Satellite-based rainfall monitoring for Africa - Time Series, Ensembles and Crop Yield Forecasting

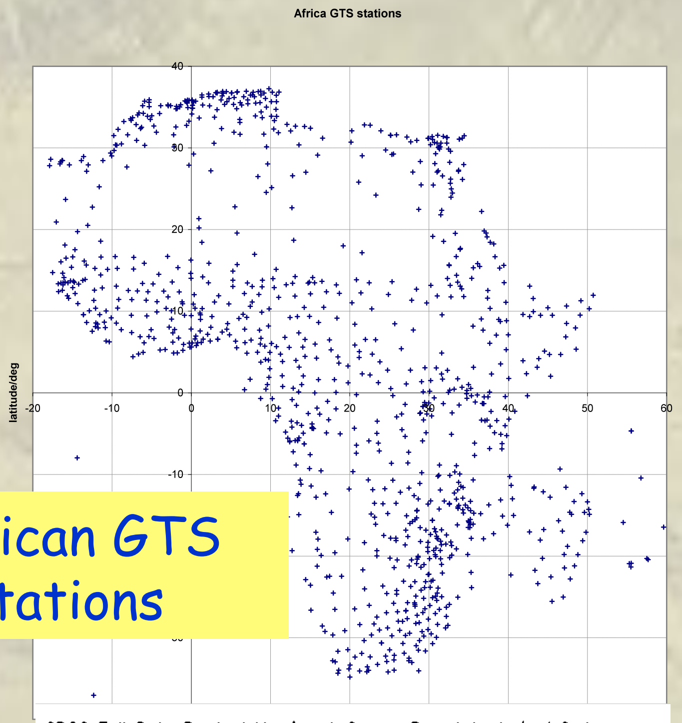
David Grimes
Elena Tarnavsky
Helen Greatrex
Ross Maidment

TAMSAT = *T*ropical *A*pplications of *M*eteorology using *SAT*ellite data

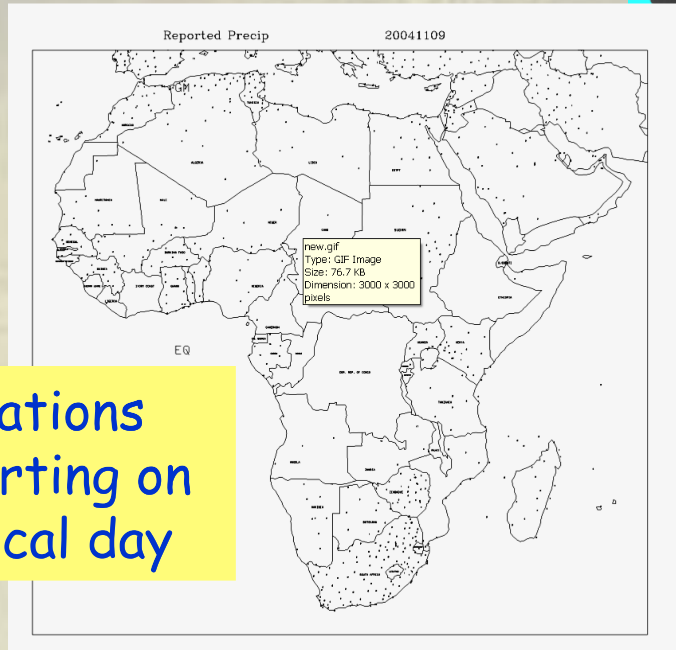
Content of presentation

- TAMSAT rainfall algorithm
- Validation of rainfall estimates
- TARCAT 29 year time series
- Rainfall ensembles from satellite data
- Crop yield forecasting
- Conclusions

