Climate impacts Group

UNIVERSITY OF LEEDS

The GLAM crop model

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Introduction

Crop modelling methods

Empirical and semi-empirical methods

+ Low input data requirement
+ Can be valid over large areas
– May not be valid as climate, crop or management change

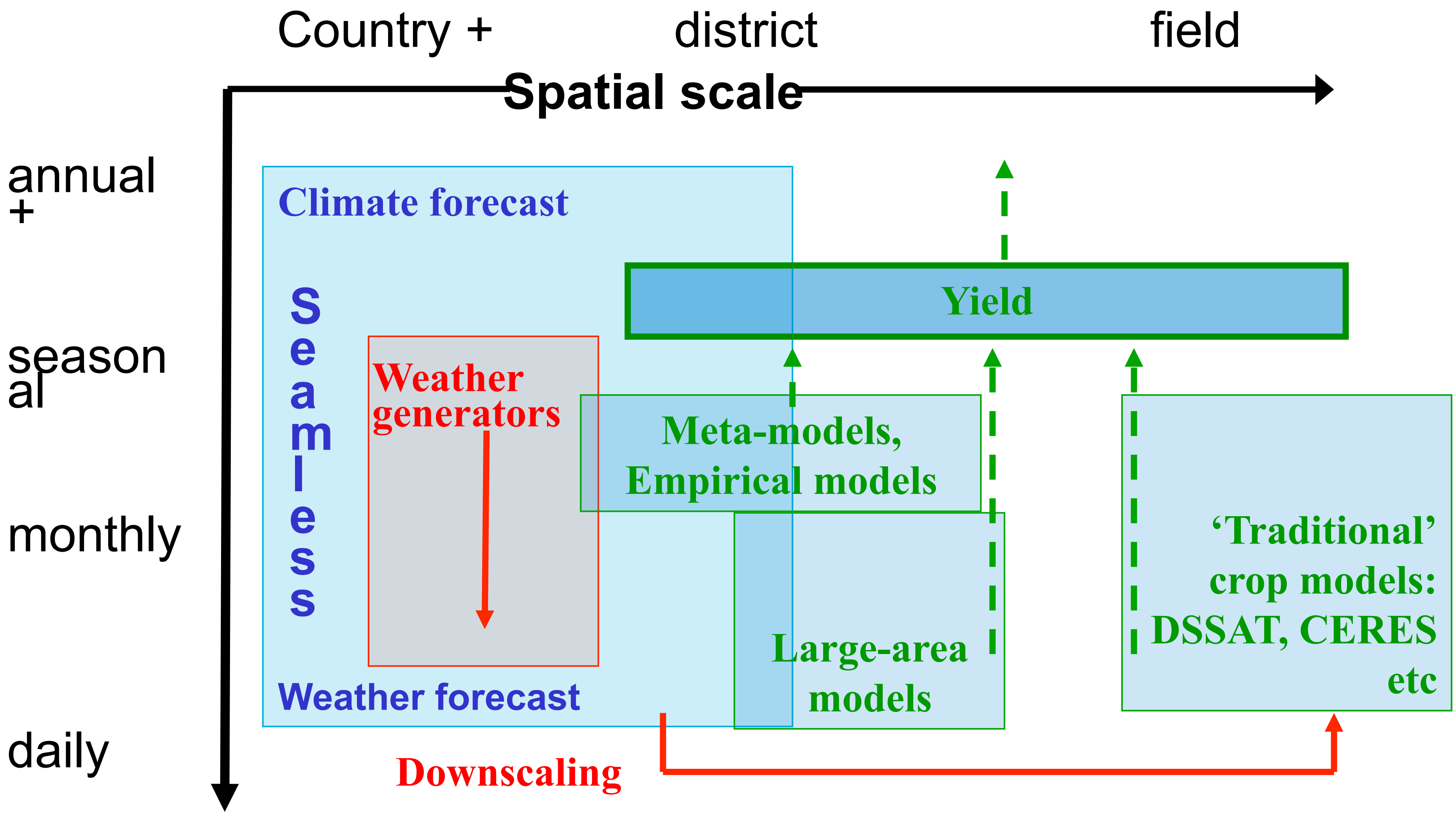
Process-based

+ Simulates nonlinearities and interactions
– Extensive calibration is often needed
– skill is highest at plot-level

⇒What is the appropriate level of complexity?

– Near to the yield-determining process on the spatial scale of interest (Sinclair and Seligman, 2000)

Combining crop and climate models



General Large Area Model for Annual Crops (GLAM)

Challinor et. al. (2004)

- Aims to combine:
  - the benefits of more empirical approaches (low input data requirements, validity over large spatial scales) ***with***
  - the benefits of the process-based approach (e.g. the potential to capture intra-seasonal variability, and so cope with changing climates)
- Yield Gap Parameter to account for the impact of differing nutrient levels, pests, diseases, non-optimal management etc.

Large-area crop modelling

1. A basis in observed relationships.

- Correlate weather/climate and crop yield at range of scales (Challinor et al., 2003)
- Beware of assigning causality (e.g. Bakker et al., 2005)
  => need process-based modelling

2. Appropriate complexity.

- ↑ processes => ↑ interactions => ↑ potential for error. (See e.g. Monteith, 1996).
- Simulate at appropriate level of organisation – mechanisms near to the yield-determining processes should be simulated (Sinclair and Seligman, 2000)

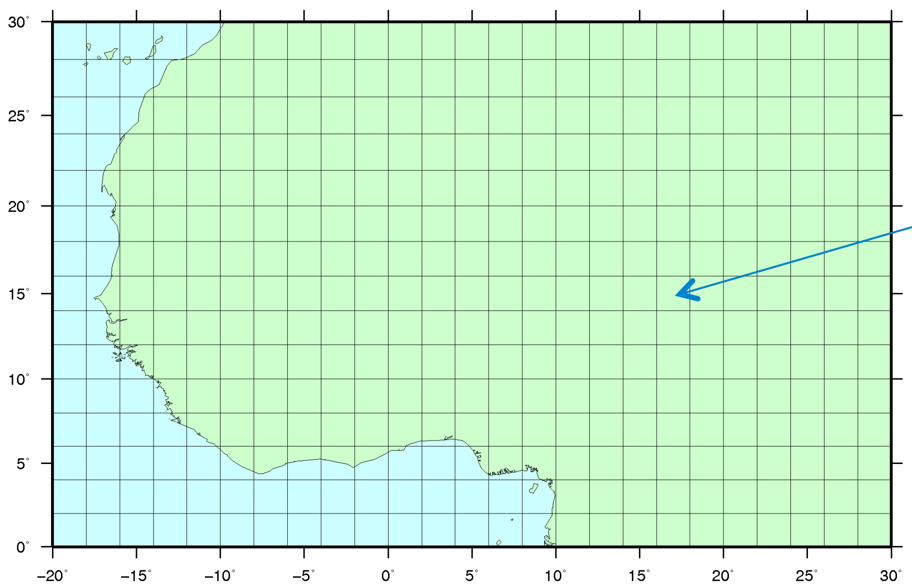
3. High fraction of observable parameters.

- Parameterisations are then directly testable (e.g. dL/dt, TE)
- Reduces risk of over-tuning
- Semi-empirical approaches as well as processes-based.
  e.g. Potgeiter (2005) related a plant water stress index to yield

GLAM (General Large-Area Model for annual crops)

- Process based crop model

- Specifically designed for use on large spatial scales
  - simulates climatic influences on crop growth and development
  - low input data requirements

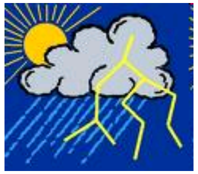


Typical climate model grid cell – GLAM can be run on this spatial scale

GLAM – Inputs and outputs

INPUTS

Daily weather data:



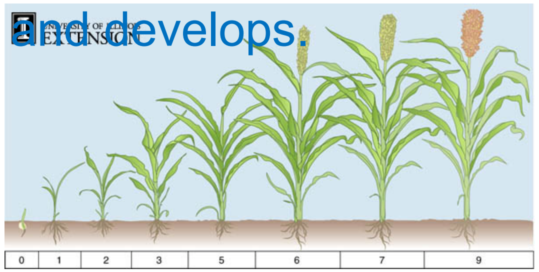
- Rainfall
- Solar radiation
- Min temperature
- Max temperature

Soil type

Planting date

CROP MODEL

For each day of the growing season, a set of equations is solved. The simulated crop grows and develops.



OUTPUTS

Crop yield:

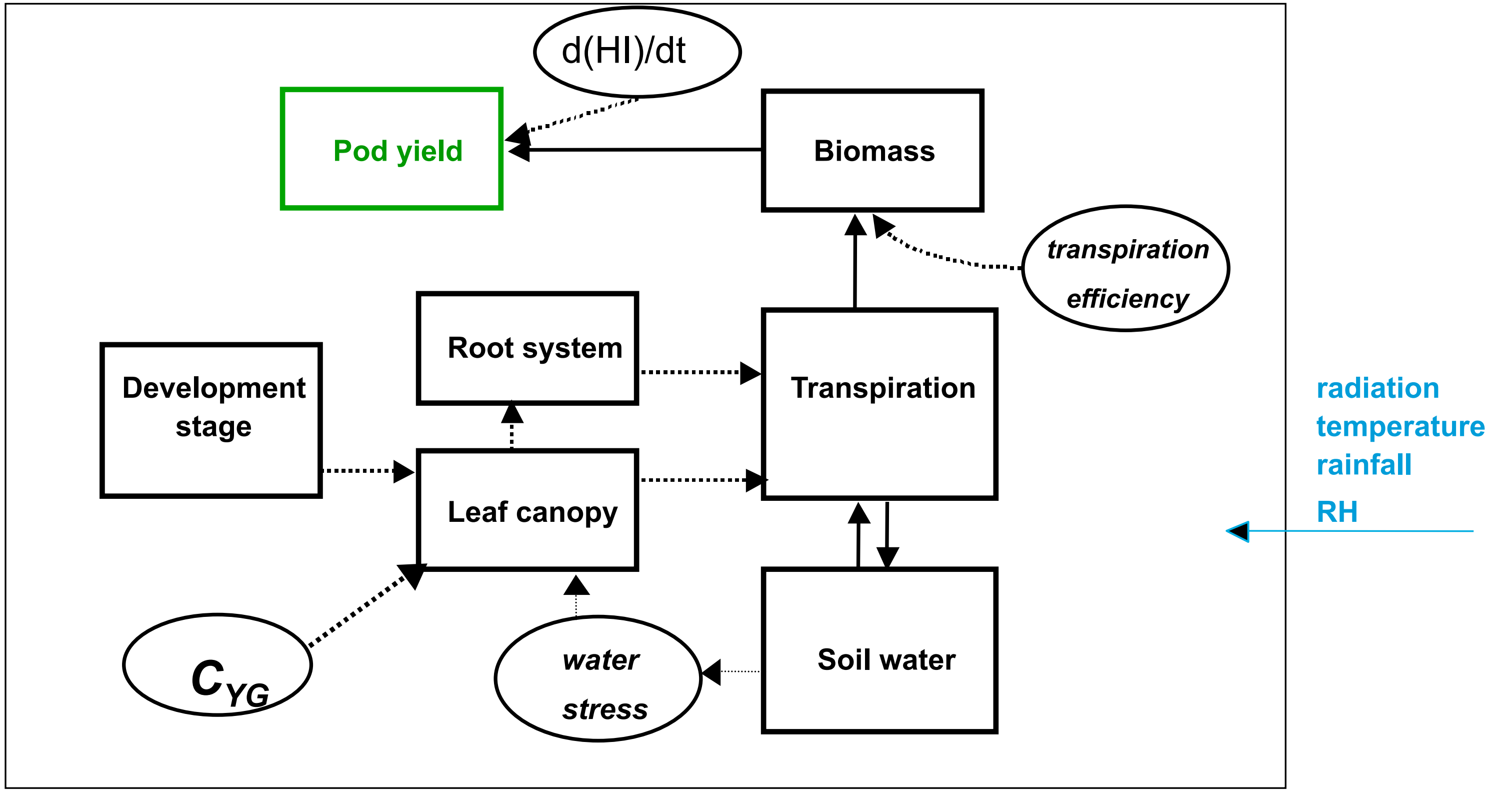
Wheat

Maize

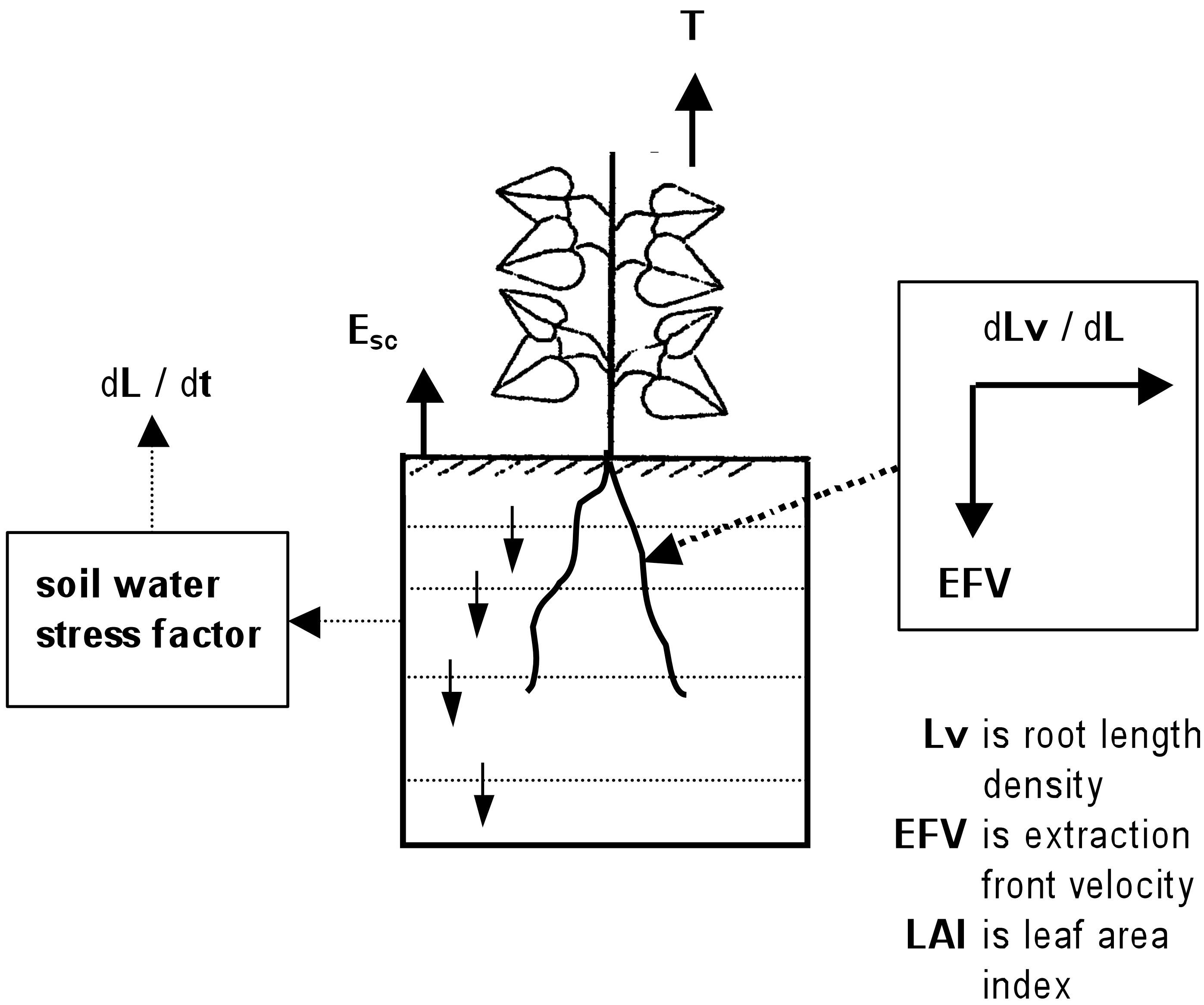
Groundnuts

Sorghum

General Large Area Model for Annual Crops (GLAM)



Relatively simple => adaptable to other annual crops or climate change adaptation scenario

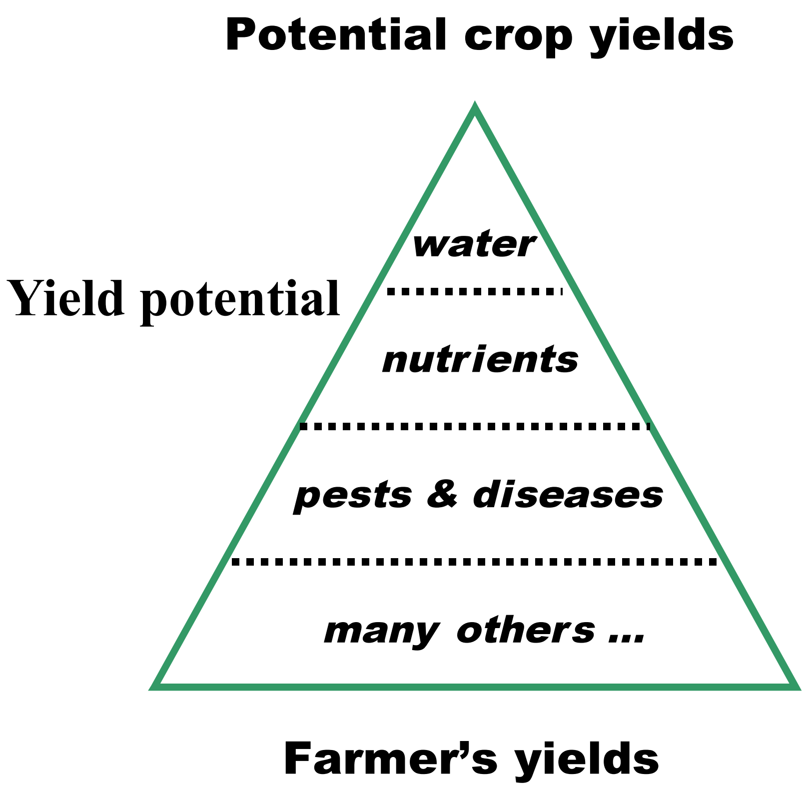

T
E_{sc}
dL / dt
soil water stress factor
dLv / dL
EFV
Lv is root length density
EFV is extraction front velocity
LAI is leaf area index

General Large Area Model for Annual Crops (GLAM): some parameters

- **Thermal duration**: Determines development rate
  - o Predict weather extremes at sensitive stages (e.g. flowering)
- **Transpiration efficiency** to calculate biomass
  - o Changes under elevated CO_2
- **Maximum rate of change of LAI**: determines growth of leaves
  - o Check model consistency by looking at Specific Leaf Area
- **Yield gap parameter**: time-independent site-specific parameter to account for the impact of differing nutrient levels, pests, diseases, non-optimal management etc.
  - o Process-based: acts on LAI to determine an effective LAI
  - o In practice, YGP can bias correct input weather data
  - o It is not the sole determinant of mean yield, however

Model calibration

Potential and actual yields



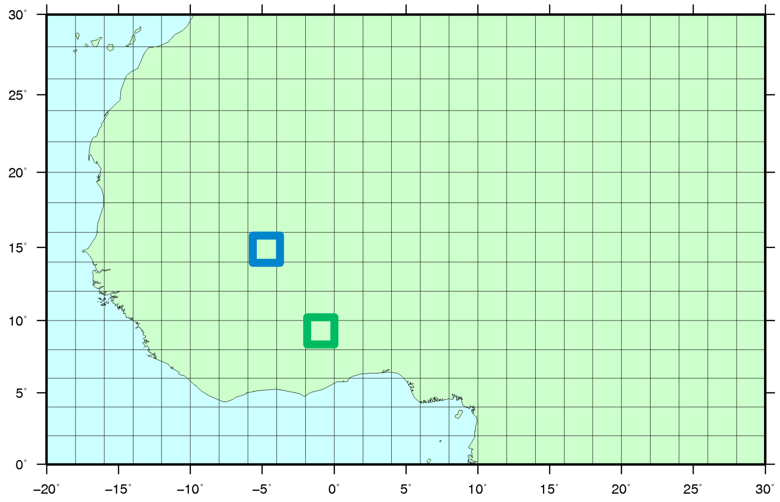
GLAM – Calibration

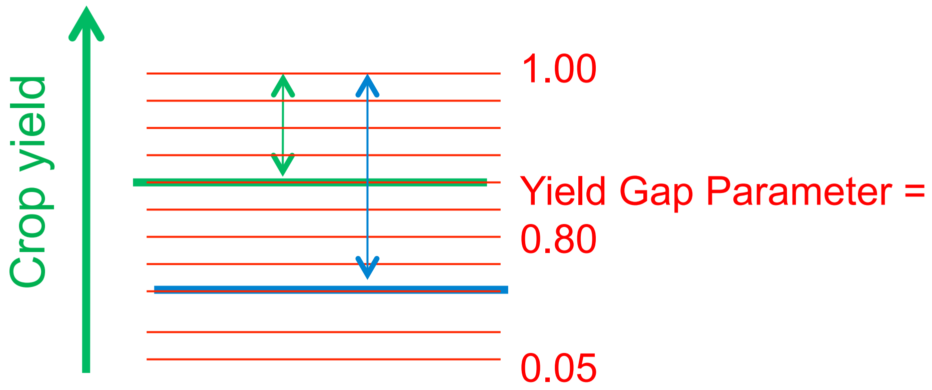
GLAM simulates the impact of weather on crop yields.

