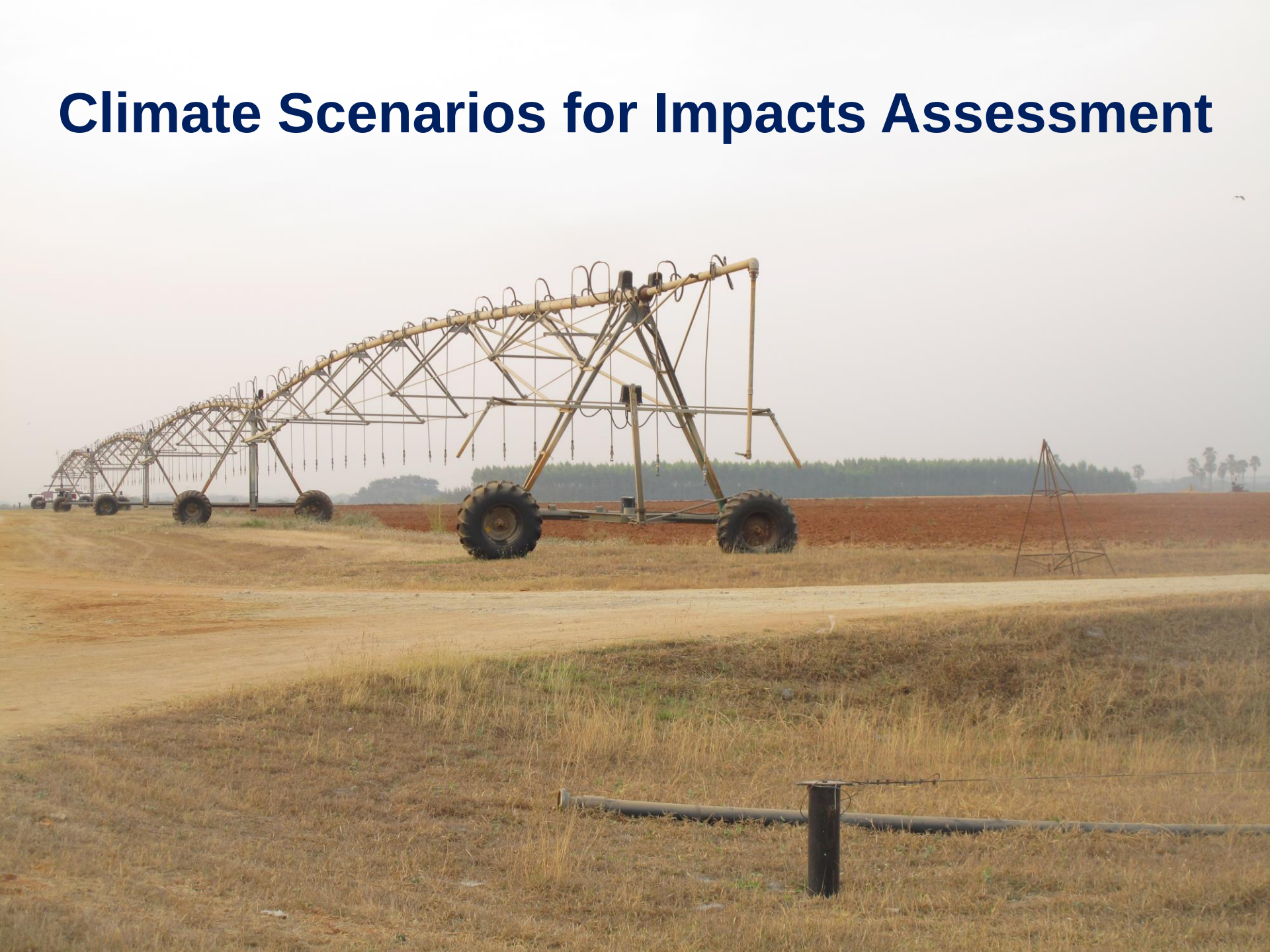
Left: Mean June-September Precipitation for Diourbel, Senegal, from synthetic historical series and projections including mean and climate variability shifts (Ruane and Greene, in preparation)



Right: Frequency of occurrence for summertime daily temperature anomalies over Northern Hemisphere land areas (Hansen et al., 2012)

- Climate change will interact with climate variability in many complicated ways
- Shifts in mean conditions can alter regular patterns of climate variability
- Long-period climate variability can lead to a perception of accelerated climate change or "climate change hiatus"
- "*It never rains but it pours*": rainfall is expected to come in less frequent, but more intense, storms (Trenberth, 2011) – observed in US (Groismann et al., 2011)
- Climate change can lead to more frequent extremes and thresholds being exceeded

Climate Scenarios for Impacts Assessment



Climate Scenario Generation

Raw GCM output is not suitable for most impacts model applications

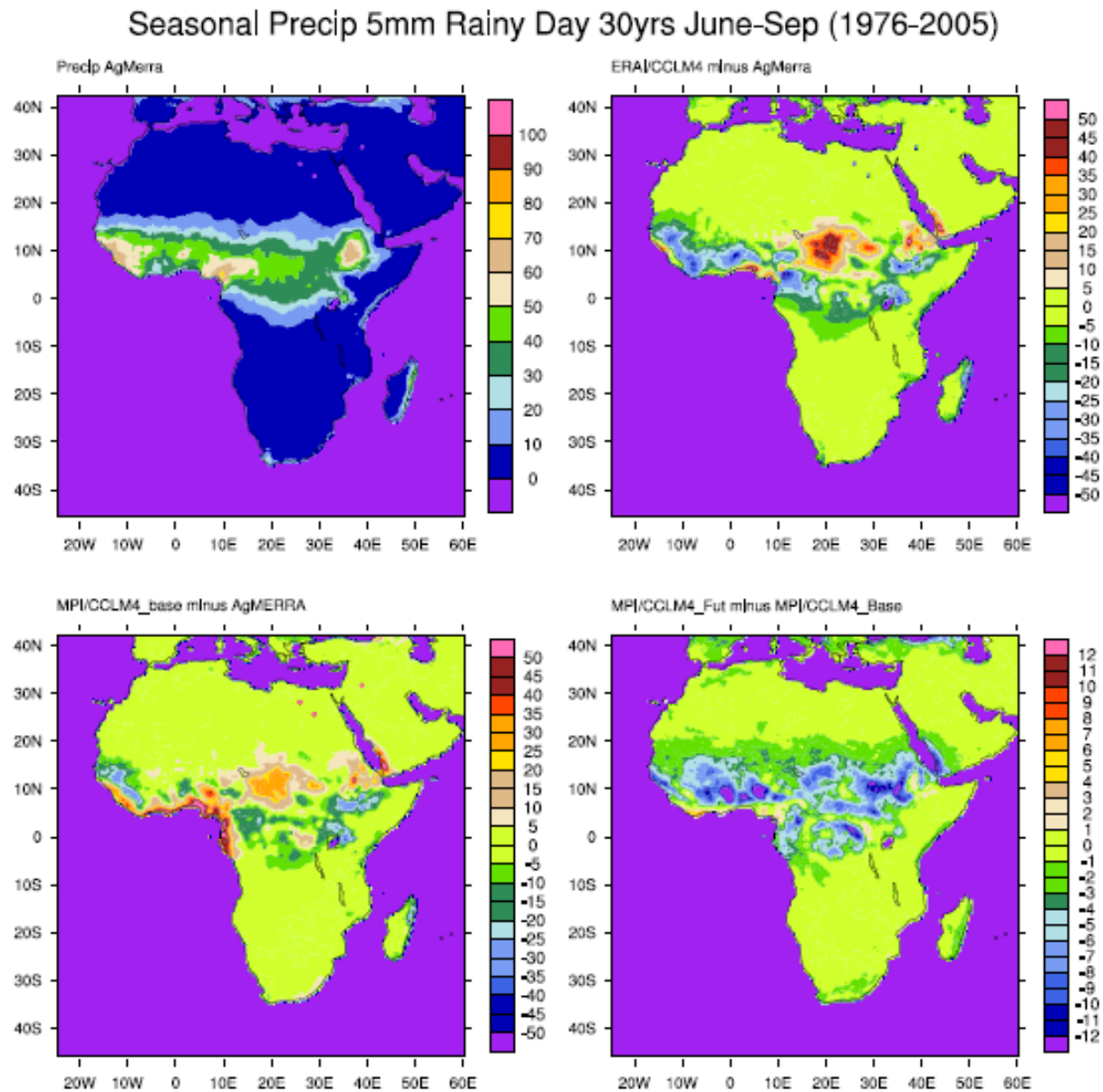
- **Mean biases**
- **Poor representation of many modes of variability**
- **Coarse resolution**