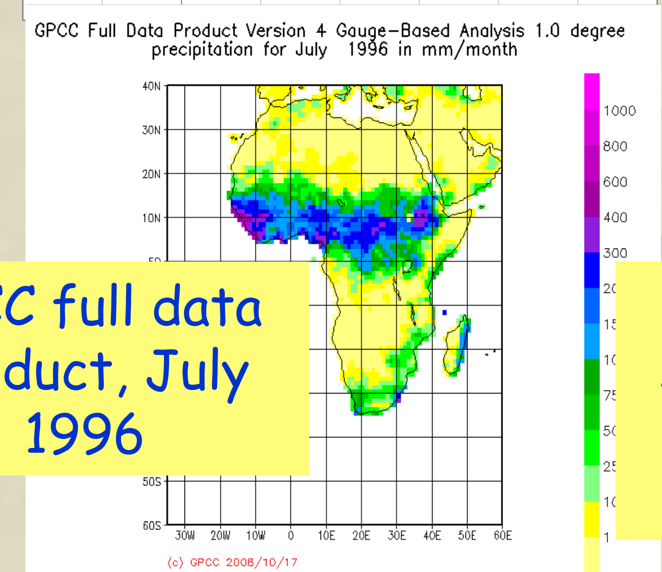
State of African raingauge network



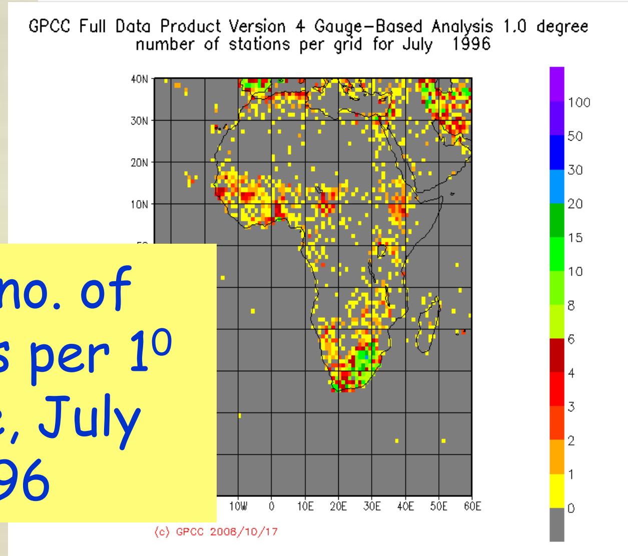
African GTS stations



Stations reporting on typical day



GPCC full data product, July 1996

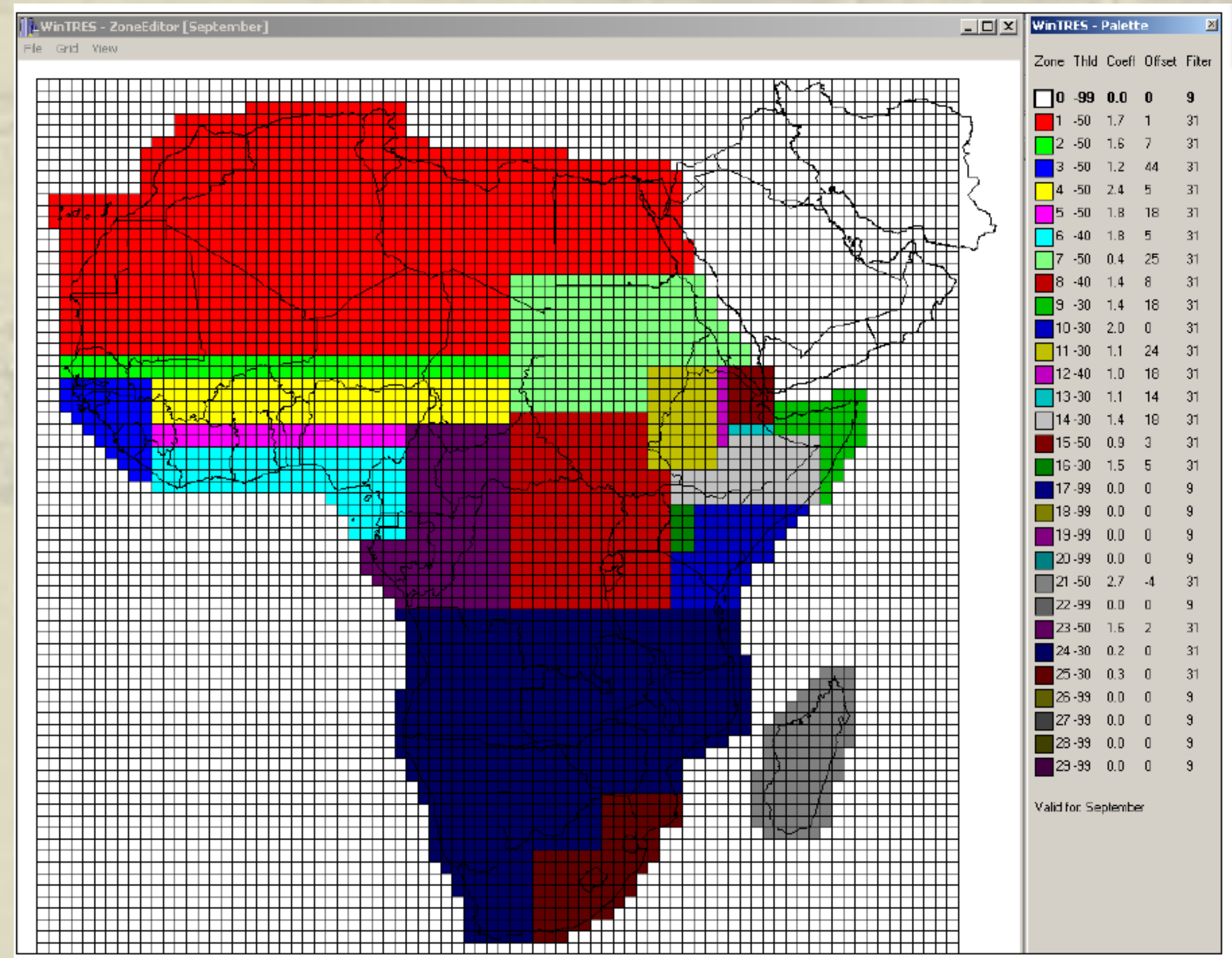


GPCC no. of stations per 1^0 square, July 1996

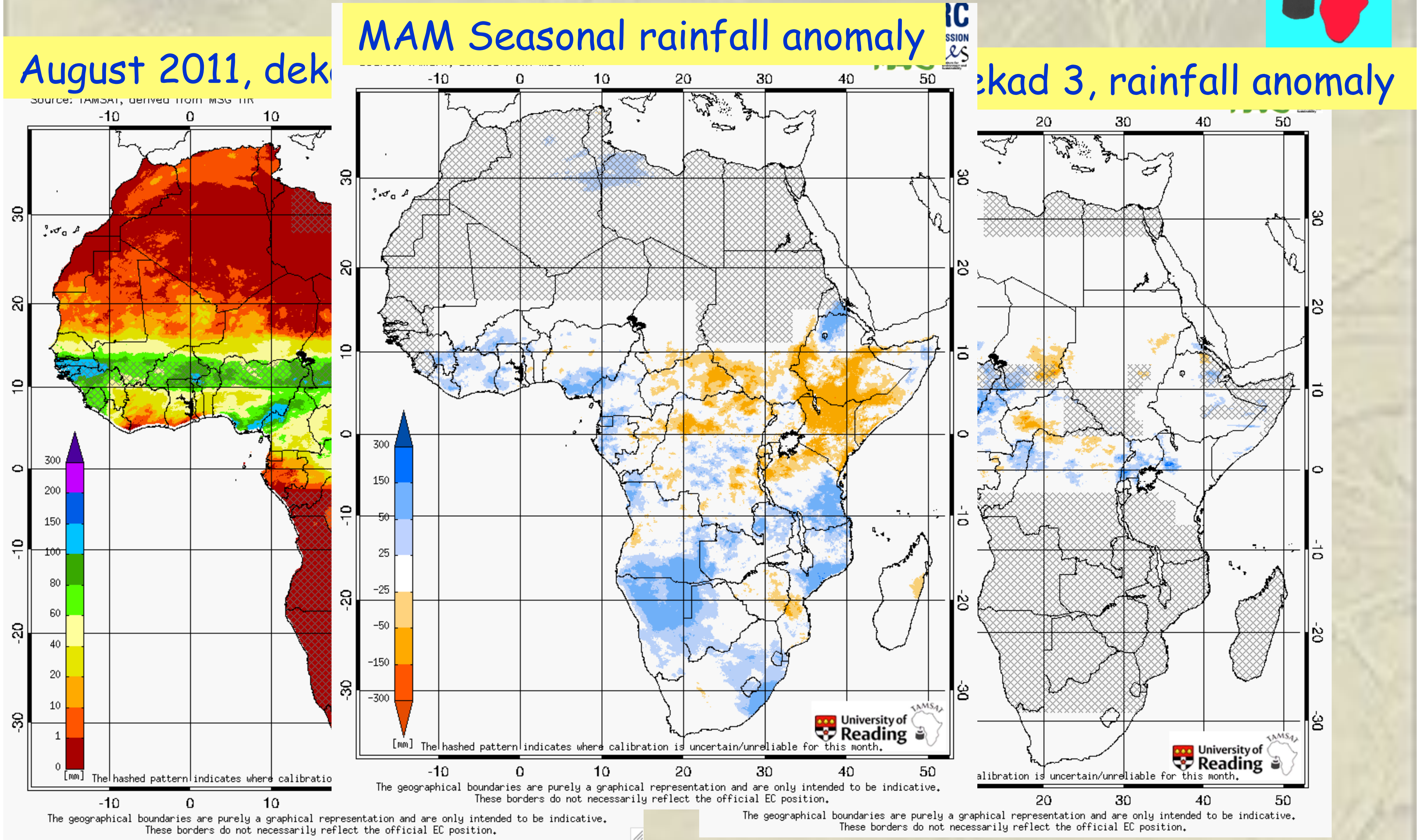
TAMSAT algorithm

- Use Meteosat TIR imagery
- Identify cloud top temperature threshold T_t distinguishing between rain and no rain
- Calculate Cold Cloud Duration (CCD) for each pixel (length of time cloud top is colder than T_t)
- Estimate rain amount as $rain = a_0 + a_1\ CCD$
- a_0, a_1, T_t calibrated against local gauges using **historic data**
- Calibration parameters vary in space and time

September calibration regions



TAMSAT rainfall estimates



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Validation of satellite rainfall

Question:

There are many methods of estimating rainfall from satellite data.

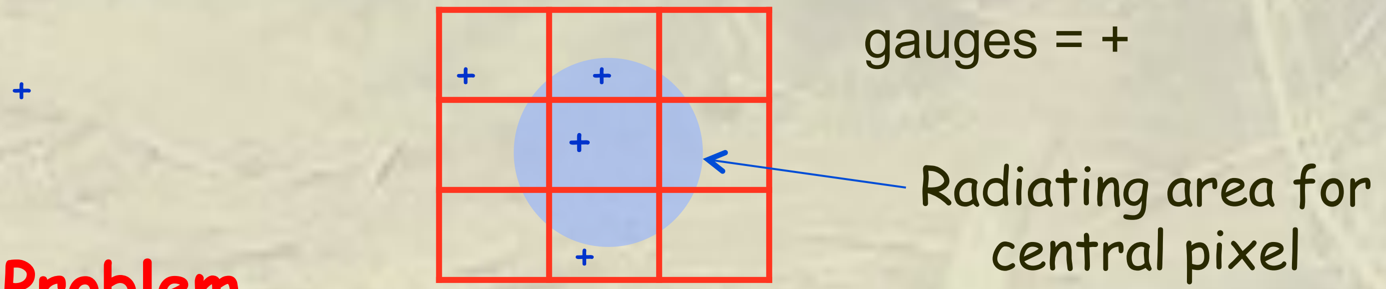
How do we know how good (or bad) are the satellite rainfall estimates?

Answer:

Compare with raingauge data

But this must be done with care!!!

Use of gauge measurements for validation



Problem

Gauge gives point value but satellite or model give area average

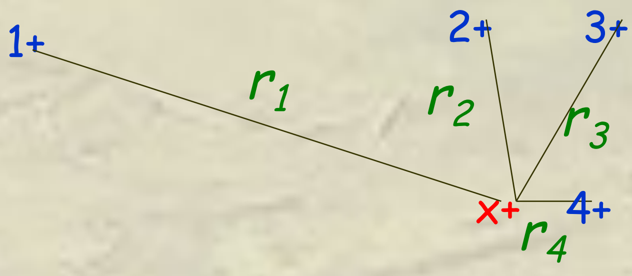
Question

How do we compare like with like?

Answer

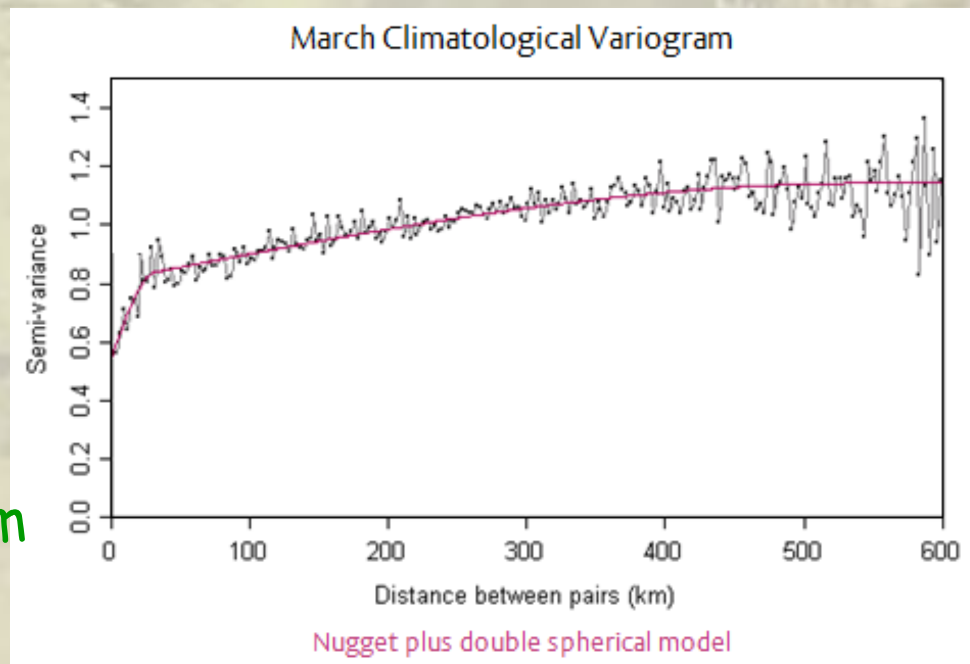
Apply kriging to each pixel or grid square and calculate 'best' area estimate + associated error