It does not explicitly simulate the impact of other factors such as nutrient deficiencies, pests, diseases, weeds

The yield gap parameter is a time-independent site-specific parameter that accounts for these factors.

It also acts to bias correct weather



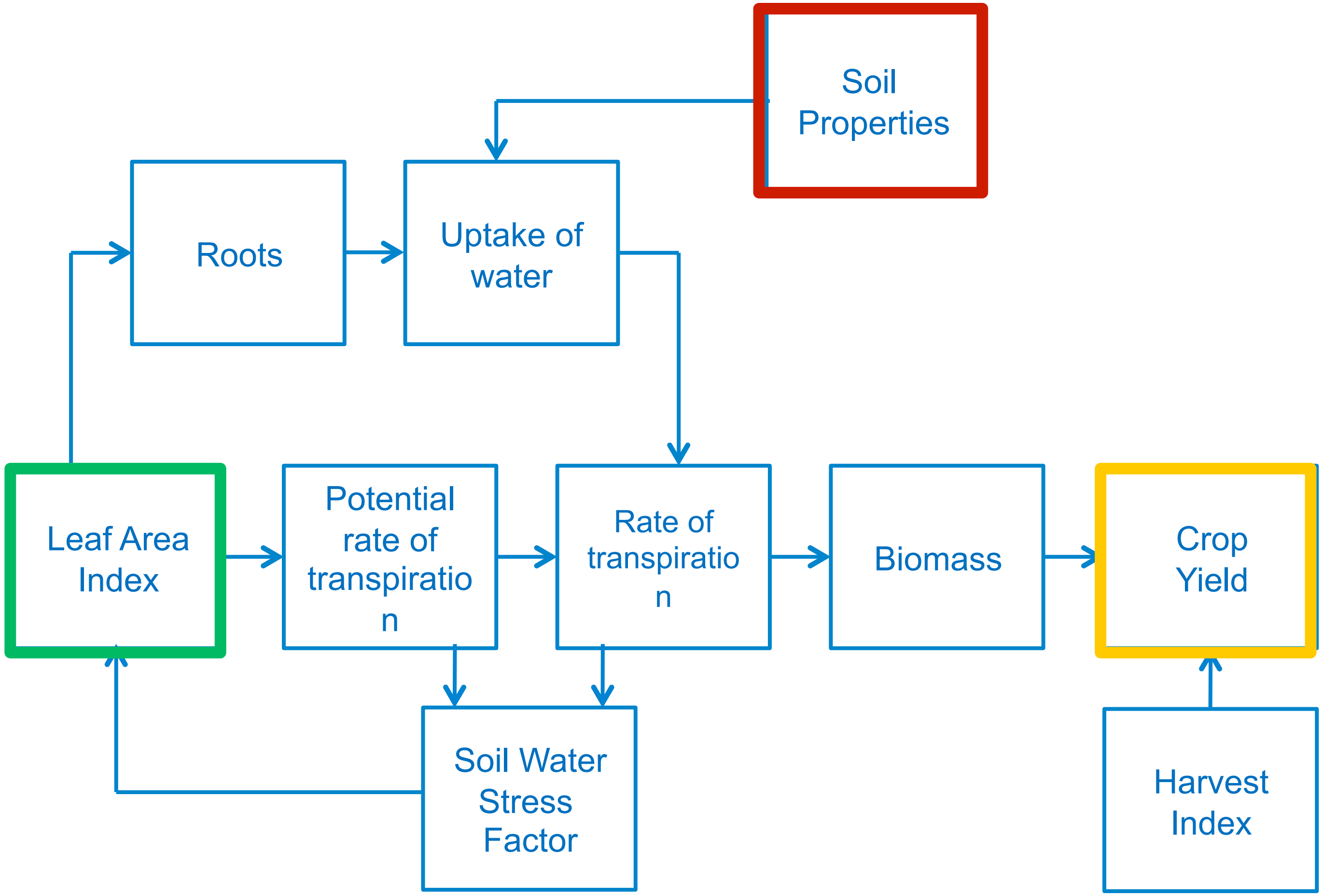


GLAM – The Yield Gap Parameter (YGP)

You can choose how the yield gap parameter reduces simulated yields.

Options include acting on:

- Crop yield
- Leaf area index
- Soil properties



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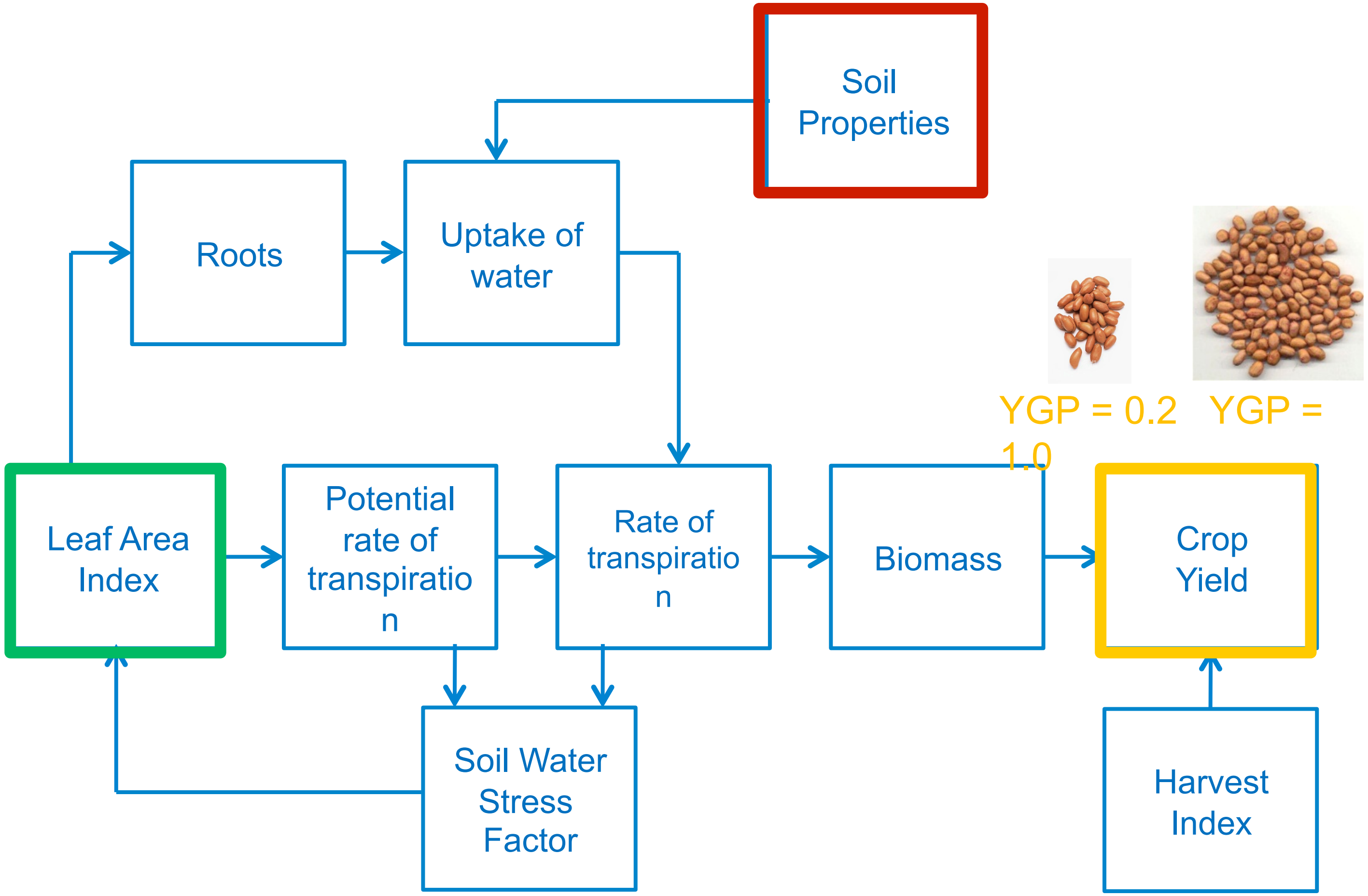

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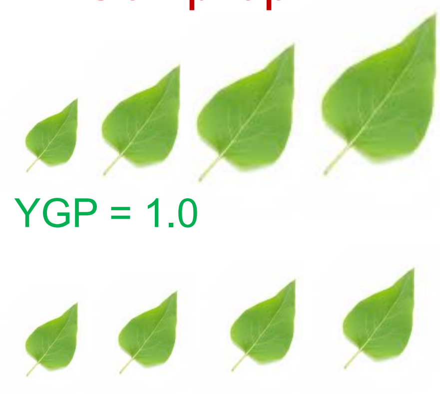