➢ **Dynamical downscaling, statistical bias-correction, and empirical statistical downscaling are three major approaches for producing climate scenarios suitable to drive impacts models**

➢ **Heavy dependence on baseline climate dataset**

➢ **Weather generators and models for estimating missing variables and time scales can also produce additional iterations for probabilistic analysis.**

Dynamical Downscaling



- **Increasing coordination in regional climate modeling to enable more useful intercomparison, ensemble approaches, and data distribution (each uses multiple GCMs and RCMs):**
  - **ENSEMBLES (Europe)**
  - **NARCCAP (N. America)**
  - **CLARIS (S. America)**
  - **CORDEX**

Donatelli et al. have created climate scenarios for crop modeling in Europe based upon ENSEMBLES outputs

- **Dynamical models should be able to capture how climate change interacts with finer scale**
  - **Local-scale circulations (e.g., mountain/valley or land/sea breezes)**
  - **Complex topography (e.g., differential heating at higher elevations**

Higher resolution does not necessarily mean higher quality

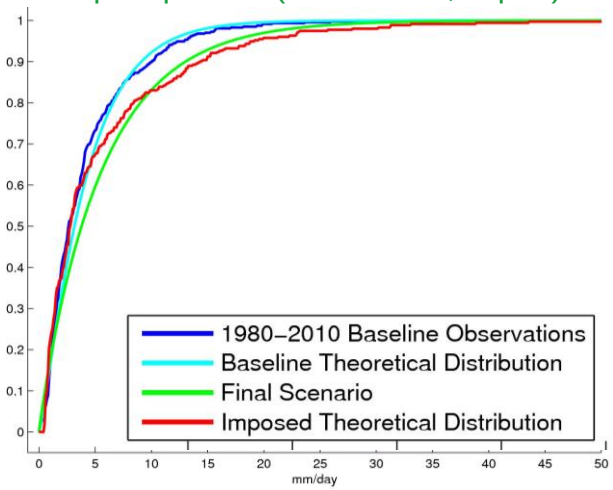
Statistical Bias-Correction

- **Statistical bias-correction maps aspects of GCM outputs onto historical observations in order to correct statistics of most important phenomena**
  - **Bias-corrected, Spatially-disaggregated (BCSD)**
  - **Bias-corrected, Constructed Analogues (BCCA)**
  - **Hempel et al., 2013 (ISI-MIP)**
  - **Delta method and enhanced delta method (Ruane et al., 2015)**
  - **Many more**

- **May also use weather generators to create time series with enough iterations for probabilistic analysis (e.g., MarkSIM, GiST, LARS-WG)**

- **Often includes inherent downscaling**

Cumulative distribution of December precipitation (Shizukuishi, Japan)



Distribution stretching for Shizukuishi, Japan (from Ruane et al., 2015)

- **Must be careful when attributing impacts to changes that were not included in the statistical method**
  - **For example, many approaches assume no change in radiation or relative humidity, so be careful if your model relies heavily on those.**
  - **Models that apply the same correction to future and baseline periods will reflect coarse resolution changes**

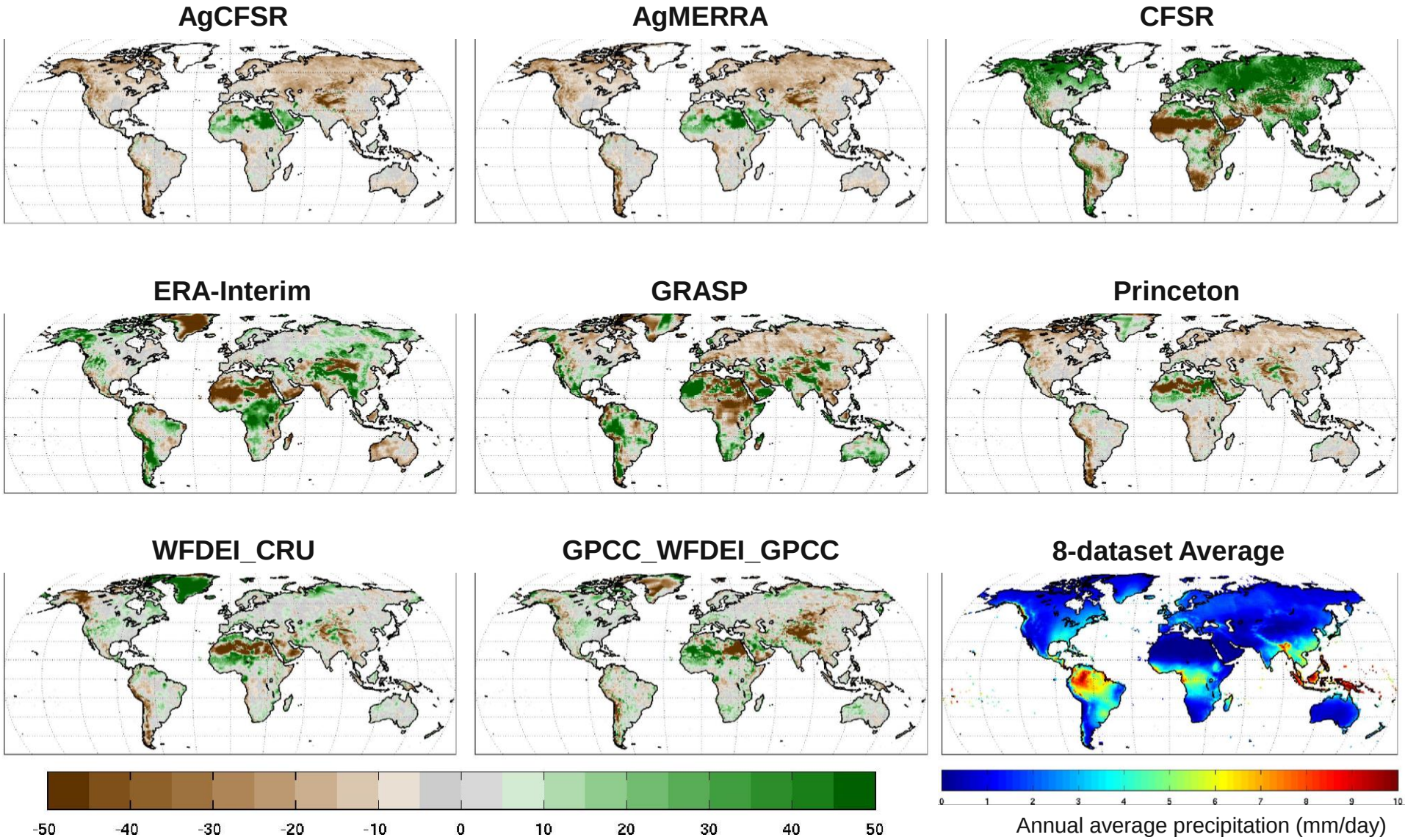
- **Can lead to spurious results when applied to values far beyond those observed in calibration period**