Interpolation using kriging (point)

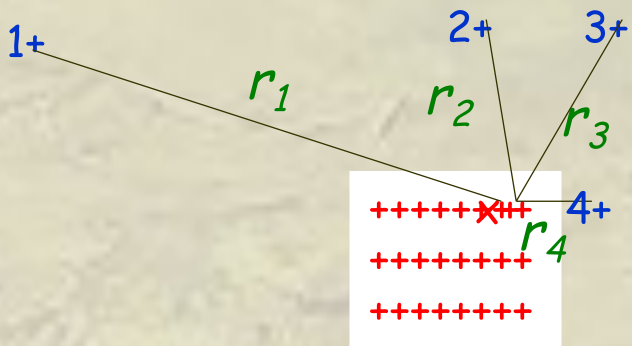


$$R_x = \sum_{i=1}^{N} w_{xi} R_i$$

- Kriging interpolates unobserved points as a weighted average of surrounding observations
  - weight w_{xi} depends on distance r_i from target point
  - weight w_{xi} depends on local spatial correlation pattern of rainfall – usually represented by variogram or correlogram



Interpolation using kriging (area)



$$R_x = \sum_{i=1}^{N} w_{xi} R_i$$

- Areal average estimated by interpolating to lots of points within area and computing mean
- Kriging gives an **error estimate** for each interpolated value

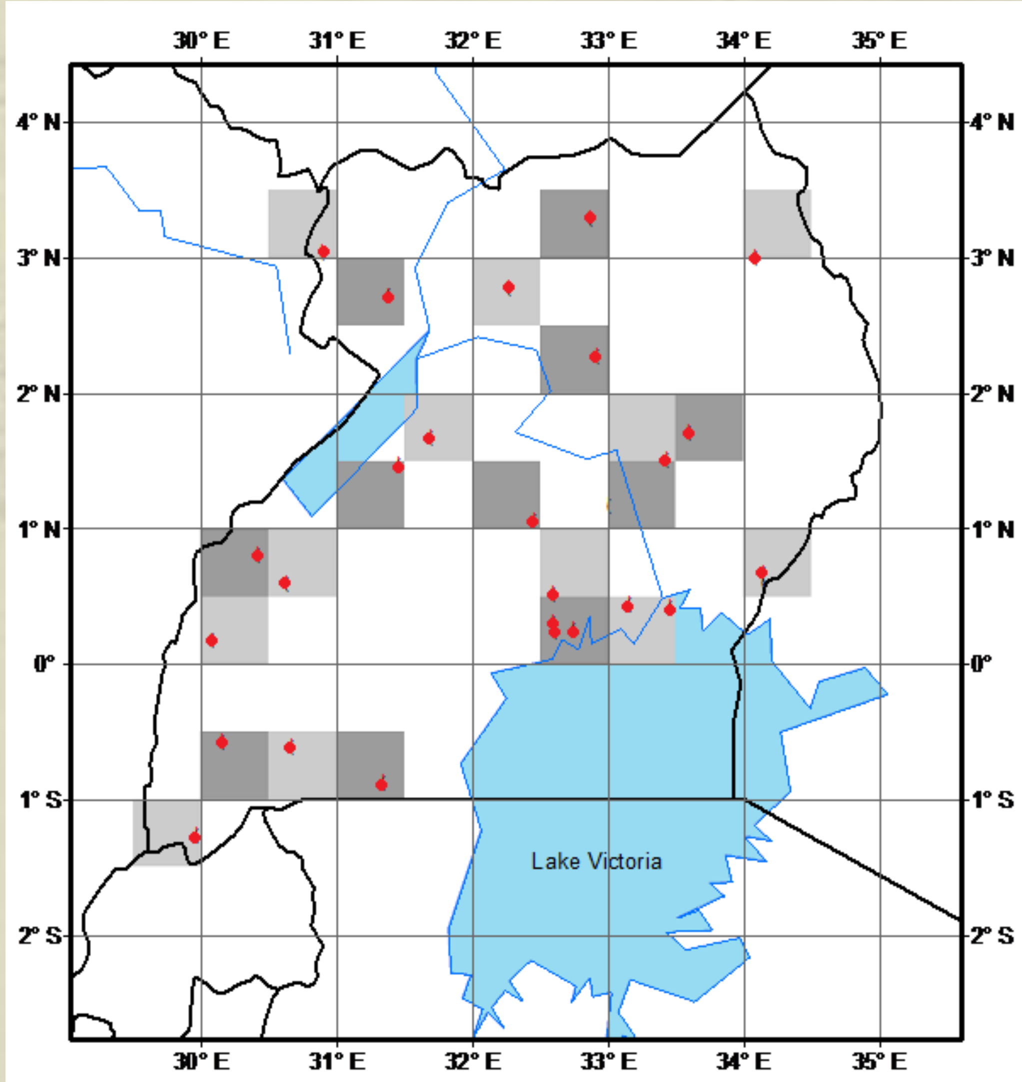
Validation studies

- Very few *careful* validation studies of satellite-based rainfall in Africa
- Three examples
  - Uganda - TAMSAT
  - Ethiopia - IRI, Univ. Columbia
  - Sahel AMMA window- Agrhymet

Validation Study 1 - Uganda

- Comparison of TAMSAT, NOAA-RFE, ERA-40 and ERA-Interim rainfall estimates for Uganda
- Time period: Feb-Jun, 2000 - 2005
- All estimates averaged to 0.5^0 spatial scale and compared against data from 25 rain gauges kriged to the same spatial scale

Validation Study 1 - Uganda
Gauge locations



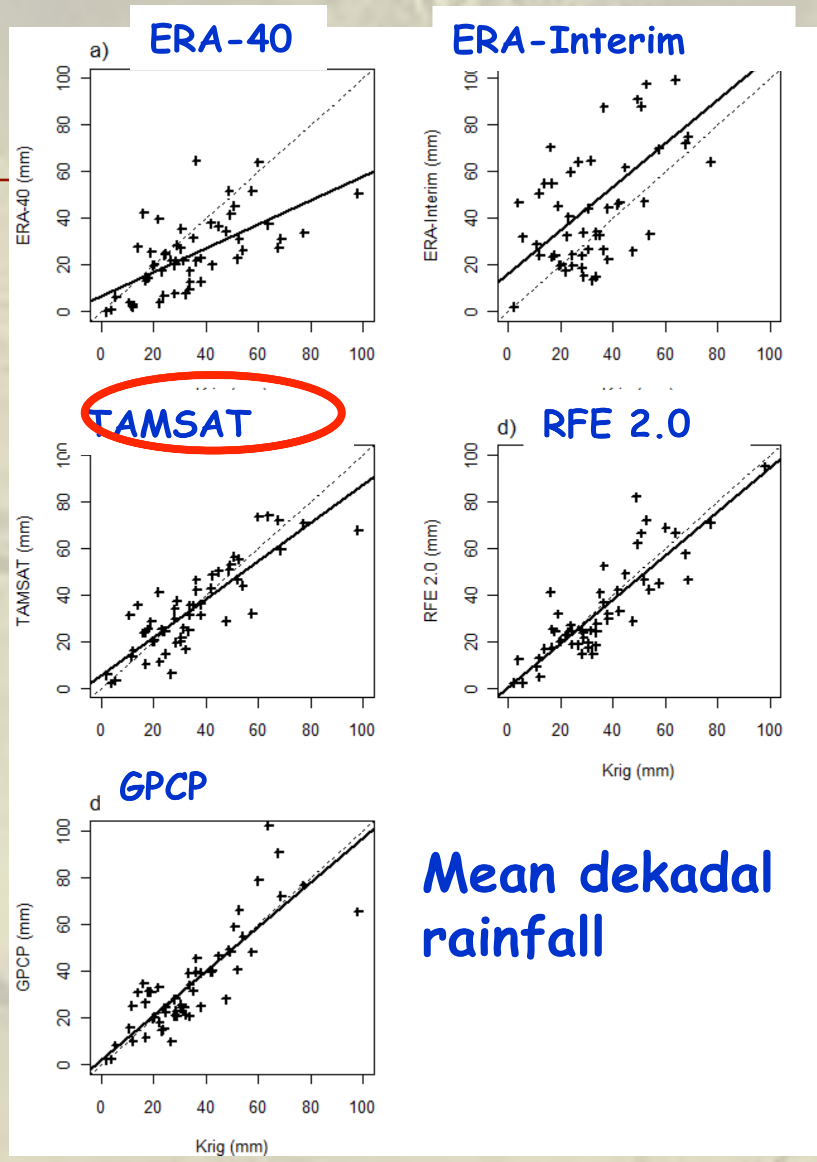
Only grid squares containing at least one gauge are used in the validation

Validation Study 1 - Uganda

Validating rainfall products against kriged gauge data (resolution: 0.5°x0.5°)