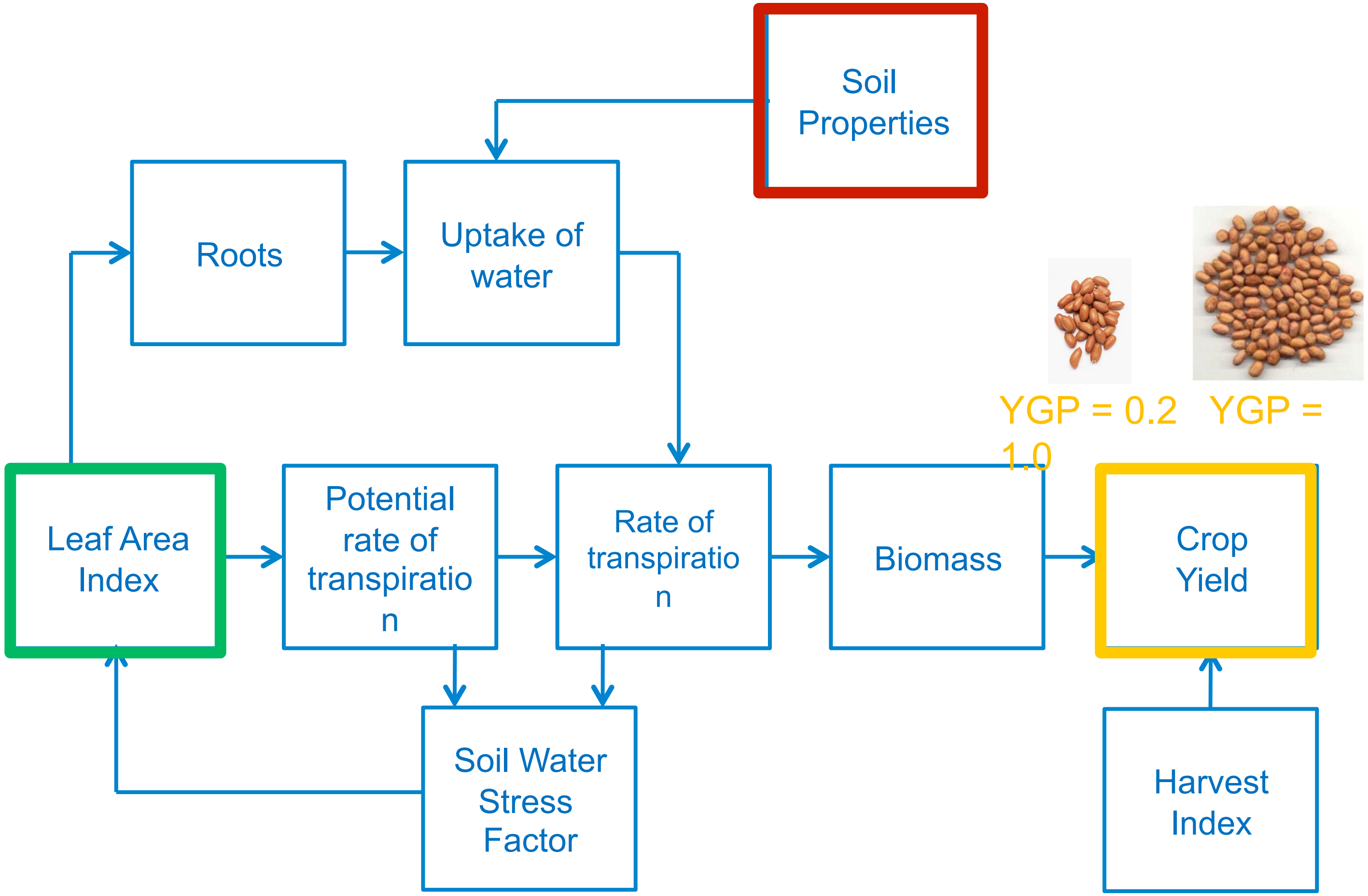

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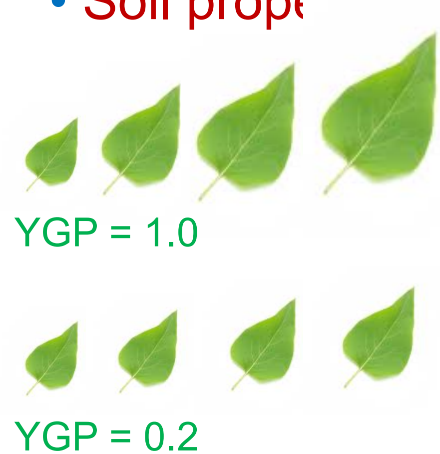
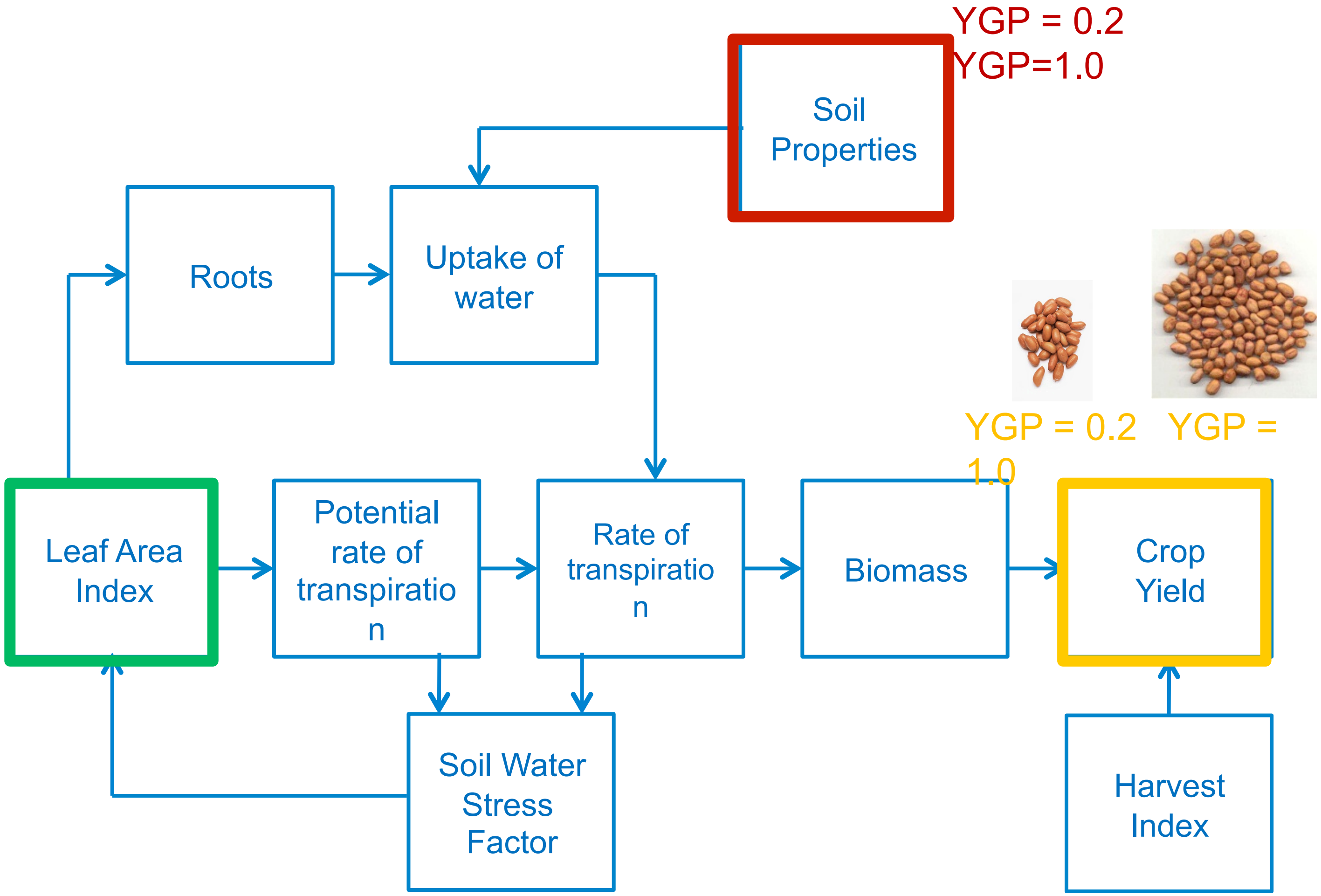


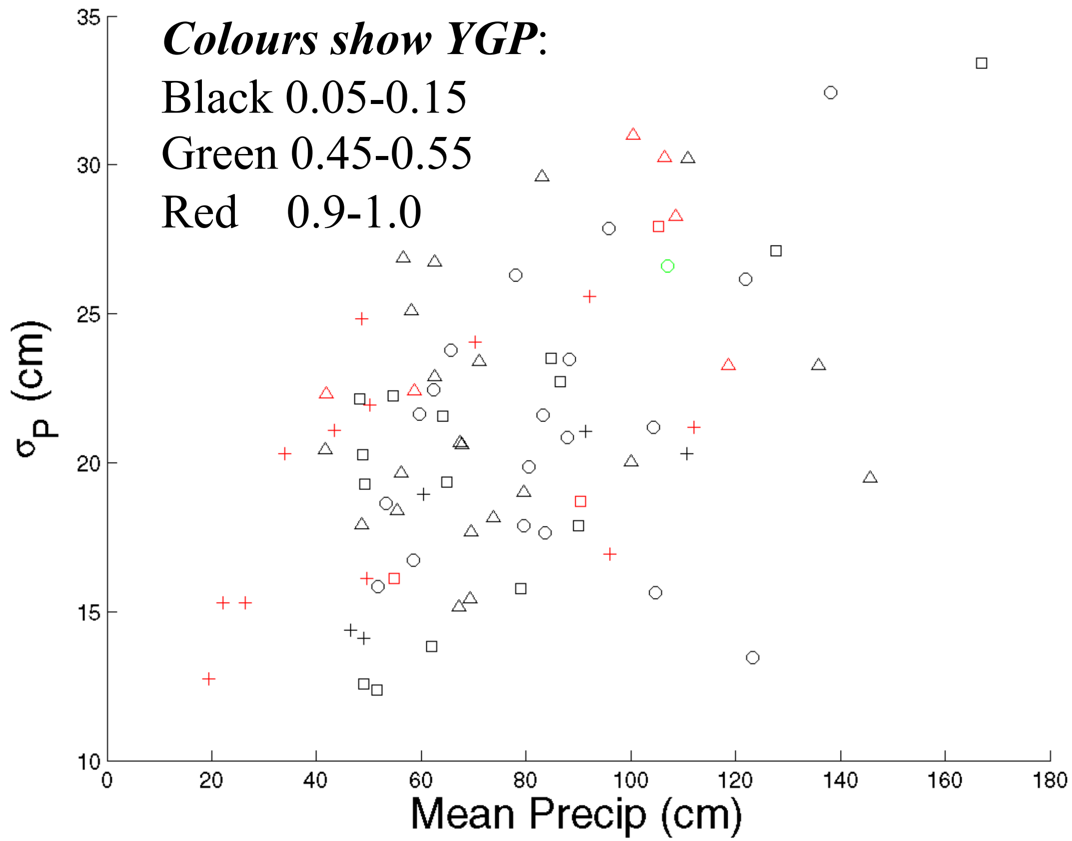


To what extent are mean yields determined by YGP?