Empirical Statistical Downscaling

- **Many of the most important climate processes are also among the most difficult to simulate**
  - **Precipitation (especially extreme precipitation events)**
  - **Drought**
  - **Heat waves**
  - **Hail**
  - **Hurricanes and tornados**

- **Empirical statistical downscaling utilizes large-scale aspects of a climate model simulation as the basis for estimating more complex local phenomena.**
  - **Pressure level heights / atmospheric pressure**
  - **Wind direction**
  - **Gradients of temperature or humidity**
  - **Predictor/Predictand relationships set with historical period dataset**
    - **Can potentially fail in non-stationary climates**

Statistical Approaches Rely on Good Observational Basis



Weather generators and meteorological models

Scenarios and datasets often based upon temperature and precipitation at either monthly or daily time scales. Other variables are often estimated from these using weather generators, rules of thumb, or dynamical models

Evapotranspiration

- **Priestley-Taylor**
- **Penmann-Monteith**
- **Hargreaves**

Solar Radiation

- **Bristow-Campbell**
- **Bristow-Donatelli**

Humidity

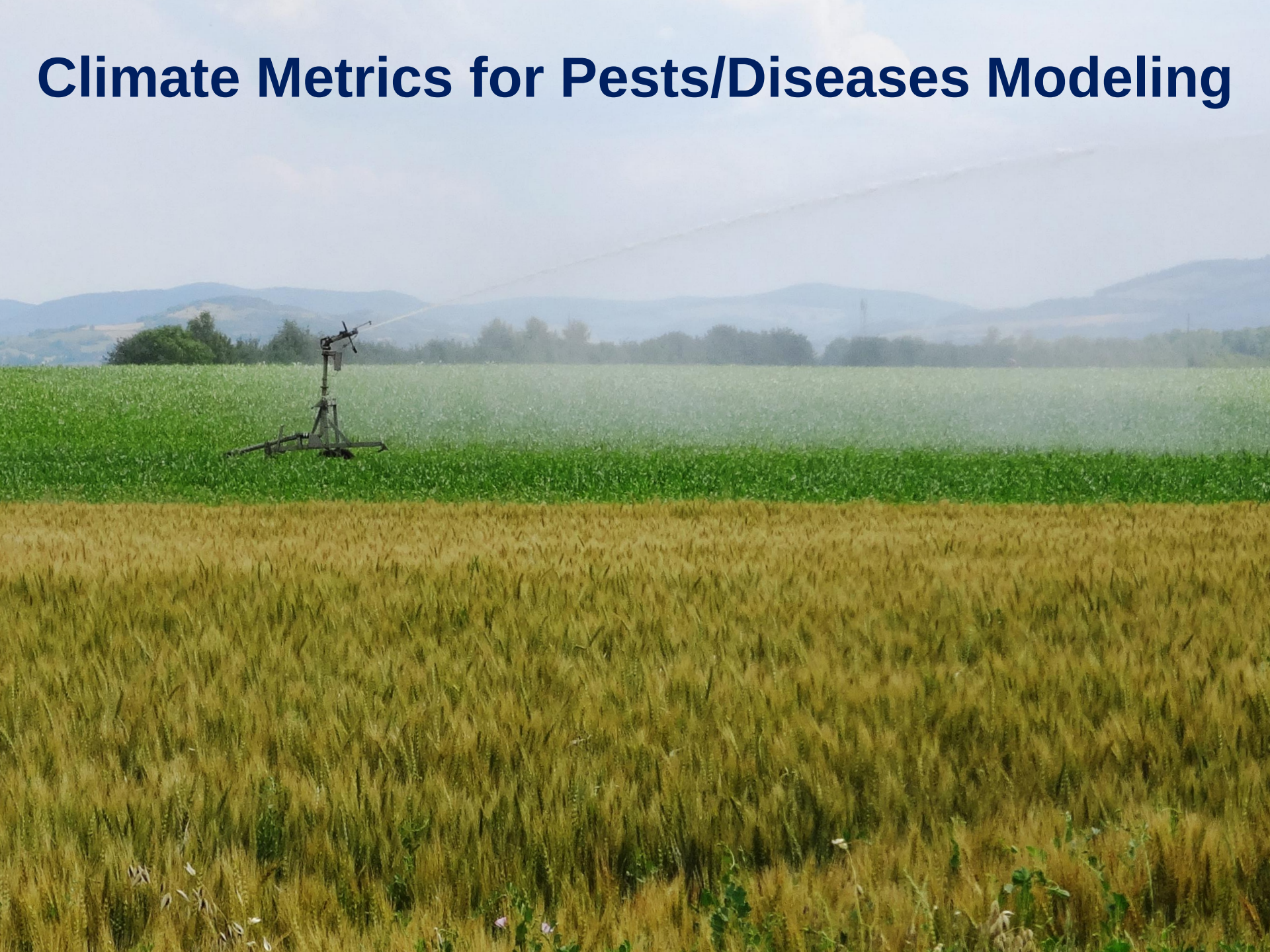
- **Sometimes assumed to be saturated at Tmin each day**
- **Hourly air relative humidity can be estimated within crop models or via independent weather generation or modeling (e.g., Donatelli et al., 2009)**