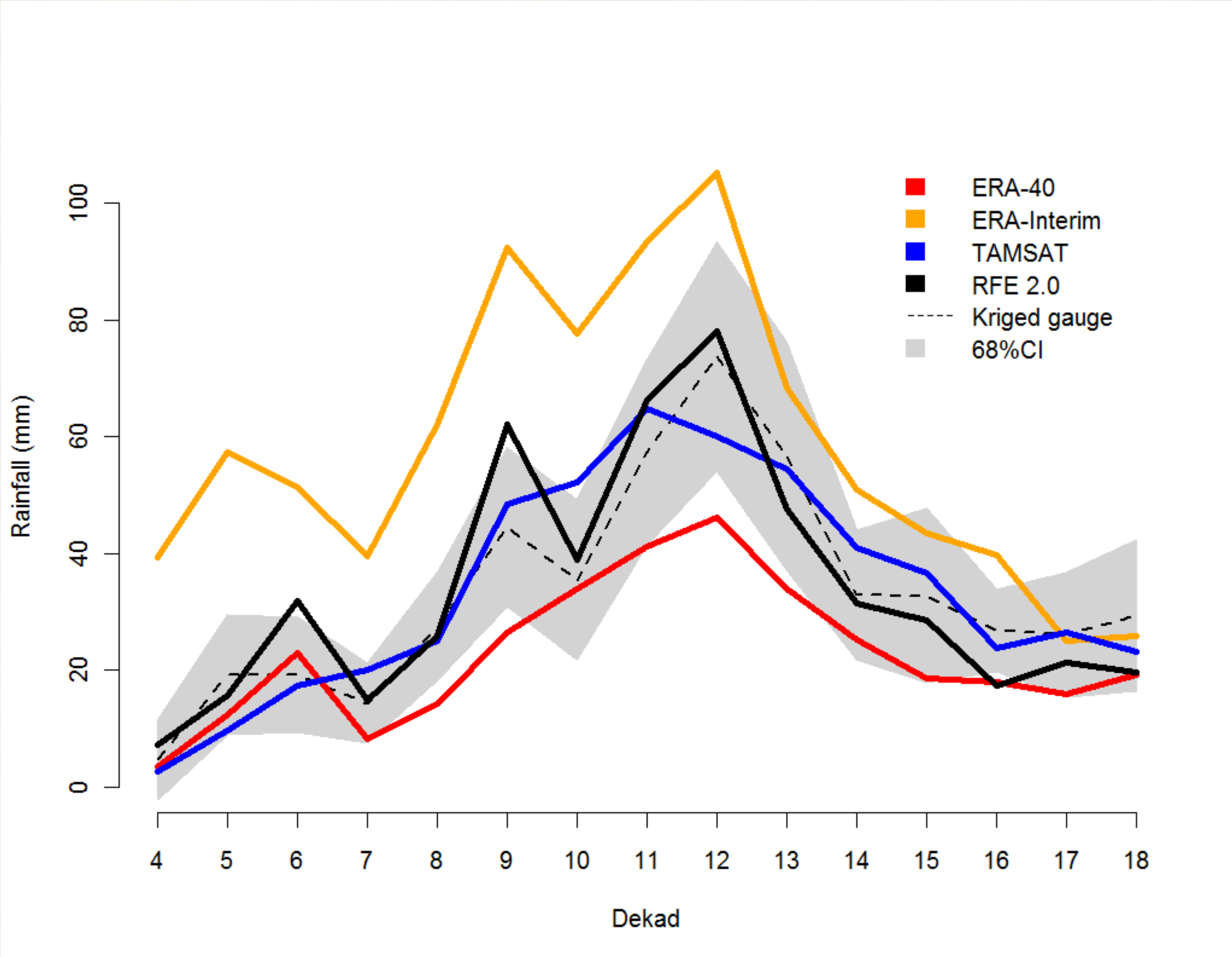
Period of study:
2001 to 2005 for first rainy season (Feb – June)

Product	Bias/mm	RMSD/mm	R^2
ERA-40	-9.86	18.09	0.41
ERA-Interim	14.06	26.55	0.39
TAMSAT	-1.01	10.41	0.72
RFE 2.0	-1.73	11.00	0.74
GPCP	0.16	11.56	0.72



Mean dekadal rainfall

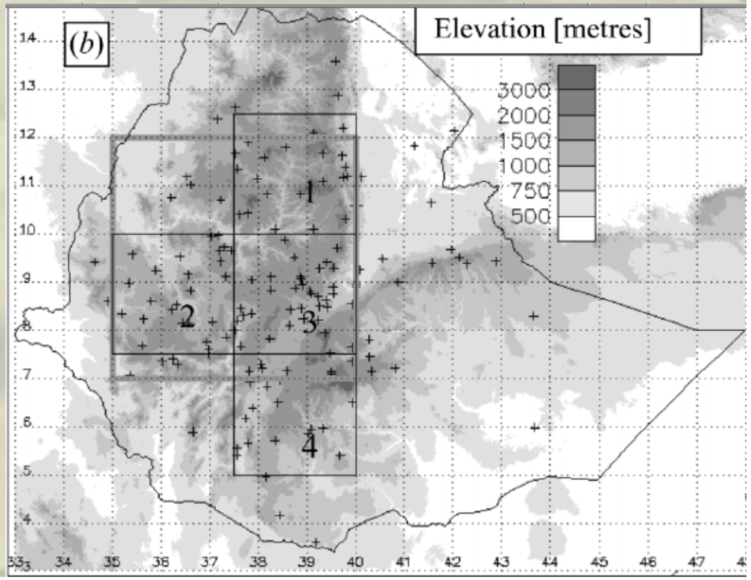
Validation Study 1 - Uganda: intra-seasonal variability



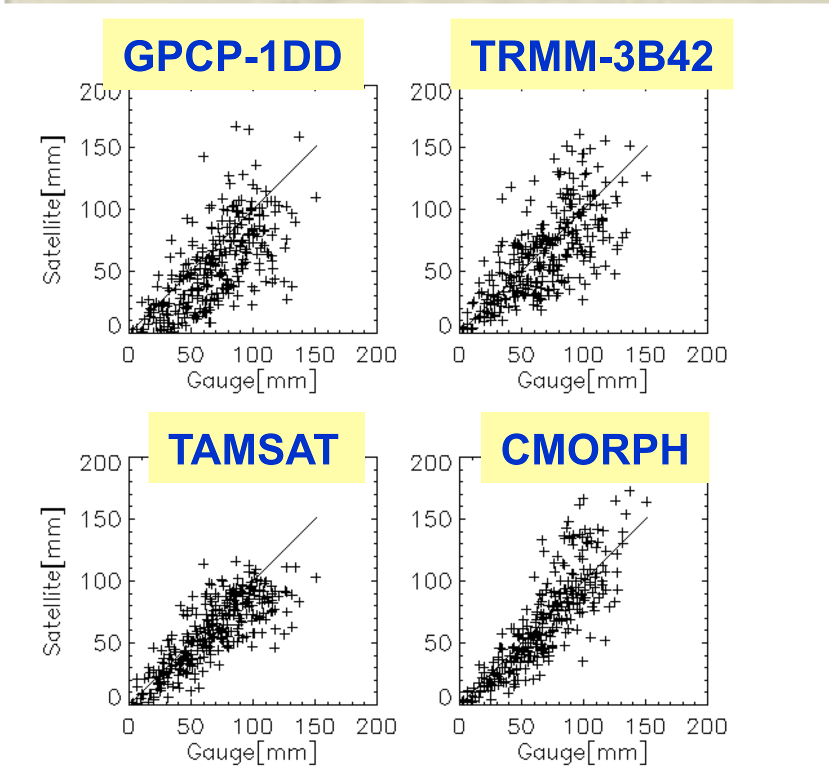
Validation Study 2

- Comparison for Ethiopia data: June - Sept 2000 to 2004 by Tufa Dinku at IRI
- Algorithms tested: TAMSAT, NOAA-RFE, CMORPH, GPCP, TRMM-3B42
- Dekadal totals evaluated for 1^0, 0.5^0, 0.25^0 gridboxes
- Validation data comprises 120 gauges interpolated geostatistically to gridbox averages
- Minimum gauge density as in table

Box size/^{0}	Min gauges
1.0	3
0.5	1
0.25	1



Validation Study 2 - results

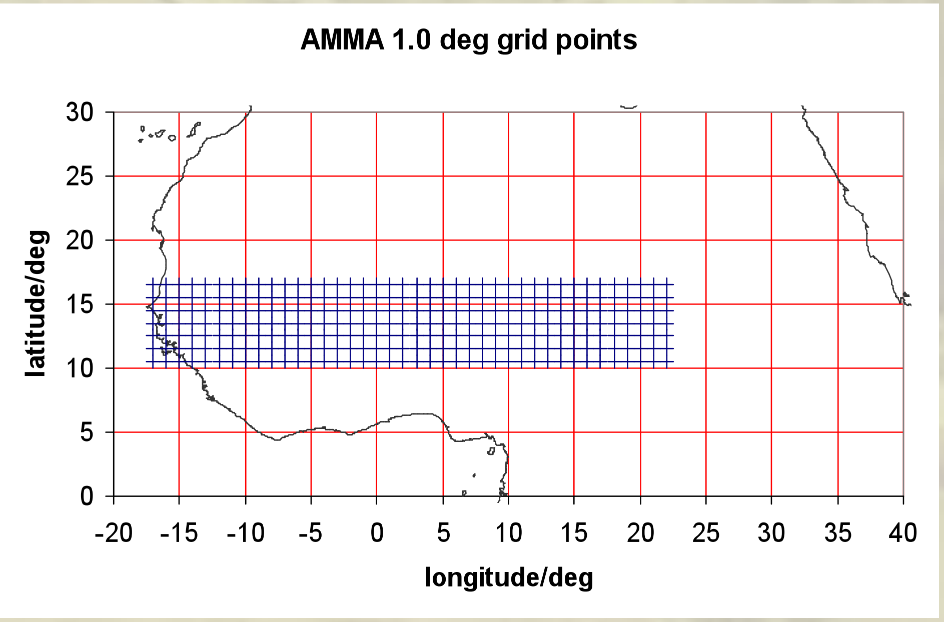


N=306	CMORPH	GPCP	3B42	TAM
R^2	**0.83**	0.68	0.68	0.79
Efficiency	0.49	0.04	0.26	**0.53**
Bias	**0.98**	0.77	0.94	0.86
RMSE	32	44	39	**31**