- YGP values differ when calibrated on different input data; Hence it contains an element of bias-correction.

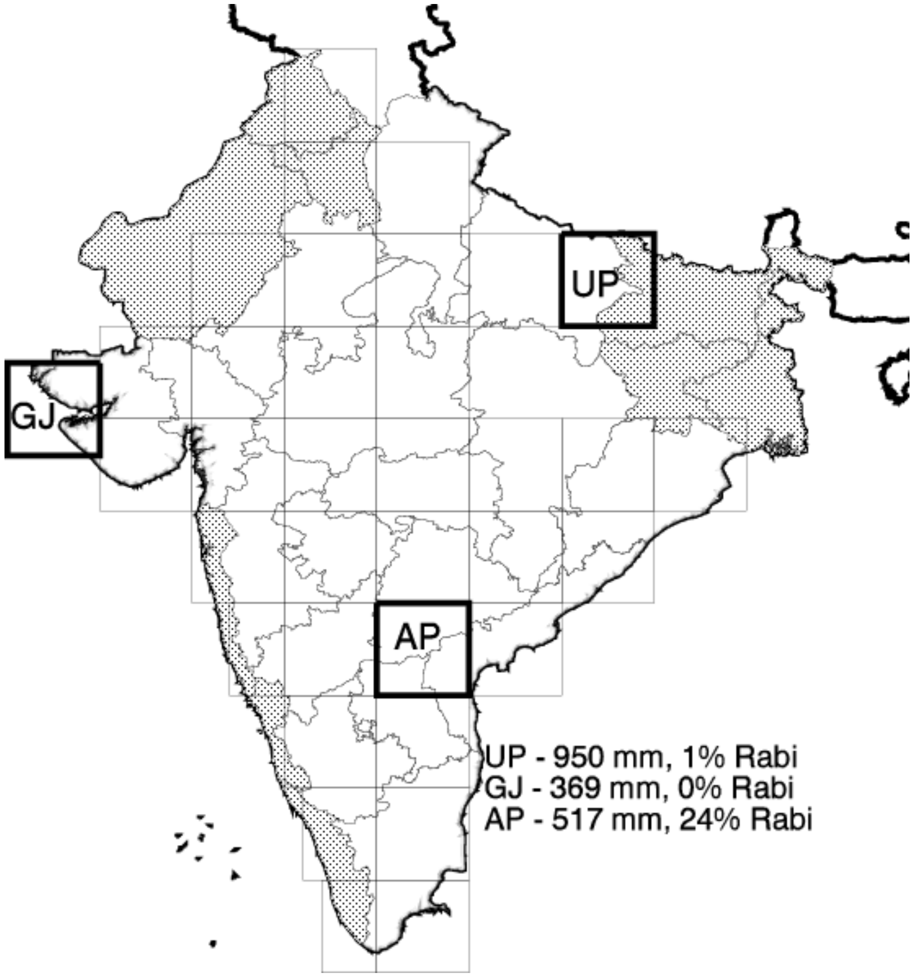
- However, does this mean that the mean yields are tuned to correct values by varying YGP?

Symbols show accuracy in simulation of mean yield:
Circles: within 5%
Squares: within 10%
Triangles: within 25%
+ : within 50%
X : within 100%



Model performance

Model configuration for groundnut in India using observed gridded data



Rainfall on 2.5x2.5^{o} grid (IITM)
Radiation 0.5 deg. (CRU)

and

IITM regional T_{max}, T_{min}
or CRU 0.5 deg. T, e

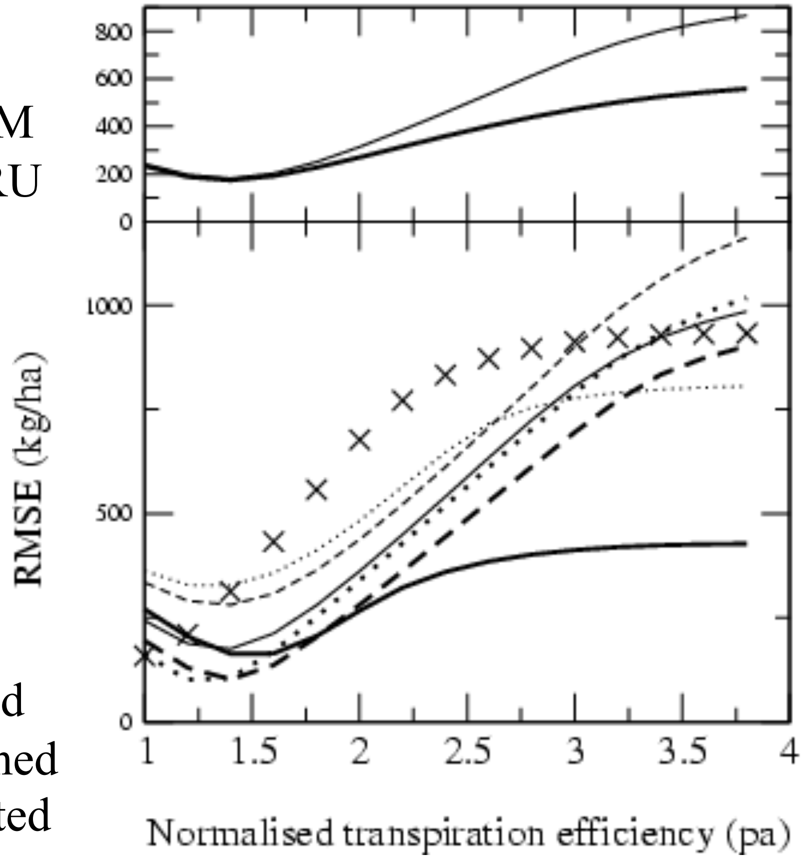
and

FAO 0.5 deg. soils data

All data monthly interpolated except for rainfall.

Optimisation of global parameters for groundnut across India

Thin – IITM
Thick - CRU



UP – solid
GJ – dashed
AP – dotted

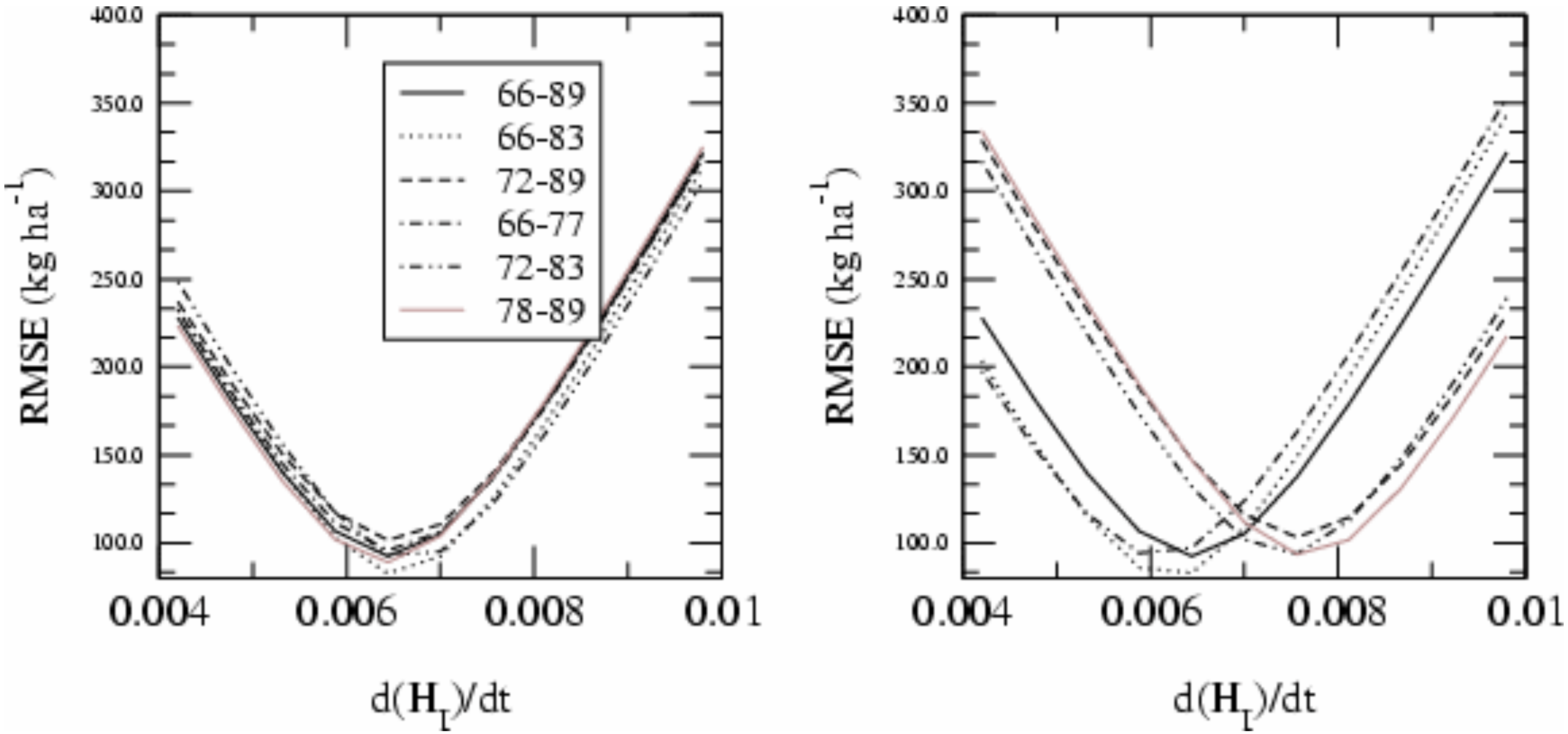
X – IITM-calibrated UP CRU run

Optimal values are within literature range (~ 1.3 - 4 Pa)

Optimal values are stable over space and input dataset provided C_{YG} is calibrated