Weather Generators

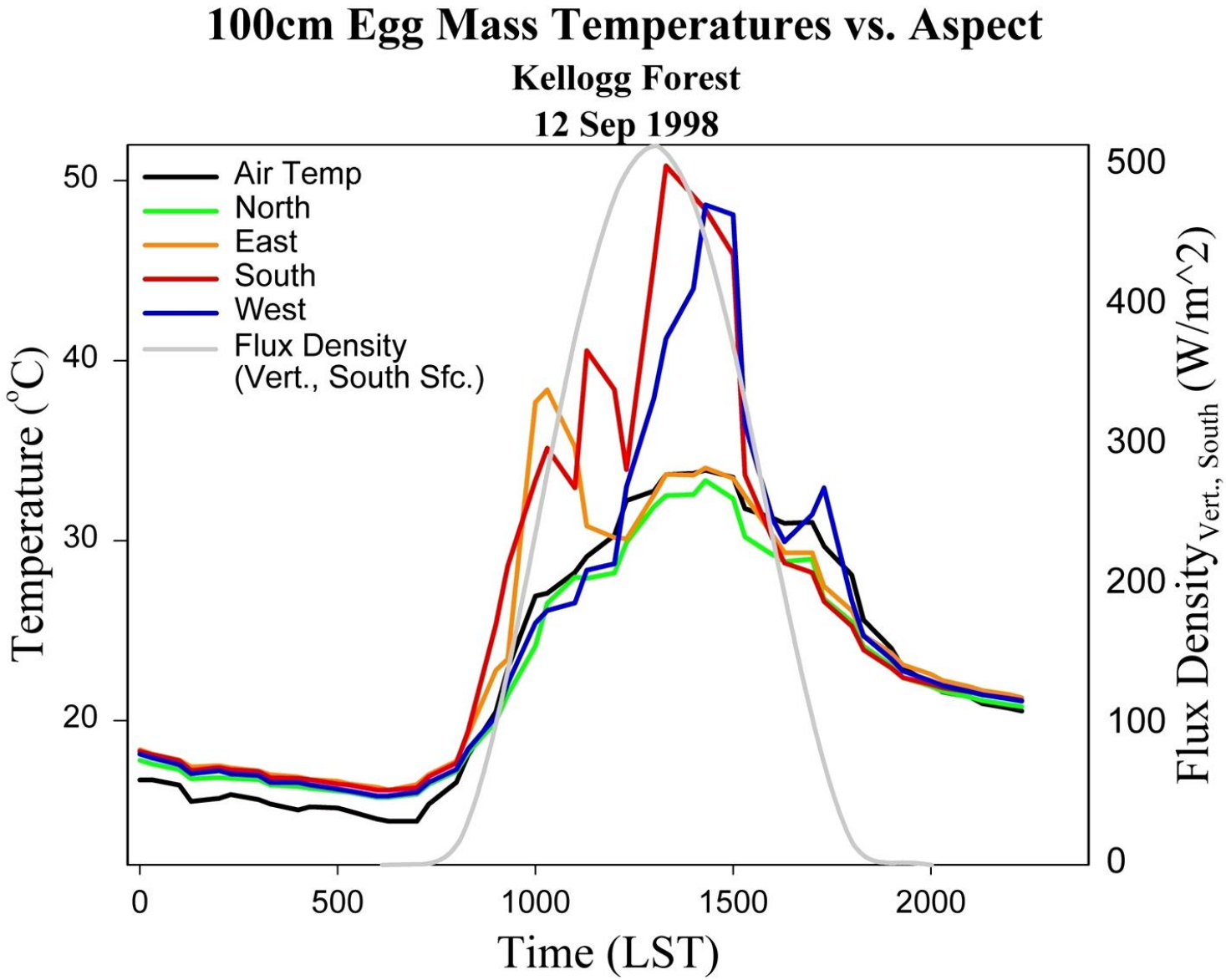
- **Dozens of these, each with unique assumptions (MarkSIM, Lars-WG, etc.)**
- **AgMIP currently organizing weather generator intercomparison**

Best when there is a long record of observations for parameter calculation

Climate Metrics for Pests/Diseases Modeling

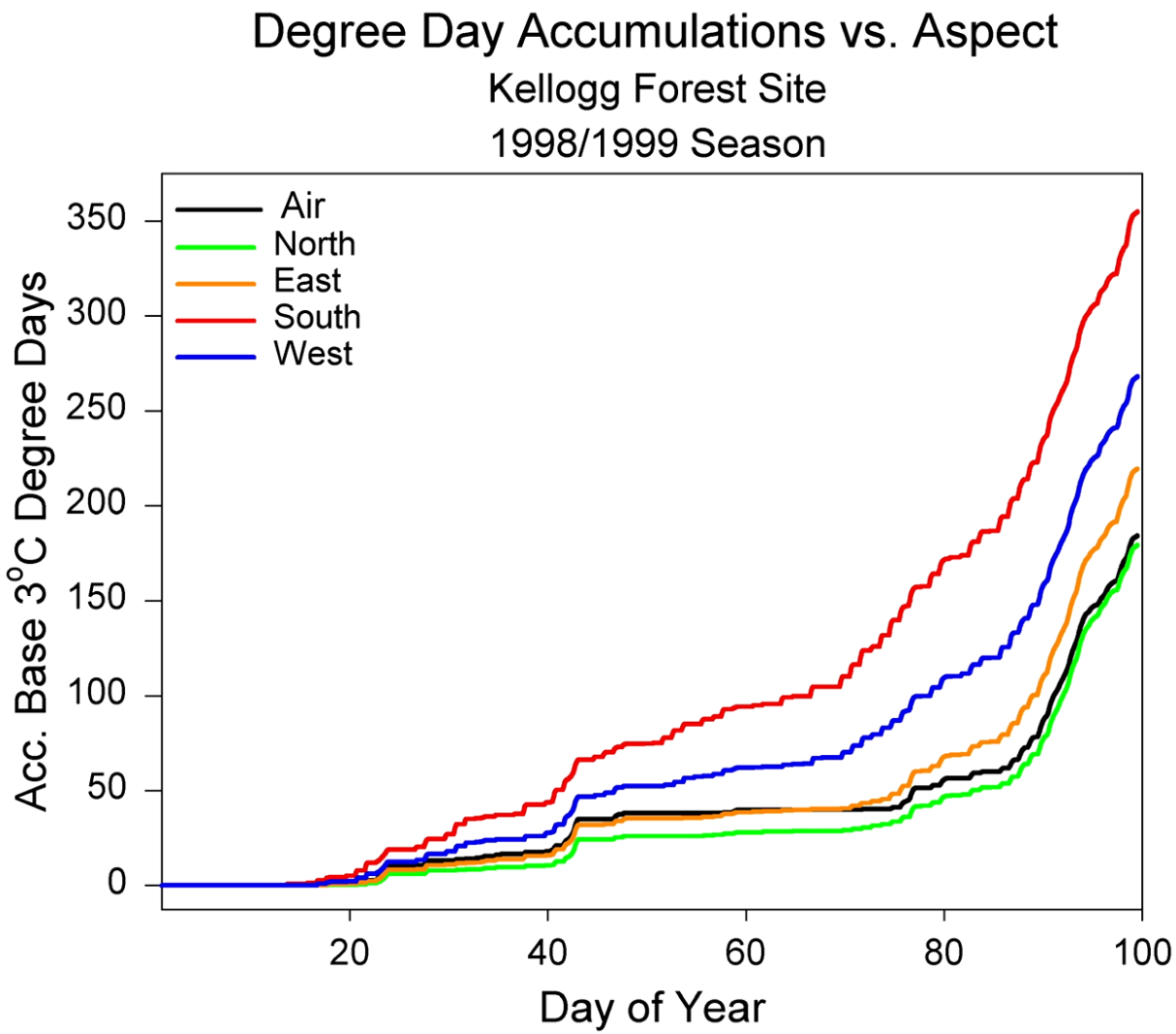


Challenges of micrometeorology and microclimatology data



Within-grove variation in gypsy moth characteristics in Southern Michigan (from Jeff Andresen)