1.0^0 resolution, dekadal total, 2003-2004
(Best 4 algorithms)

Validation Study 3

- Dekadal rain gauge data interpolated by to 0.5^0, 1.0^0, 2.5^0 grid using kriging
- Comparison of TAMSAT, NOAA-CPC, LMD, CMORPH + other algorithms carried at LMD, Paris



Agrhymet validation results 2004-2006 monthly data (May-Sept)

	0.5x0.5	BIAS (mm)	RMSD (mm)	WRMSD	NRMSD	R^2	SKILL
2004 - 2006 RAINY SEASONS (ALL 10-DAY PERIODS)	EPSAT-SG	5	17	1,6	1,4	0,71	0,7
	NOAA-RFE	0	19	1,7	1,6	0,61	0,6
	TAMSAT	**3**	**20**	**1,7**	**1,7**	**0,63**	**0,6**
	GPCP-1dd	7	23	2,0	1,9	0,60	0,4
	GSMaP_MVK	-11	24	2,0	2,0	0,50	0,4
	TRMM-3B42	-4	26	2,3	2,1	0,46	0,3
	GPI	16	28	2,6	2,3	0,58	0,2
	TRMM-3B42RT	8	37	3,2	3,0	0,46	-0,5
	CMORPH	22	39	3,6	3,2	0,54	-0,7
	PERSIANN	45	63	5,7	5,2	0,49	-3,4
9001 grid cells	**Ground Data**	MIN RAIN (mm)	0,00	MAX RAIN (mm)	265,02	MEAN RAIN (mm)	41,75

Algorithms ranked by skill score

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Tamsat African Rainfall Climatology And Time series (TARCAT)

TARCAT

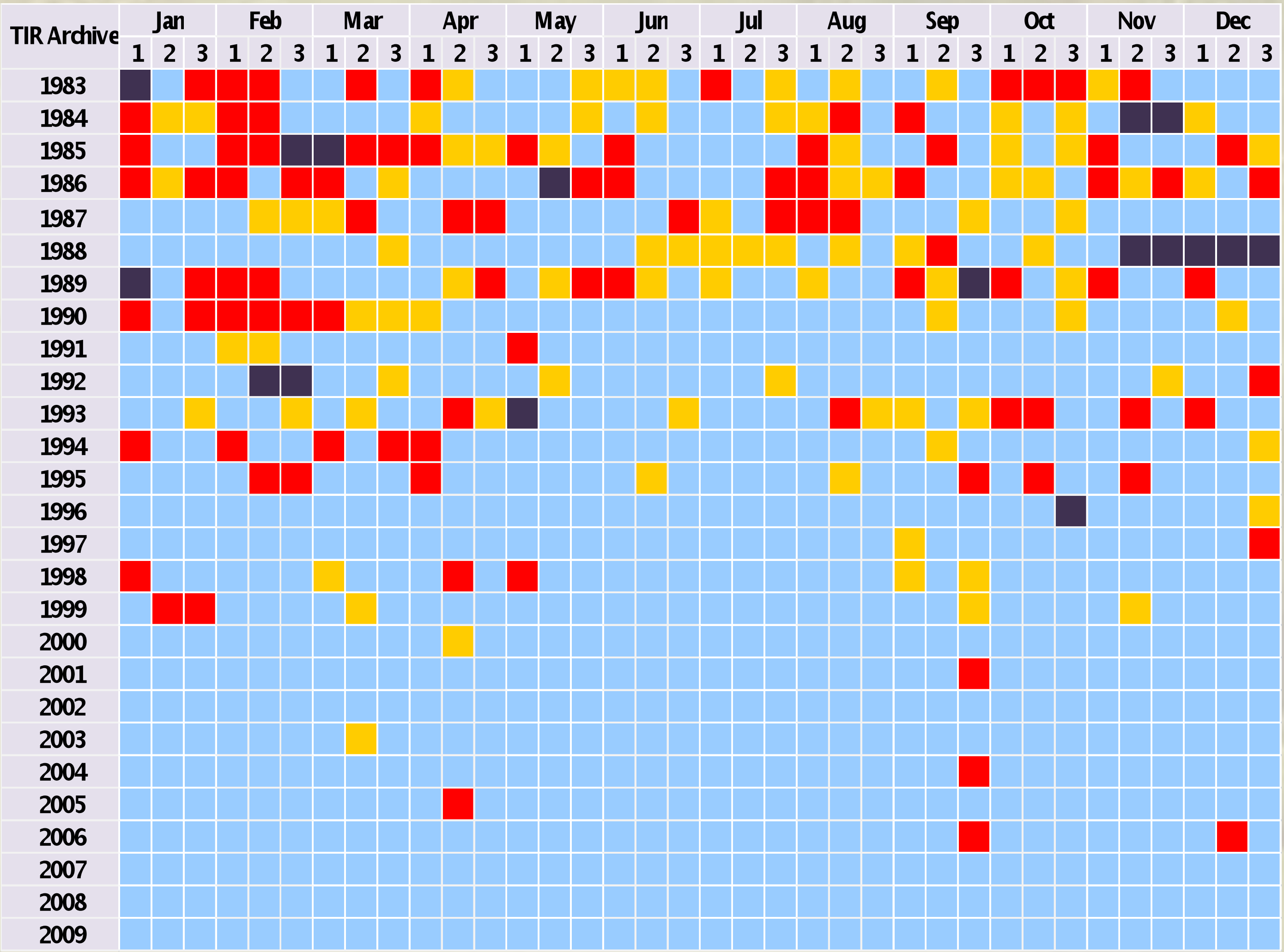
Motivation

- Current climate variability and trends are not well monitored
- Currently available time series
  - o not homogeneous in time (based on varying mixes of satellite and gauge data - eg GPCP)
  - o based on very few long term gauges (GPCC)
  - o short (CMORPH)

TARCAT Aims

- Use full Meteosat archive to extend TAMSAT algorithm back to 1983
  - o Homogeneous in time + complete spatial coverage
  - o 10 day 0.05^{0} nominal resolution (eventually daily resolution)
- Applications
  - o Analysis of trends and variability with near-complete spatial coverage
  - o Verification of model rainfall output
  - o Calibration/validation of application models
    - e.g. hydrological, crop yield, health and seasonal forecast

TARCAT TIR archive



Missing data

< 180 min

< 360 min

> 360 min

Dekad Failed

All dekads should be recoverable apart from the those coloured black

TARCAT current status (1)

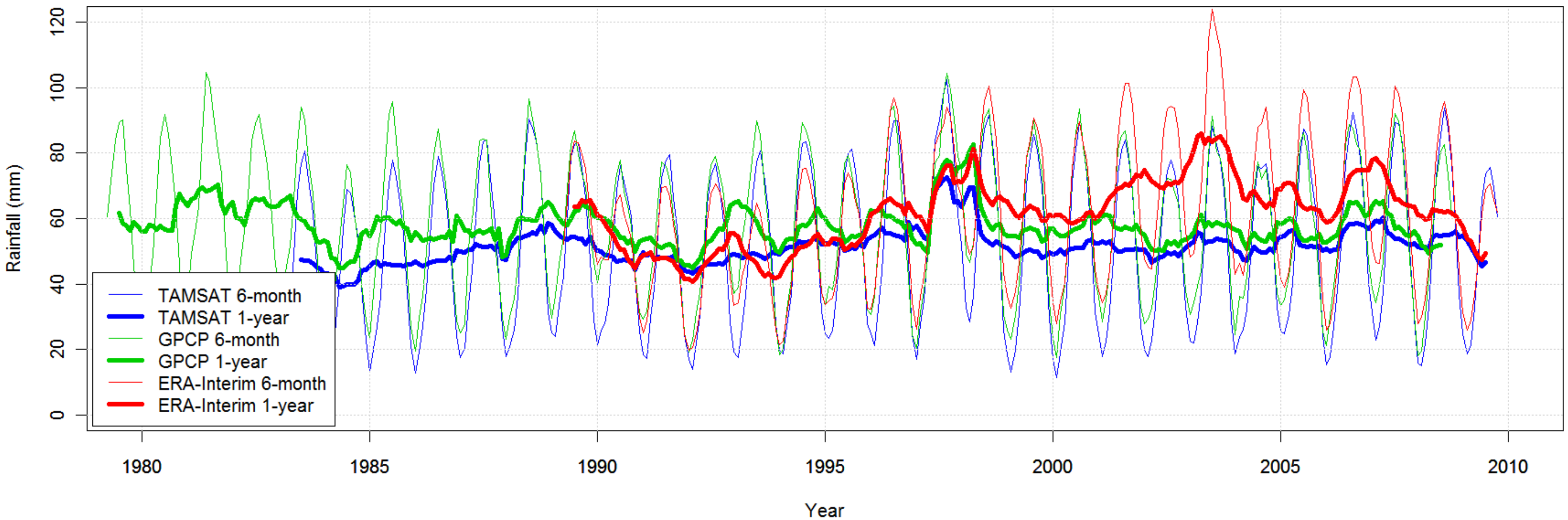
- All available TIR data has been obtained from Eumetsat
- Currently processing data with regard to
  - o interpolation of small gaps
  - o removal of calibration anomalies
  - o homogenisation of data format
- Preliminary 28 year data series now completed
- Images available from web site (dekadal estimates, 2000-2009 climatologies, anomalies)
- Data will be publicly available after some validation tests