C_{YG} can correct for (some) data input bias

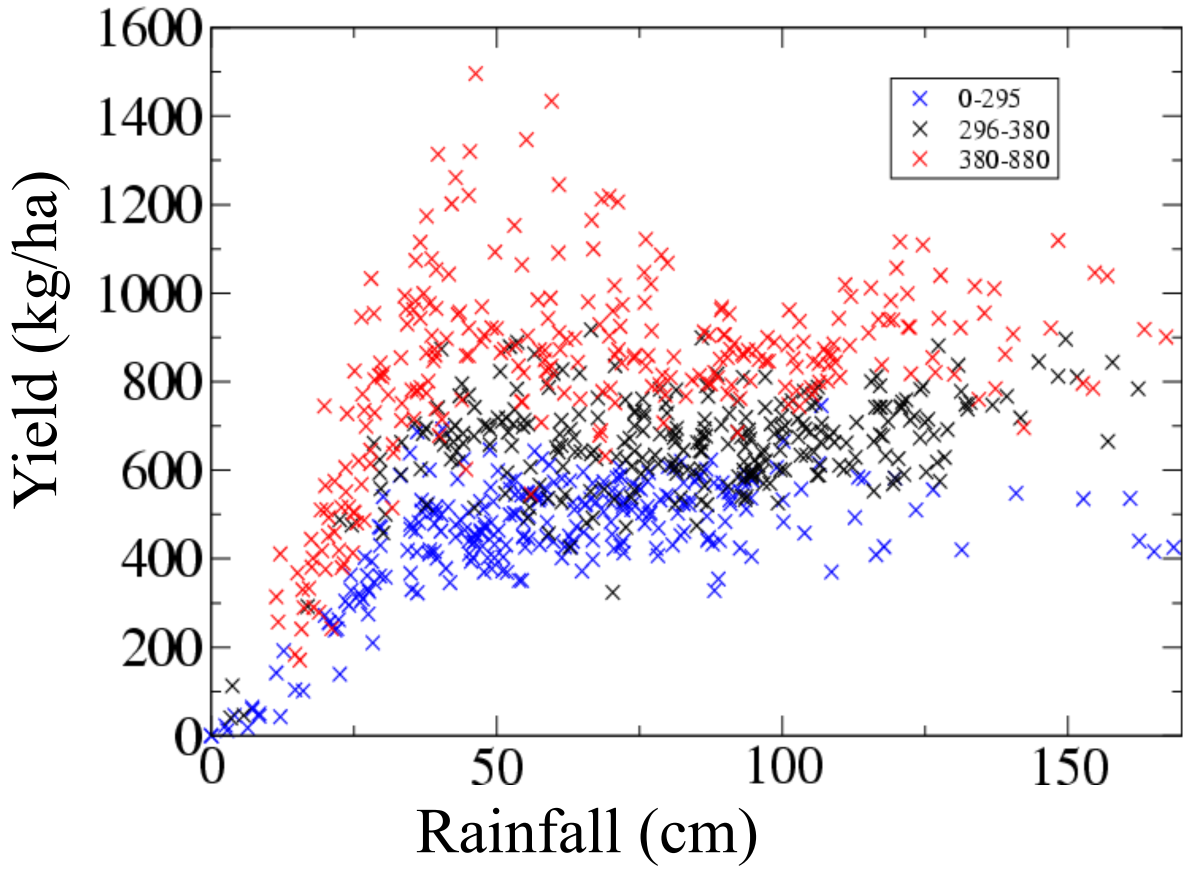
Optimisation II – stability over time



AP

Optimal values are stable over time provided the full baseline period is used for detrending

Model response to rainfall and radiation



Irrigated GLAM RUE = 0.71, 0.99, 1.00 g/MJ

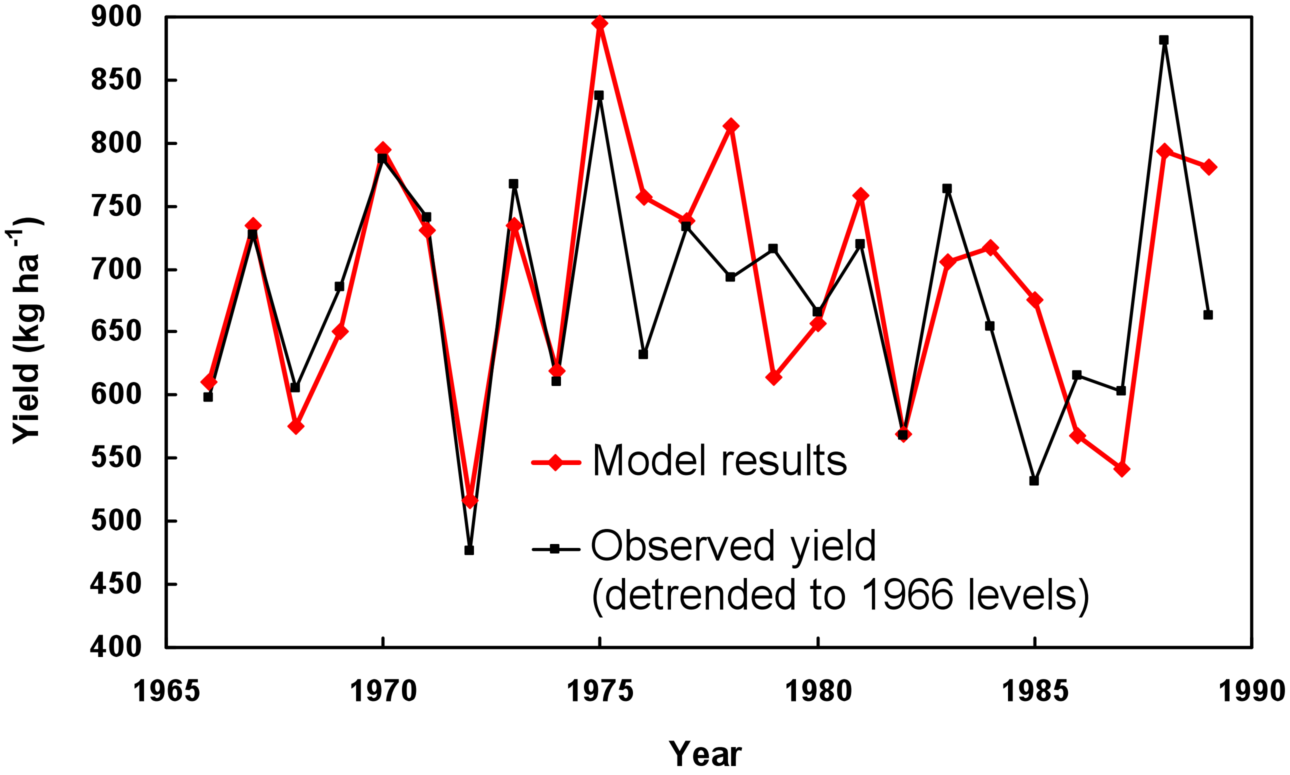
Rainfed GLAM RUE = 0.83, 0.63, 0.40 g/MJ

Observed values e.g. 0.74 (Azim-Ali, 1998), 1.00 (Hammer et. al. 1995) g/MJ

UP, AP, GJ

General Large-Area Model for annual crops

Results: all-India groundnut yield

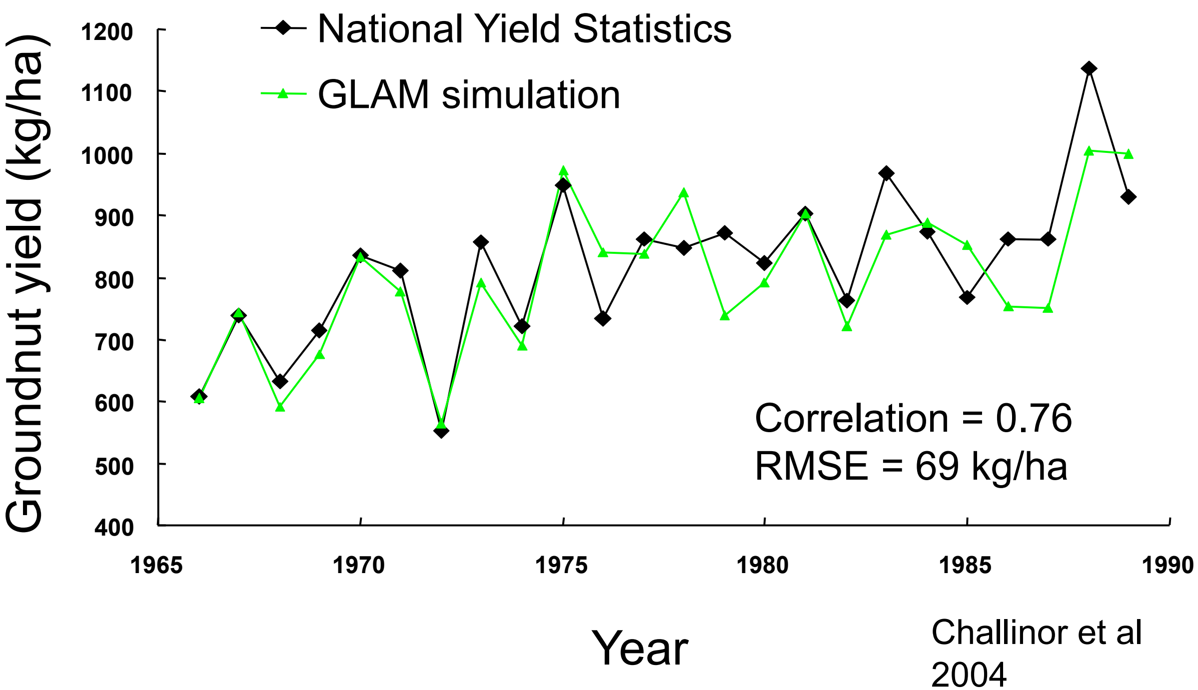


Challinor, A. J., T. R. Wheeler, J. M. Slingo, P. Q. Craufurd and D. I. F. Grimes (2004). Design and optimisation of a large-area process-based model for annual crops. Agricultural and Forest Meteorology, 124, (1-2) 99-120.

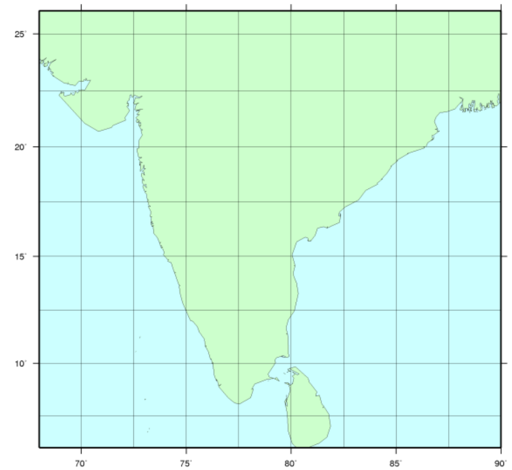
GLAM – Model performance

GLAM was used to simulate groundnut yields in India.