Challenges of micrometeorology and microclimatology data



Within-field variation in gypsy moth characteristics in Southern Michigan (from Jeff Andresen)

Shading and other micro-scale issues accumulate throughout growing season and can lead to different phenology and impacts

No high-quality, global climate dataset with variables and resolutions required for many pest and disease models

From Global/Decadal Scale to Micrometeorology

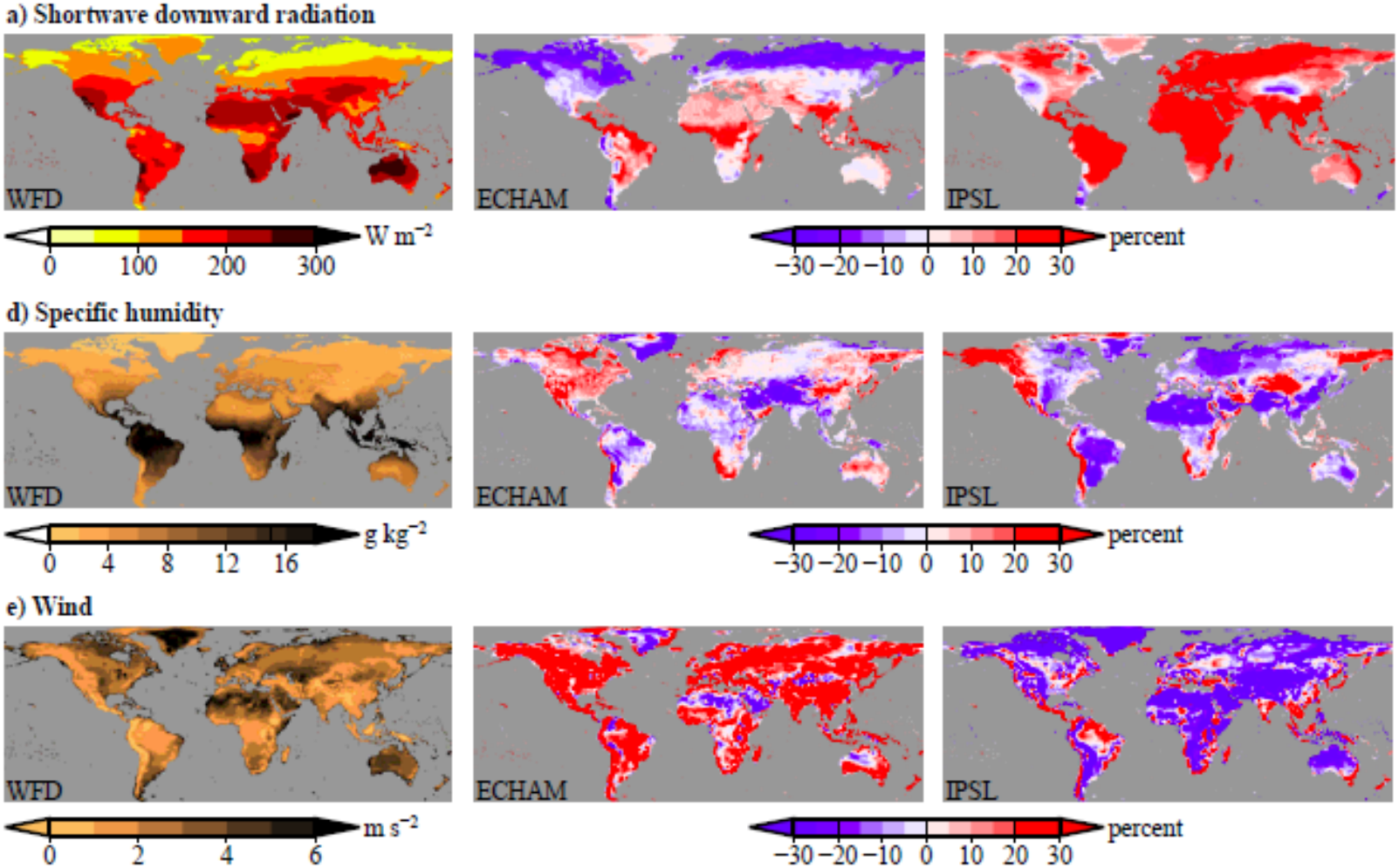
- **Considerable challenges as global climate models address very long time scales and very large spatial domains compared to needs of many pest and disease models.**

  Global models produce outputs on ~10,000km^2 spatial scale (among higher resolutions)

- **GCMs are evaluated primarily on climate sensitivity, general circulation, and water/energy/carbon balances**

- **Projections of daily climate variability, humidity, soil moisture, winds, leaf wetness, and extreme events are not the primary focus but are crucial for agricultural applications**

Bias-correction of GCMs



Haddeland et al., 2012

Relative Humidity, Wind Speed, and Radiation Changes

Trenberth et al. (2013): no clear trends in wind speed or relative humidity from GCMs on global basis.

- Regional effects expected to generally follow precipitation change patterns (e.g., Pierce et al., 2013, project declines in RH over the western US between 0.1-0.6 percentage points per decade).