TARCAT current status (2)

- Calibration updated under JRC MARSOP and Ethiopia-Google projects
- Calibration workshops in Addis Ababa (December 2009) and Uganda (May 2011) have produced excellent results for the Horn of Africa
- Funding being sought for more calibration workshops in other regions/countries

Climate trends in Ethiopian rainfall – Initial results

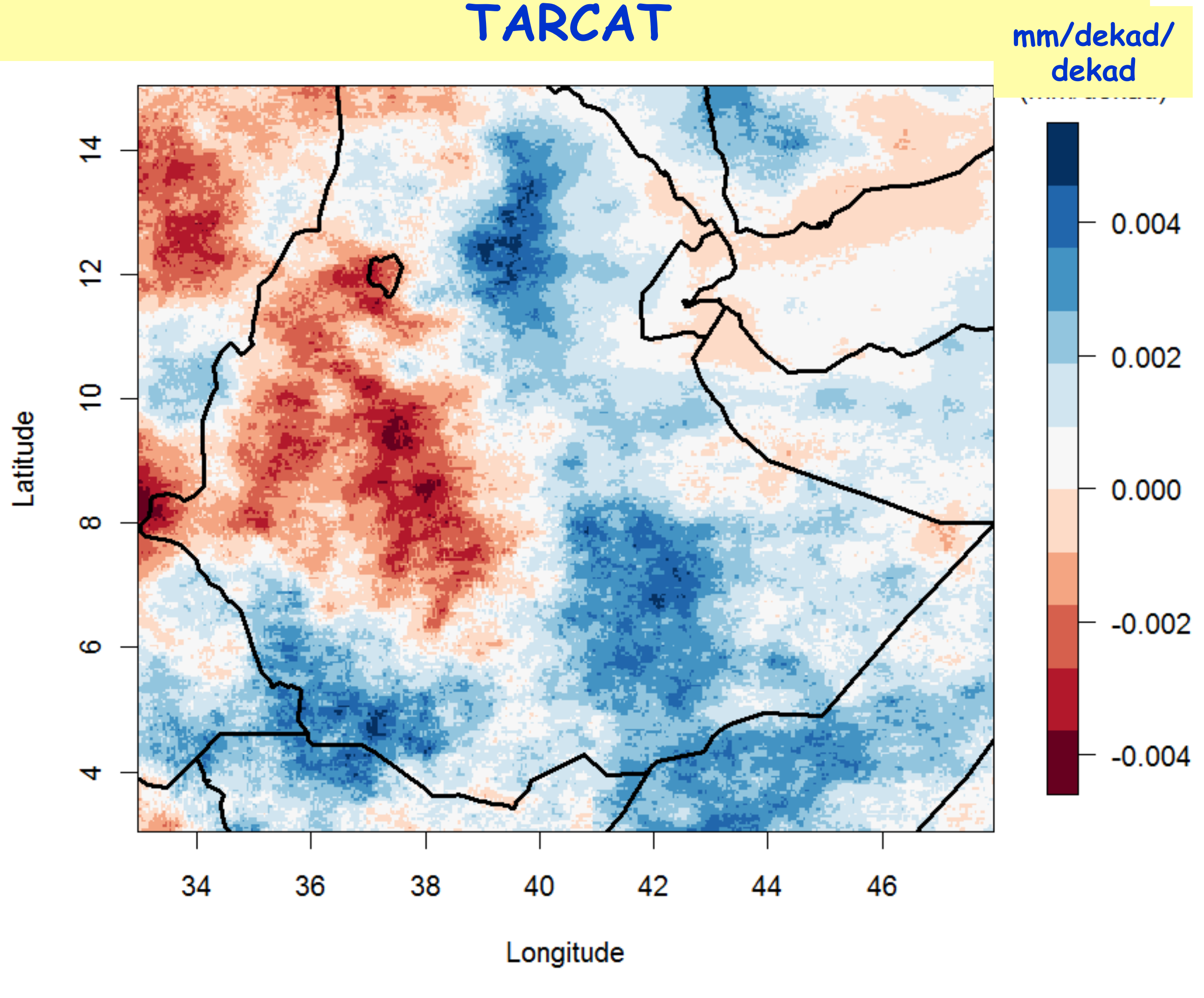
6 Month & Annual Running Mean – Mean Monthly Rainfall



	TAMSAT (1983-2009)	GPCP (1979-2008)	ERA-Interim (1989-2009)
N (no. of months)	324	360	252
Mean (*mm*)	51.24	57.90	61.42
Standard deviation (*mm*)	40.11	37.87	36.62
Variance (*mm*^{2})	1609.83	1434.81	1341.69
Trend (*mm/month*)	0.024	-0.007	0.071
Min (*mm*)	0.07	1.3	1.42
Max (*mm*)	159.16	204.20	171.3

Climate trends in Ethiopian rainfall – Initial results

Linear trend in annual rainfall 1983 – 2009 TARCAT



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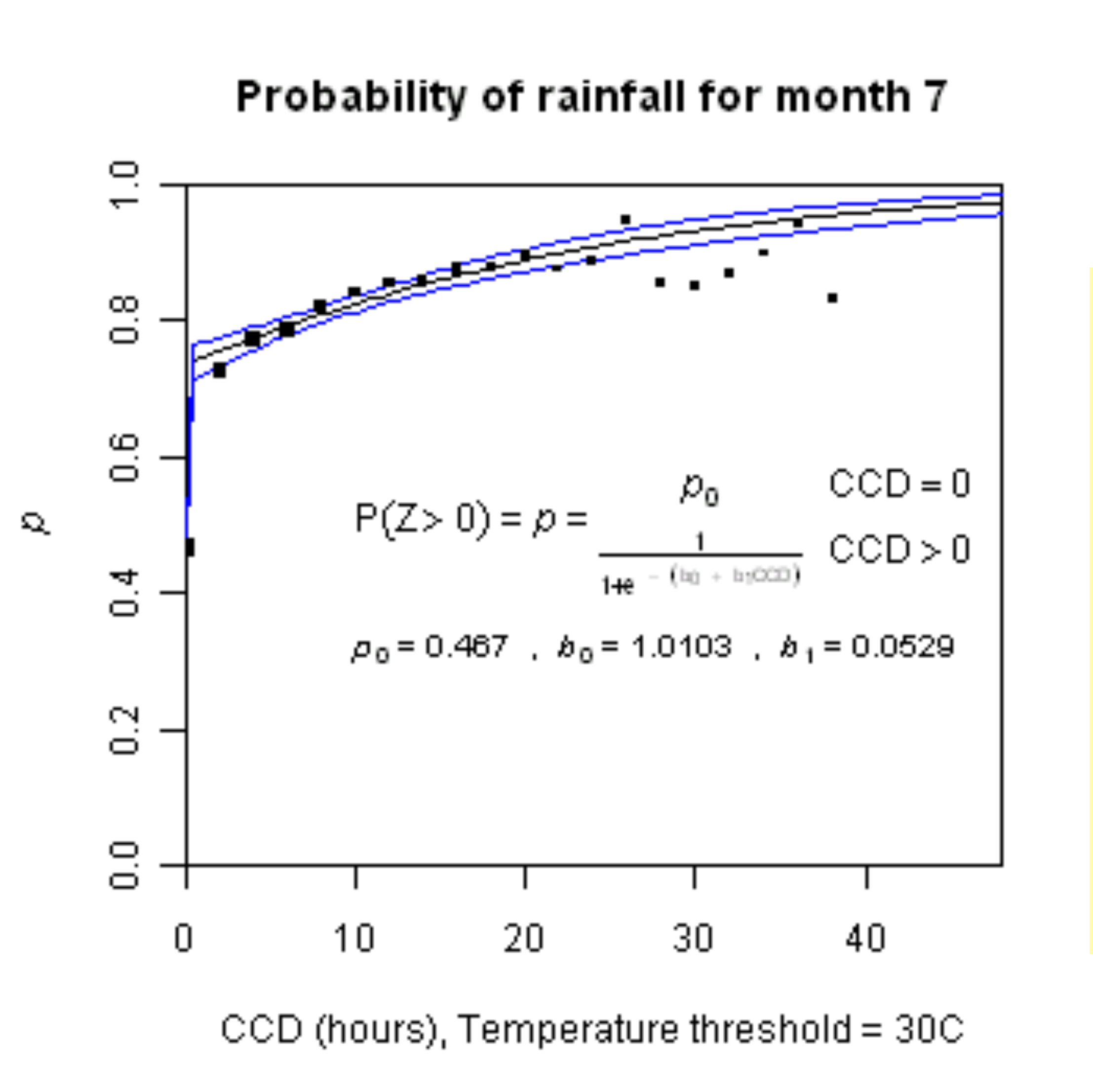
Satellite-based rainfall ensemble

Overview

1. **Look at statistics of daily CCD compared to gauge data.**
   - Probability of rain/no-rain for given CCD
   - Distribution of rainfall amount for given CCD

2. **Use these relationships to produce an ensemble of daily rainfall fields**
   - For each pixel, the ensemble of values must agree with the observed statistics
   - For each ensemble member, the inter-pixel correlation must agree with the observed geostatistical relationship.