- Run on a 2.5° x 2.5° grid
- Years simulated 1966-1989
- Observed weather data



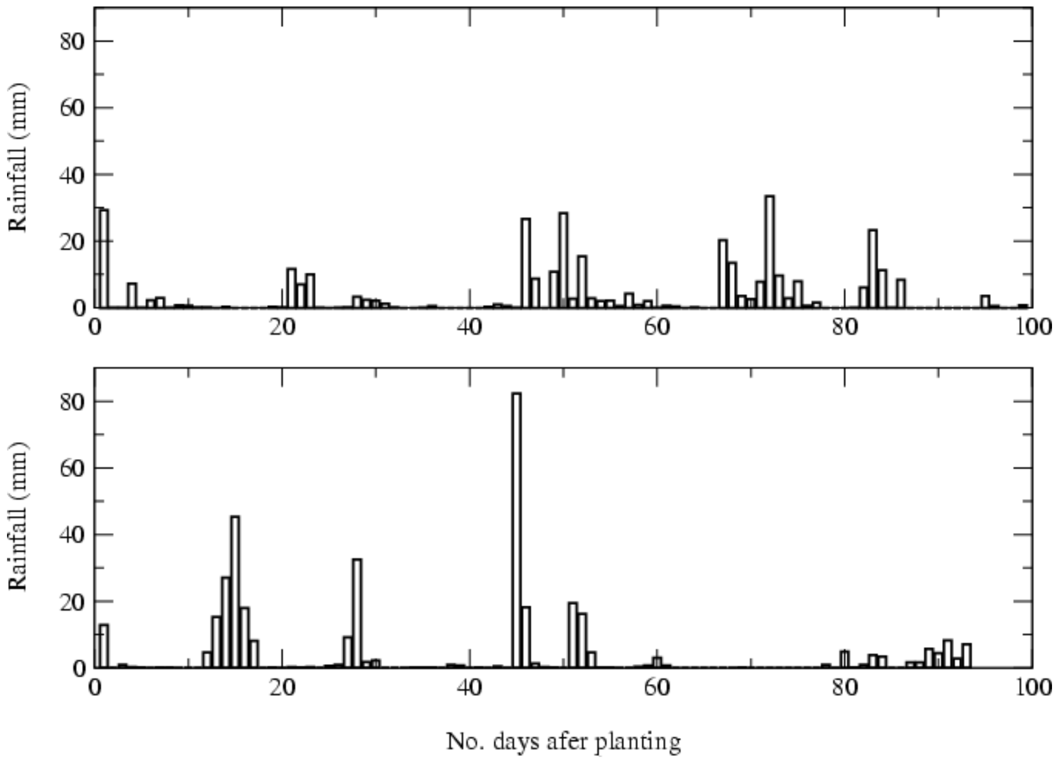
Challinor et al 2004



GLAM – Model performance

GLAM can capture the effects of sub-seasonal variability on crop yield.

Rainfall time series for one of the grid cells in India:



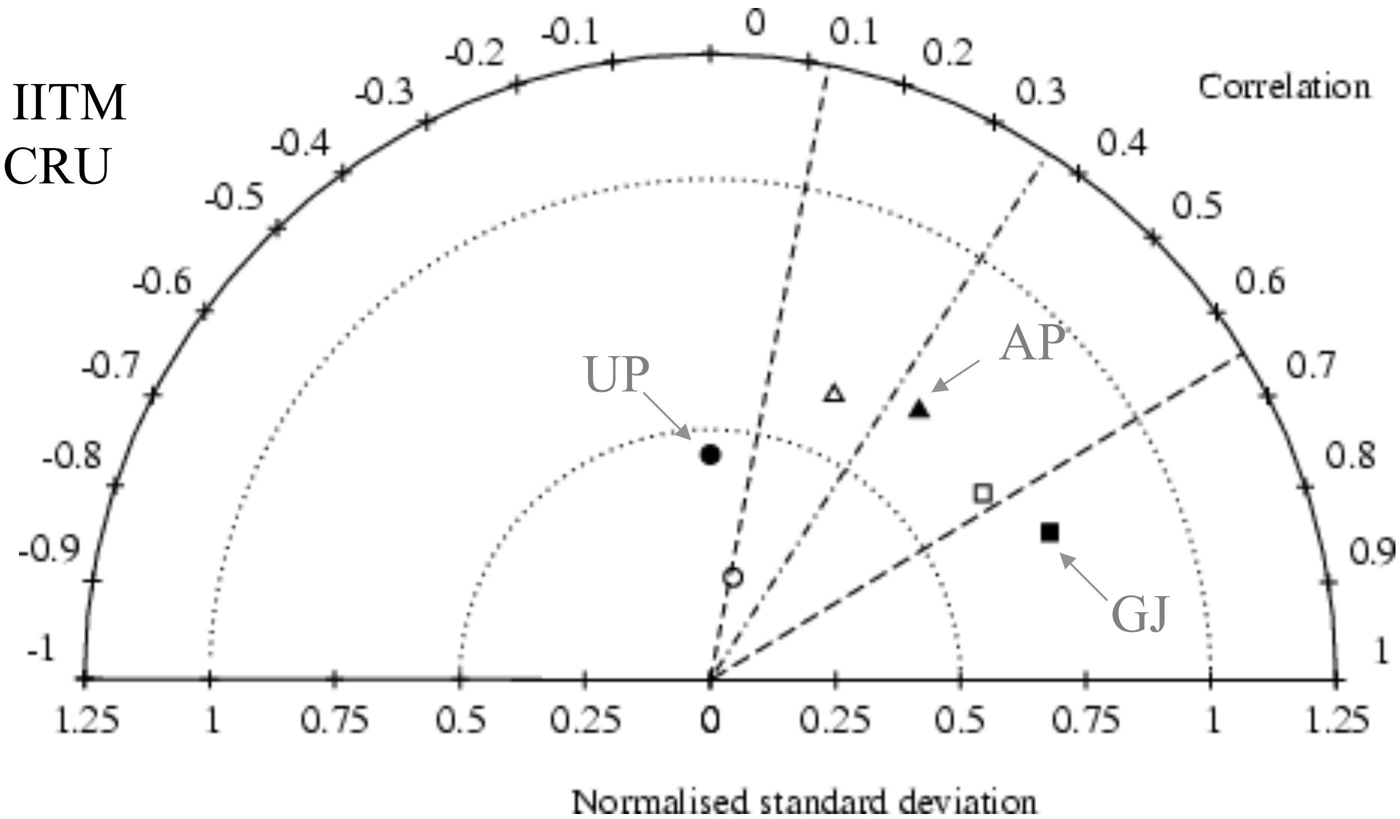
Challinor et al 2004

1975
Total rainfall 394 mm
Observed yield 1360 kg/ha
Simulated yield 1059 kg/ha

1981
Total rainfall 389 mm
Observed yield 901 kg/ha
Simulated yield 844 kg/ha

Summary of model performance

Filled = IITM
Open = CRU



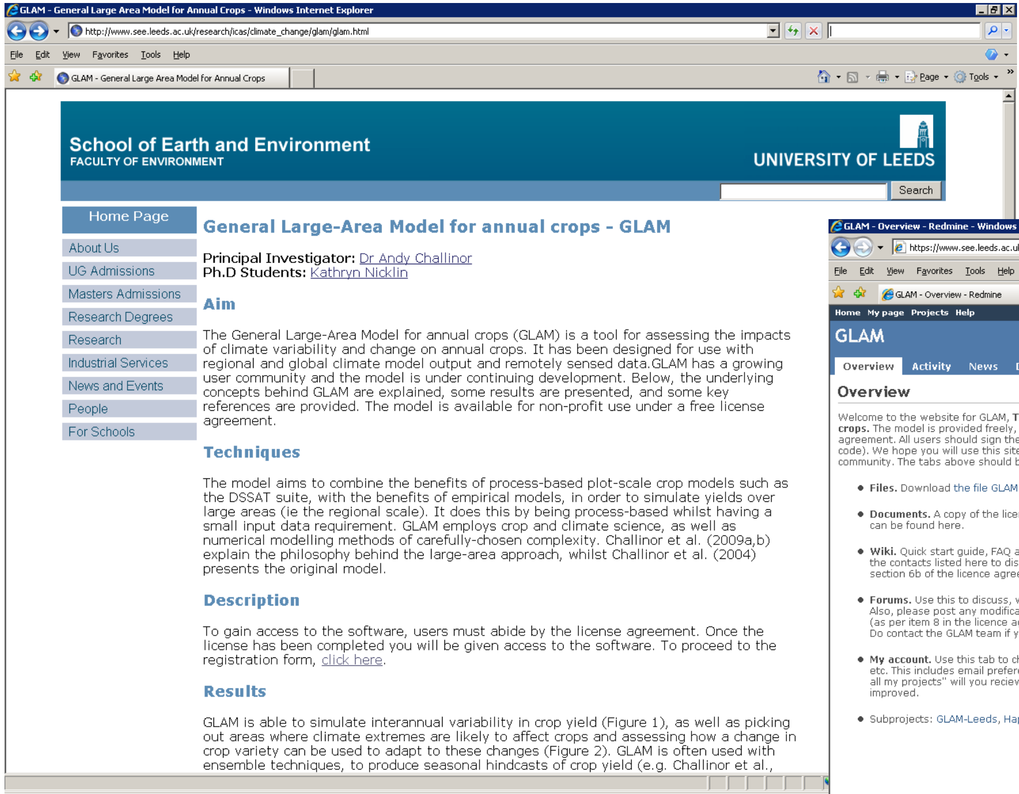
Taylor diagram (Taylor, 2001)