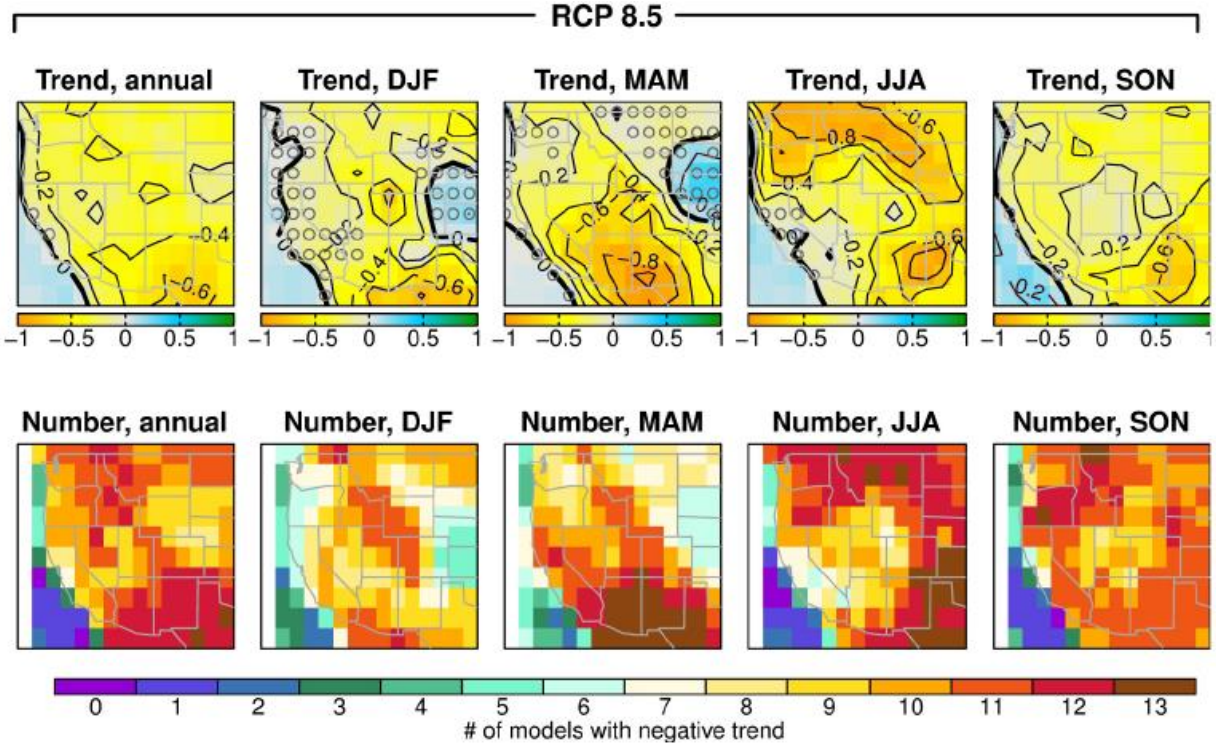


Fig. 7. Mean RH trends (percentage points per decade), and number of models with a negative RH trend, found in a set of 12 CMIP5 simulations with the rcp 4.5 (upper panel) and rcp 8.5 (lower panel) concentration pathways. Contour interval: 0.2. Grey circles indicate trends that are not significant at the 0.05 level.

- Larger changes in interior as these depend more on precipitation recycling (Koster et al., 2004).
- Expectation that relative humidity will become more variable as ET and precipitation become more intense.
- Solar radiation changes generally follow changing precipitation patterns

Pierce et al., 2013

Leaf Wetness

Difficult to observe

- Often simulated (empirically or dynamically) for wider applications
- Requires hourly meteorological data (especially relative humidity)

Dewfall could be accelerated

- Clausius-Clapeyron suggests larger condensation and evaporation for same shifts in temperature. Energy approach would reduce diurnal range of temperature by increasing minimum temperature on humid evenings.

Bregaglio et al., 2011 has nice review and intercomparison including model and meteorological estimation sources of uncertainty for several pathogens

Would be interesting to better understand how various crop/pest/disease models estimate missing variables and hourly time series from daily data.

AgMIP Climate Data and Scenarios

The AgMIP Climate Team

Agro-climatic Analysis

Baseline Analysis and Intercomparison

- Local station observations
- Gridded climate datasets

Climate Sensitivity Scenarios

- Mean T, P, [CO_2]
- Impacts response surfaces
- Extreme events

Future Climate Scenarios

- Enhanced GCM delta method
- Gridded climate scenarios
- Near-term scenarios
- Probabilistic analysis

Weather Generators

AgMIP Climate Data and Scenarios

- **Historical climate data estimation: AgMERRA**

- **Emphasis on sensitivity tests**

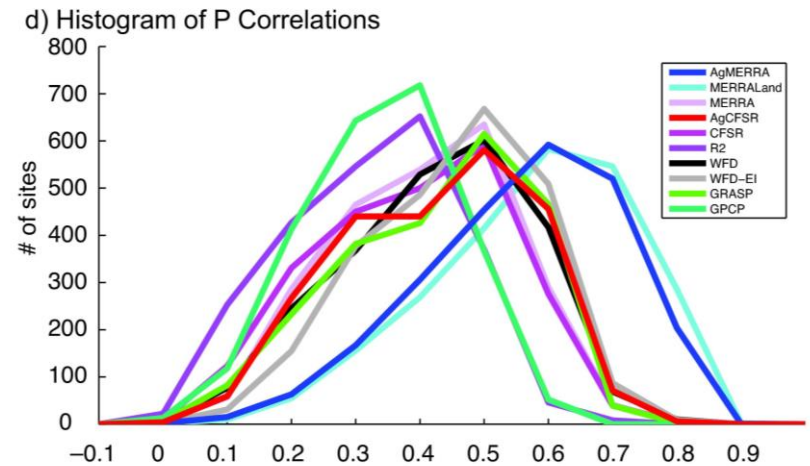
- **R scripts for GCM-based scenarios**
  - **20 CMIP5 GCMs**
  - **Mean-change-only**
  - **Mean-and-variability-changes**

- **Focus on climate variables of particular interest for pests and diseases modeling**

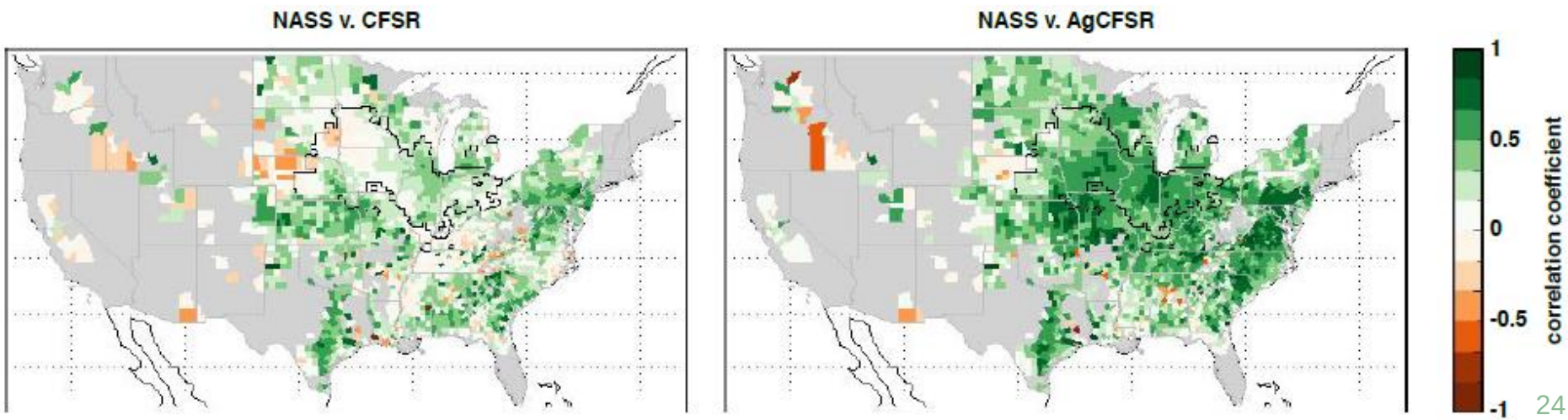
Historical Climate Datasets

- AgMIP often utilizes **AgMERRA**
  - Based upon NASA MERRA reanalysis
  - Integrates monthly gridded climate observations and remotely sensed rainfall and solar radiation observations
  - Daily, 0.25º x 0.25º resolution from 1980-2010
  - Tmax, Tmin, and Relative humidity at maximum temperature
    - Large diurnal cycle of relative humidity; responds to water budget exchanges and temperature changes
    - Vapor pressure and specific humidity are less variable than relative humidity
    - RH@Tmax is similar to RHmin

- **AgCFSR** created using same methodology for NCEP CFSR
- **Regional datasets** also helpful (DayMet, MARS, others)