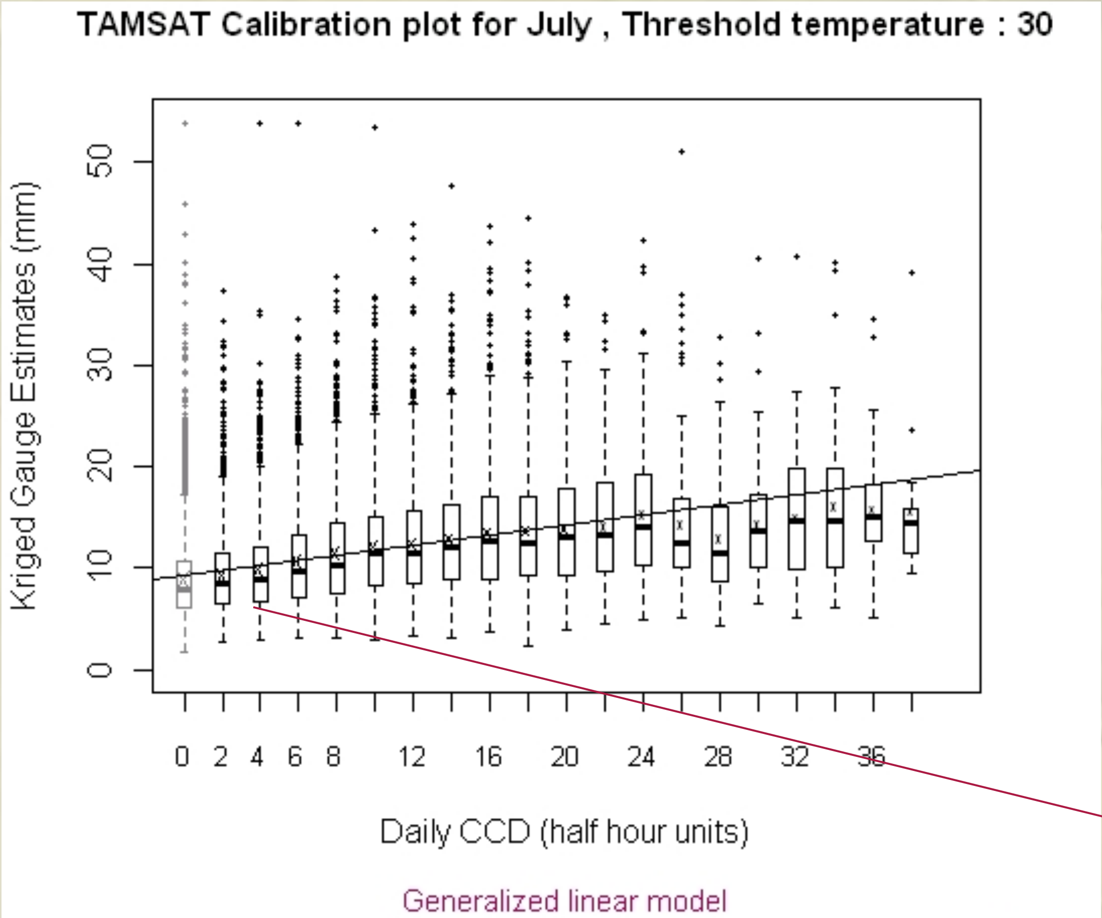
1a. Probability of rain vs CCD



Relationship between probability *p* of rain and CCD can be expressed in terms of logistic regression

Use existing data to calibrate for b_0, b_1

1b. Rainfall distribution



$$\mu_+ \equiv E\left[Z \mid z > 0, CCD\right] = a_0 + a_1 \times CCD \qquad (2)$$

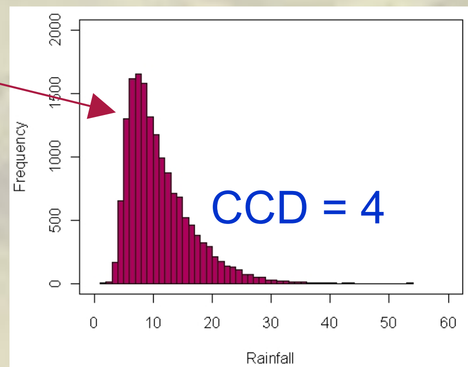
$$\sigma_+^2 \equiv Var(Z \mid z > 0, CCD) - \sigma_k^2$$

$$\sigma_+^2 = (\kappa_z \mu_+^{\theta_z})^2 - (\kappa_b \mu_+^{\theta_b})^2 \qquad (3)$$

Rainfall distribution *when rainy* is described in terms of the mean μ_+ and variance σ_+^2

Variance is estimated as an empirical function of μ_* after allowing for block kriging error.

Existing data are used to calibrate a_0, a_1, A, θ



2a. Generate ensemble of rainfall field

Rain or no-rain? - Sequential Indicator Simulation

Produce rain/no rain map
from CCD - initial seeding

10	2	0
2	1	0
4	6	1

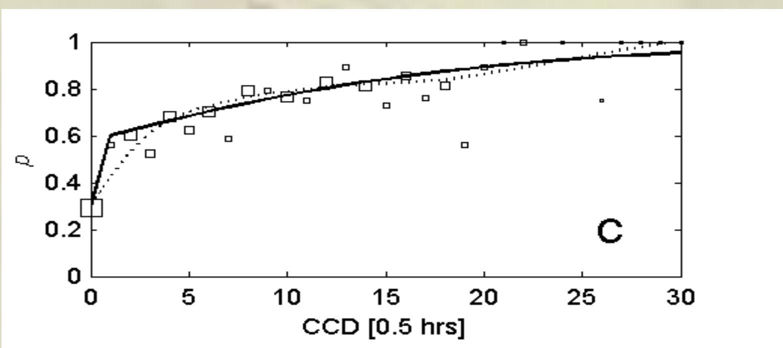
0.75	0.60	0.32
0.60	0.43	0.32
0.45	0.72	0.43

		0
1		

1. CCD

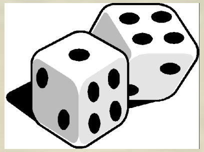
2. Prior probability based on Eqn (1)

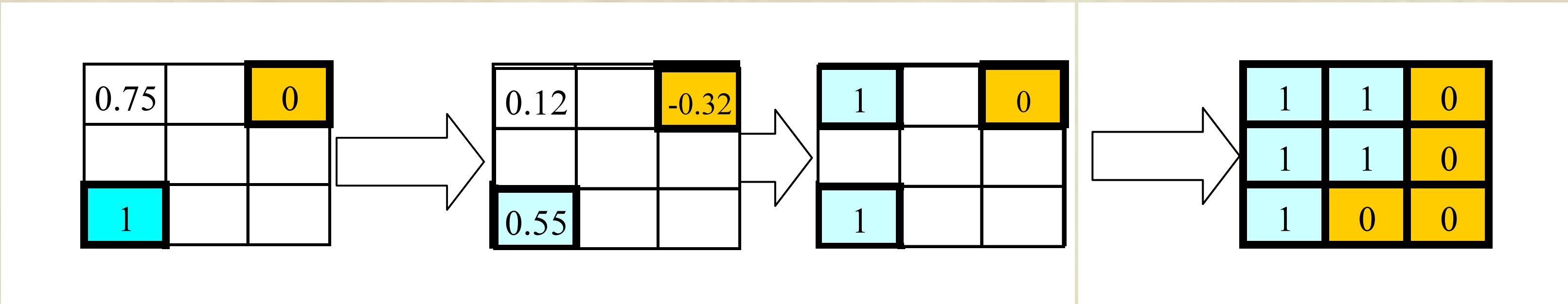
3.Select seed pixels and assign rain/no rain based on prior probability



2a. Generate ensemble of rainfall fields-
Rain or no-rain? - Sequential Indicator Simulation