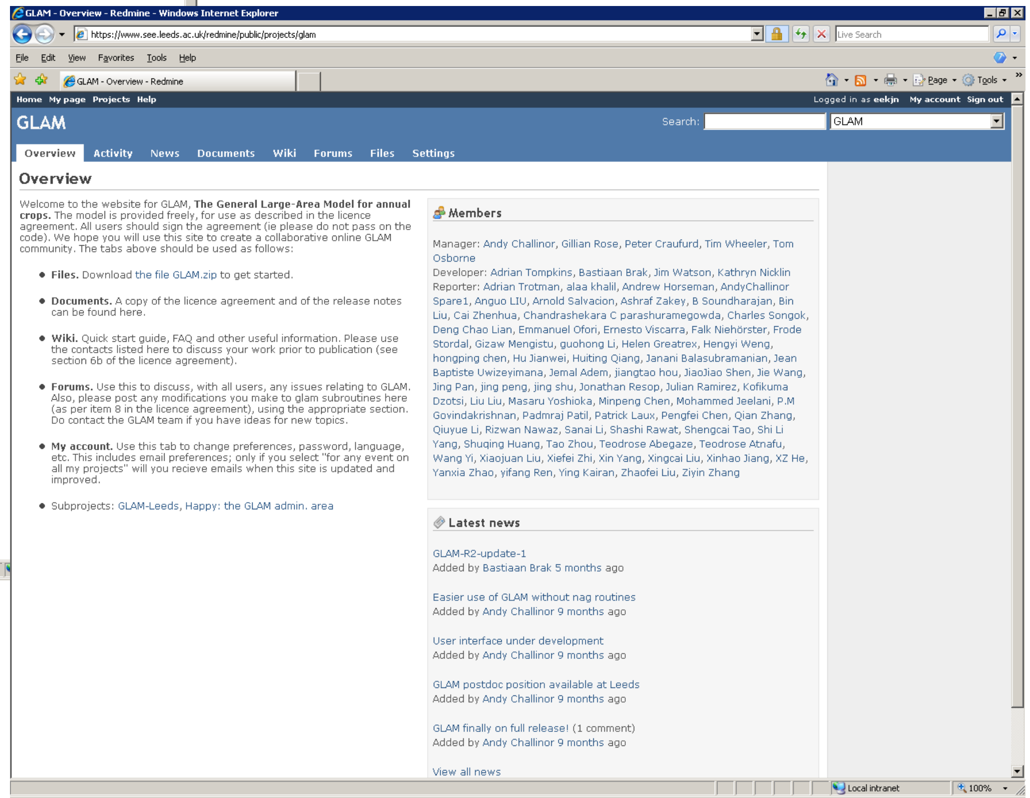
Case studies for lab class

GLAM lab class

First download GLAM

www.see.leeds.ac.uk/research/icas/climate_change/glam/glam.html





GLAM lab class

Then **choose case study:**

- Ghana
- China

For details see
https://www.see.leeds.ac.uk/redmine/public/projects/glam/wiki
(unique username and password needed)

And **decide whether to use a text edit or the beta version GUI**

See https://www.see.leeds.ac.uk/redmine/public/projects/glam/wiki/blabla

Ghana

Step 1: Decide on the grid cells/regions GLAM will be run for.

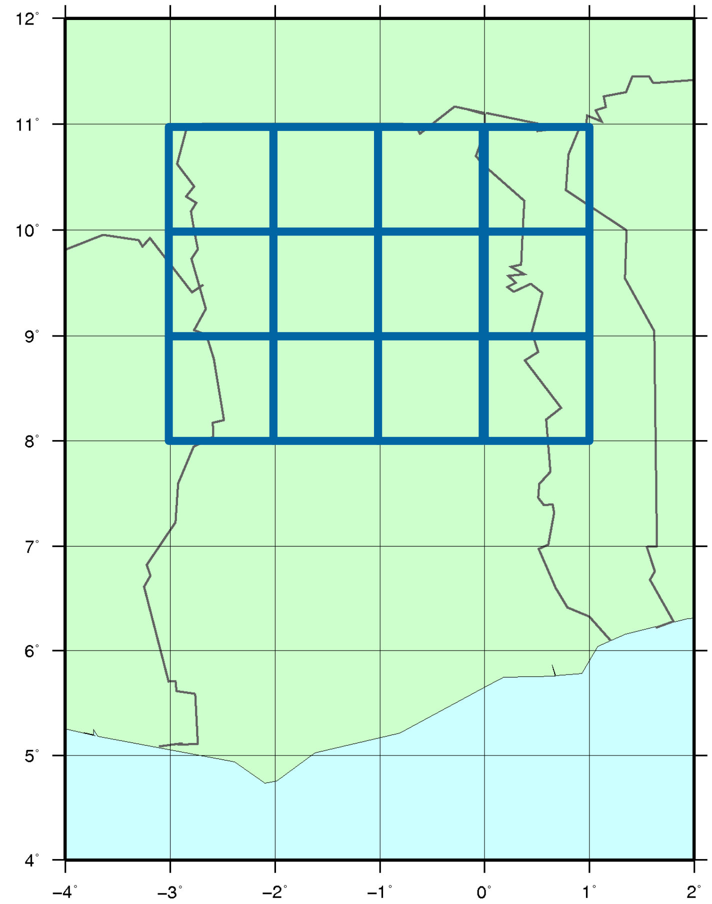
Depends on:

• Available input data

• Scale of relationship between weather and yield

• Aim of the project

Ghana – GLAM will be run on 1°x 1° gridcells



Ghana

Step 2: Collect and organise input data

Daily weather data

Rainfall, min and max temperature, solar radiation.

Ghana - ERA-Interim data (reanalysis data from the ECMWF)

- Global Precipitation Climatology Project (GPCP) rainfa

Ghana

Step 3: Collect and organise input data

Daily weather data

Rainfall, min and max temperature, solar radiation.

Ghana – ERA-Interim data (reanalysis data from the ECMWF)

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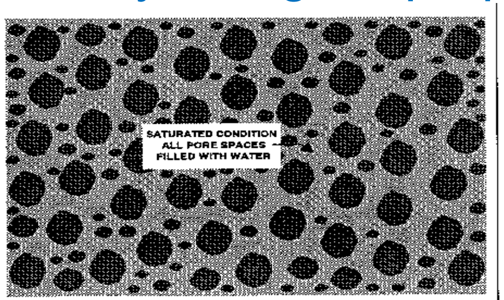
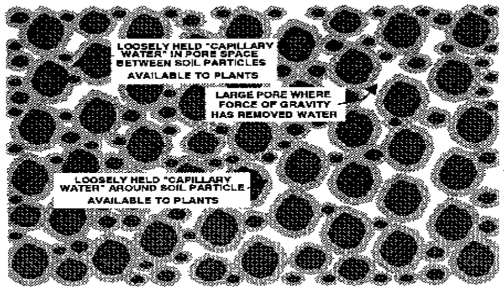
Soil data

Soil hydrological properties (can be found from soil texture):

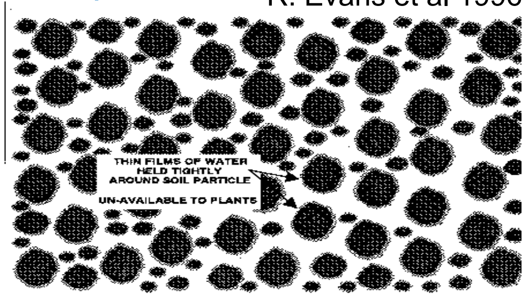
R. Evans et al 1996



Saturation limit:
maximum amount of
water in the soil.



Drained upper limit:
water held after thorough
wetting and drainage



Lower limit:
any remaining water
can not be extracted.

Ghana – Soil texture information from FAO soil map of the world

– Data averaged onto model grid

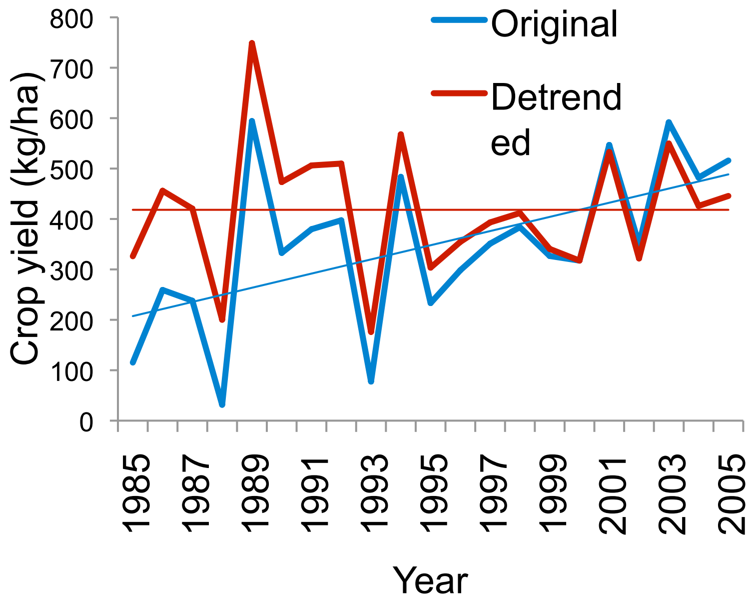
Ghana

Step 4: Collect and organise input data

Planting date information
Exact planting date or start of 'intelligent sowing window'
Ghana – Literature (e.g. Naab et al 2005)

Observed yield data

Crop yield (kg/ha) = Production (kg) / Cultivated area (ha)

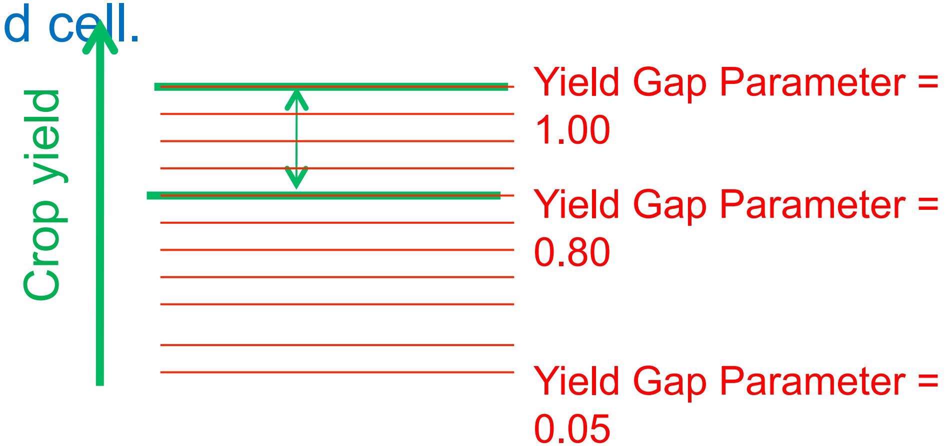


Ghana – District level data from Charles Yorke (Ghana Met Agency)
– Calculate yield data for model grid cells
– Remove 'technology trend'

Ghana

Step 5: Check parameter values are appropriate for local cultivars.

Step 6: Run GLAM in 'calibration mode' to find the yield gap parameter (YGP) for each grid cell.



Step 7: Run GLAM using these YGPs – compare simulated yields to observed yields.