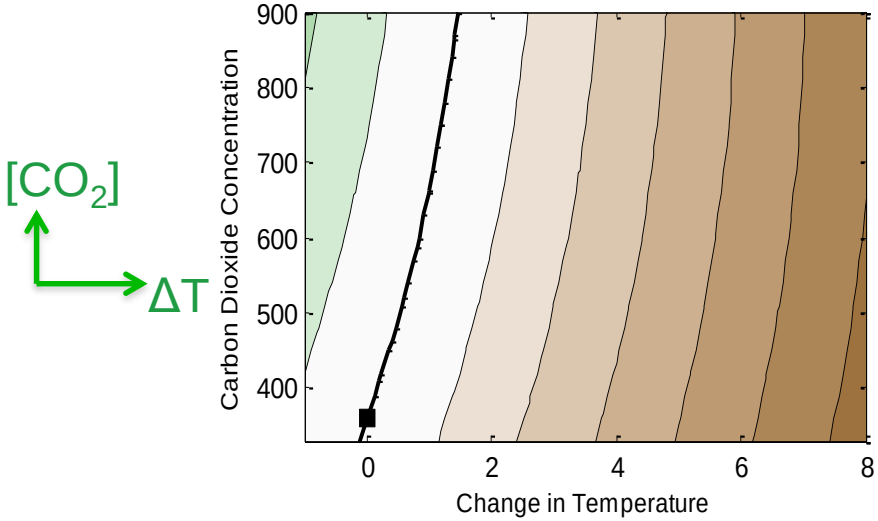
Comparison of daily precipitation correlations at 2326 meteorological stations in agricultural areas (from Ruane et al., 2014).



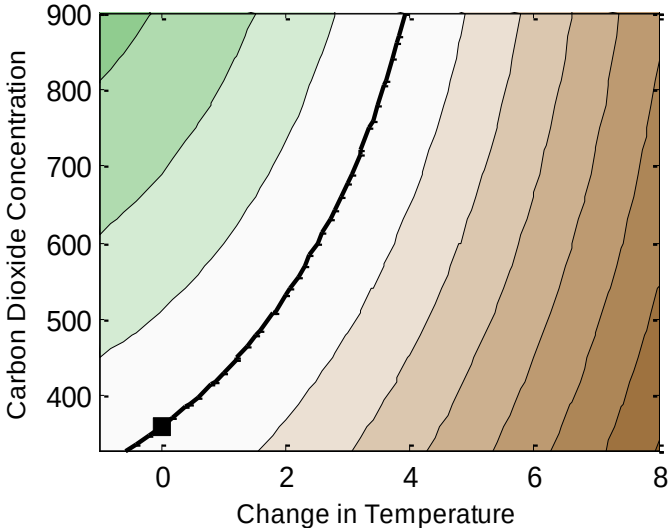
Improvement in simulation correlation with county-level NASS maize yields; 1980-2010 (from Glotter et al., in preparation)

Sensitivity Tests to Explore Key Responses

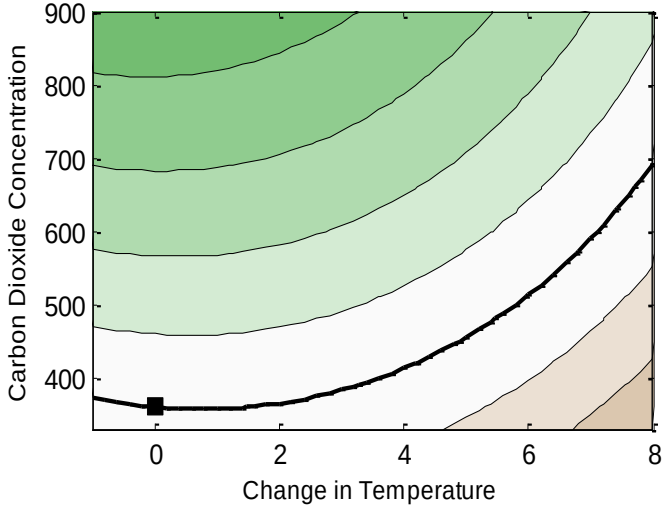
Maize (135 sets)



Rice (48 sets)



Winter Wheat (75 sets)



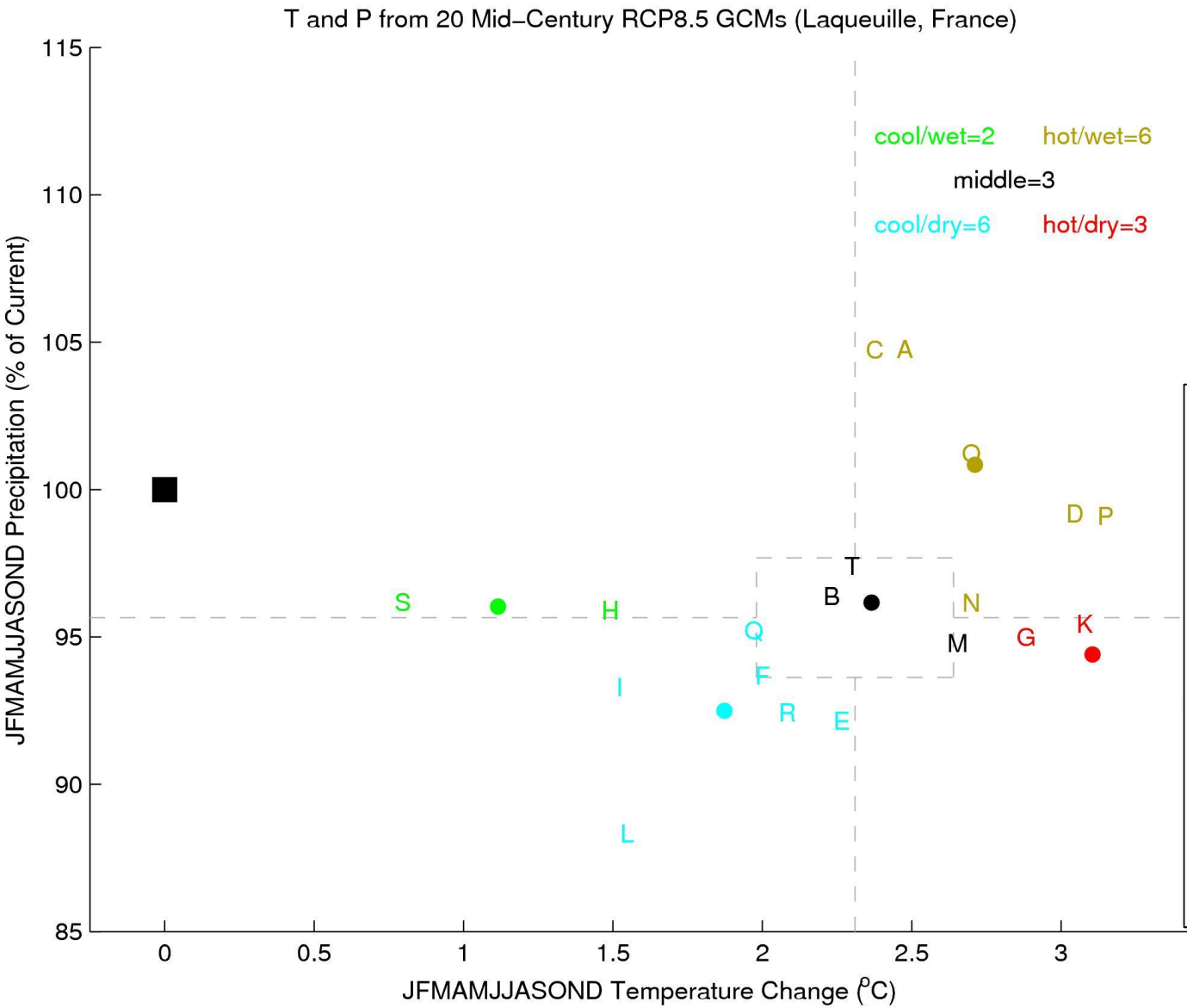
AgMIP's Coordinated Climate-Crop Modeling Project (C3MP; www.agmip.org/c3mp) has organized protocol-based sensitivity tests on more than 1100 simulation sets representing ~20 crop species and ~20 crop models (Ruane et al., 2014; McDermid et al., 2015).

Allows for comparison of carbon, temperature, and precipitation change responses.

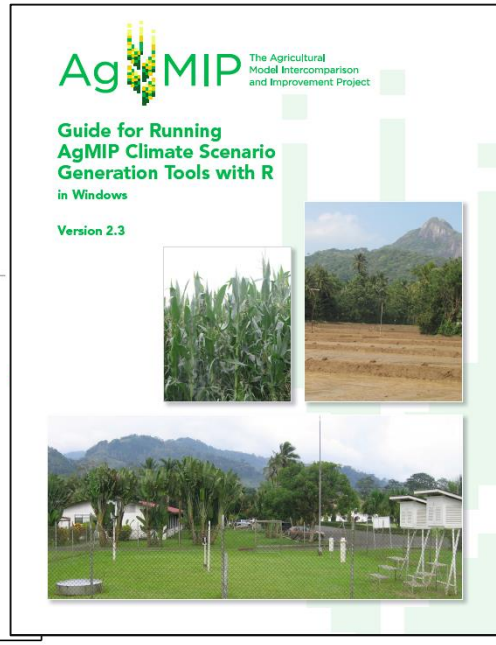
Similar approach could be taken for various pests and disease responses (RH and T).

Preliminary results from C3MP; article forthcoming

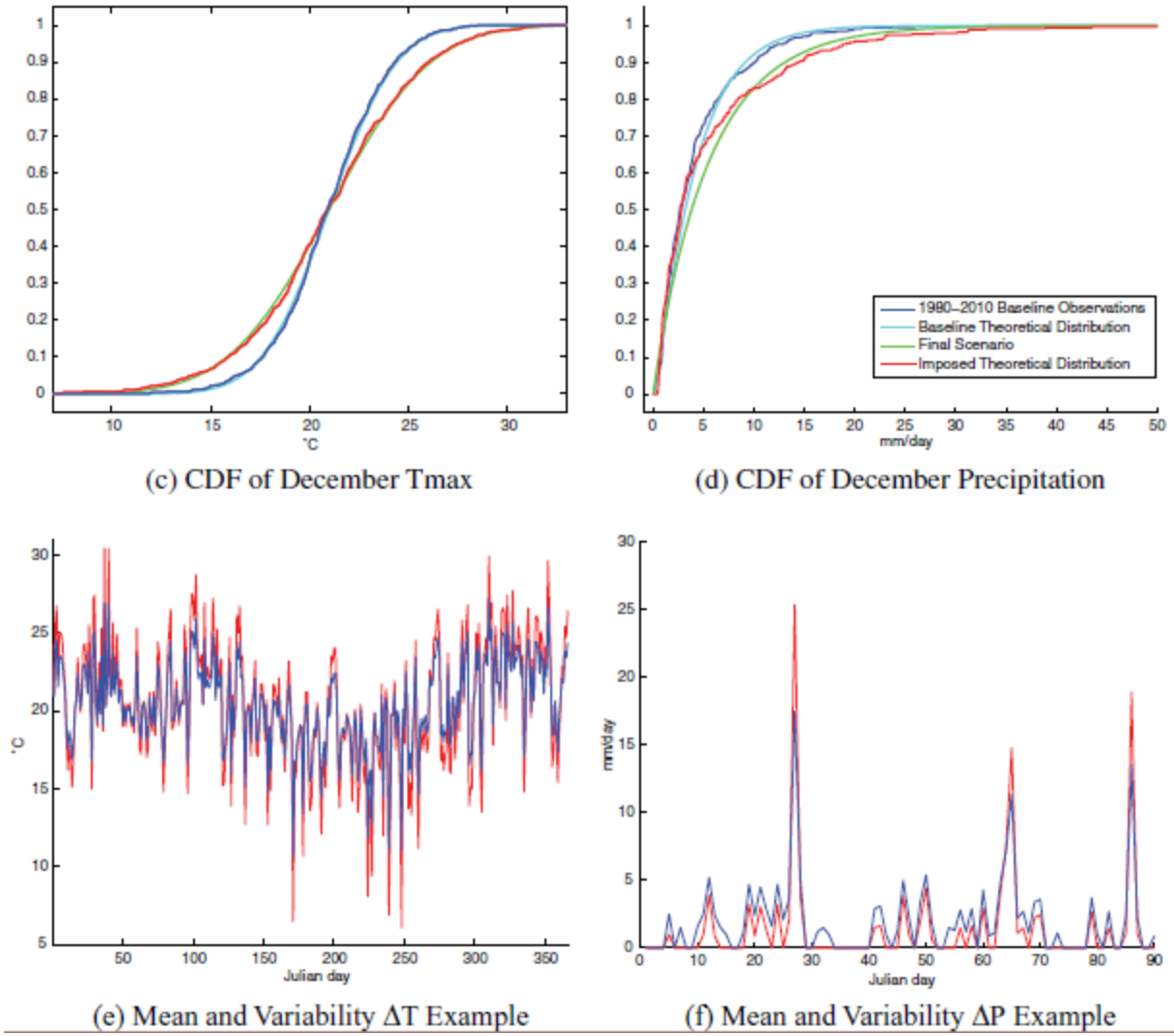
Representing wider GCM ensemble via subsets



AgMIP has developed an R script package and guidebook to help with scenario generation (www.agmip.org)



Enhanced Delta Method



(c) CDF of December Tmax

(d) CDF of December Precipitation

(e) Mean and Variability ΔT Example

(f) Mean and Variability ΔP Example

Recognizable historical time series adjusted to impose climate changes drawn from CMIP5 models.

Adjusts each month's:

- Mean Tmax, Tmin
- Standard deviation of daily temperatures
- Mean precipitation
- # rainy days
- Shape of rainfall distribution

Does not adjust:

- Solar radiation
- Wind speed
- Relative humidity at Tmax (although vapor pressure and VPD changes)

GCM Δvariability is less reliable than Δmeans

Shizukhuishi, Japan, hypothetical scenarios from Ruane et al., 2015

Summary

Summary

- **Pest/disease/crop models should utilize climate information and approaches that have been created to suit needs of particular application (historical data, sensitivity tests, and future scenarios)**

- **Major scale and data challenges**

- **Climate projections are a critical source of uncertainty**
  - **Must take probabilistic or scenario-based approach**
  - **Can't just look for mean or "best single" scenario**

The AgMIP Climate Team is eager to help you deliver the climate data and scenarios needed for climate impact applications of crop, pest, and disease models.

Please contact us if we can help in any way

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