Produce rain/no rain map
from CCD - SIS





1. Select target pixel, and compute the *prior* probability

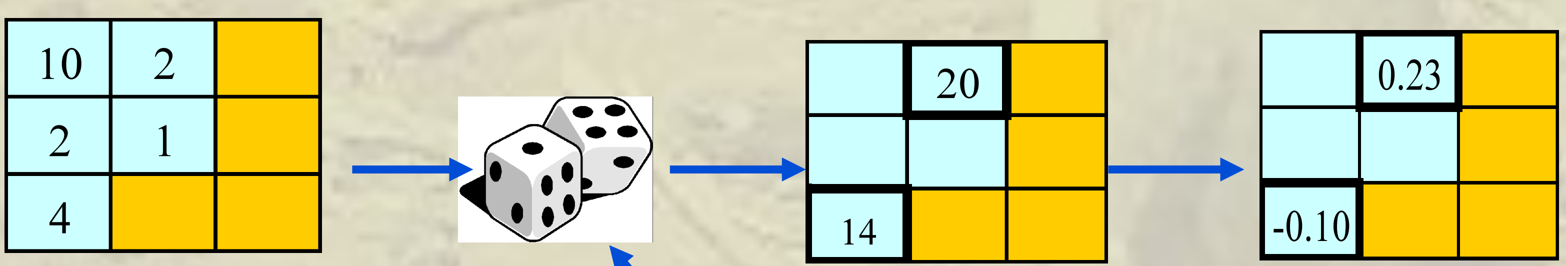
2. Calculate seed pixel residuals and krig to get target pixel residual

3. Adjust target probability and assign 1 or 0

4. Repeat until all pixels are assigned

2b. Generate ensemble of rainfall field - *How much rain? Sequential Gaussian Simulation*

Generate rainfall for rainy pixels - initial seeding

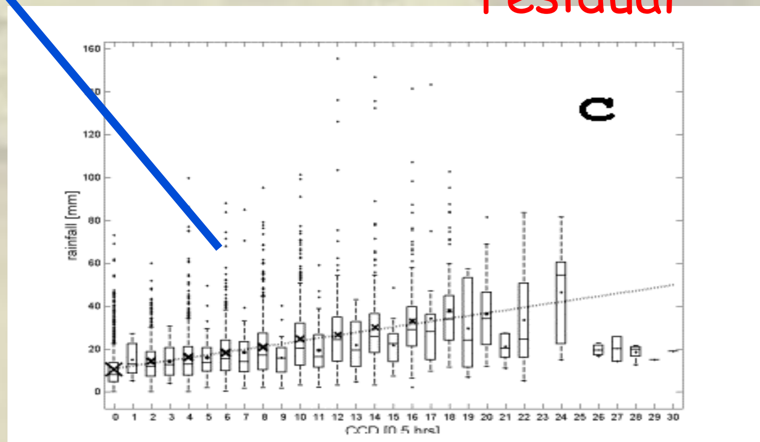


Original CCD values

Sampled rainfall

Norm transformed residual

Randomly select seed pixels from among the the rainy pixels and sample rainfall amounts from calibration distribution



2b. Generate ensemble of rainfall field -
How much rain? Sequential Gaussian Simulation

Generate rainfall amount for target pixel

0.12	0.23	
-0.10		

1. Select target pixel and krig to get target residual

0.10	0.23	
-0.10		

2. Select from kriging distribution to give new value

35	20	
14		

3. Back-transform and add to calibrated rainfall to give target pixel value

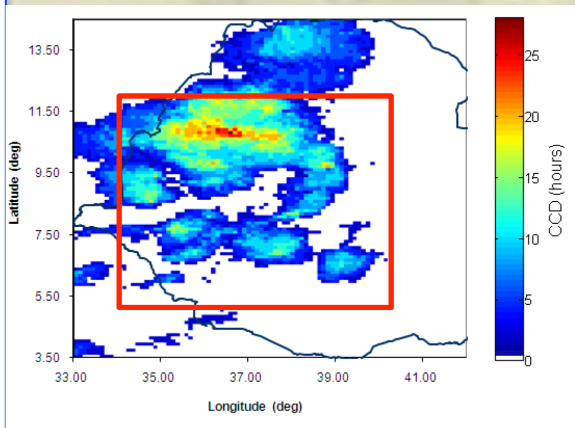
4 Add target to set of seed pixels.

Select new target and repeat until all cells filled

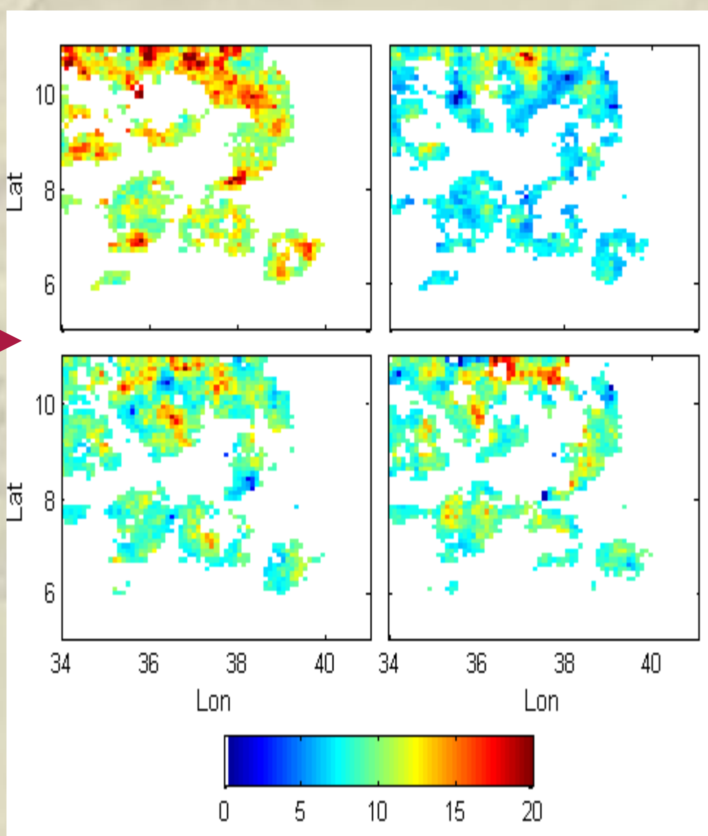
35	20	
31	16	
14		

Satellite ensemble approach for Ethiopia

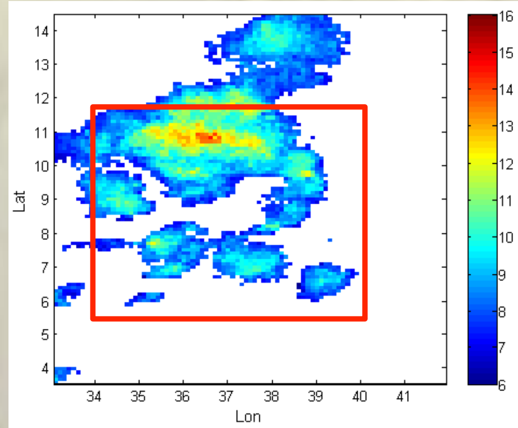
CCD



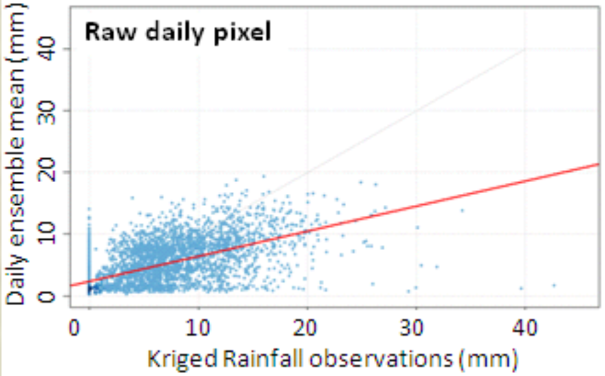
Individual ensemble members

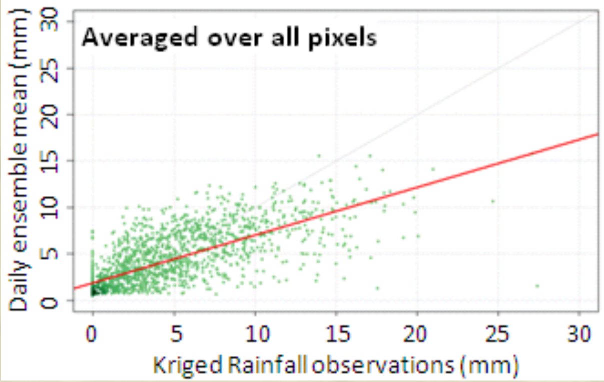


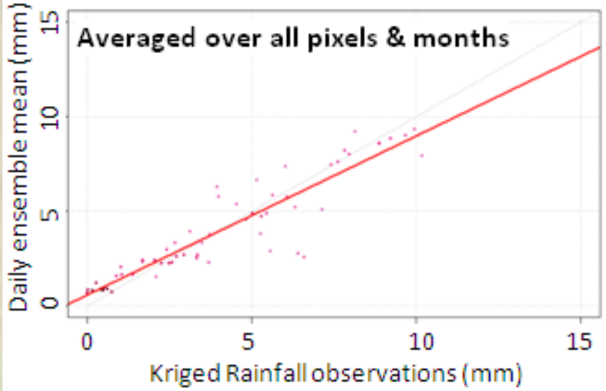
Ensemble mean

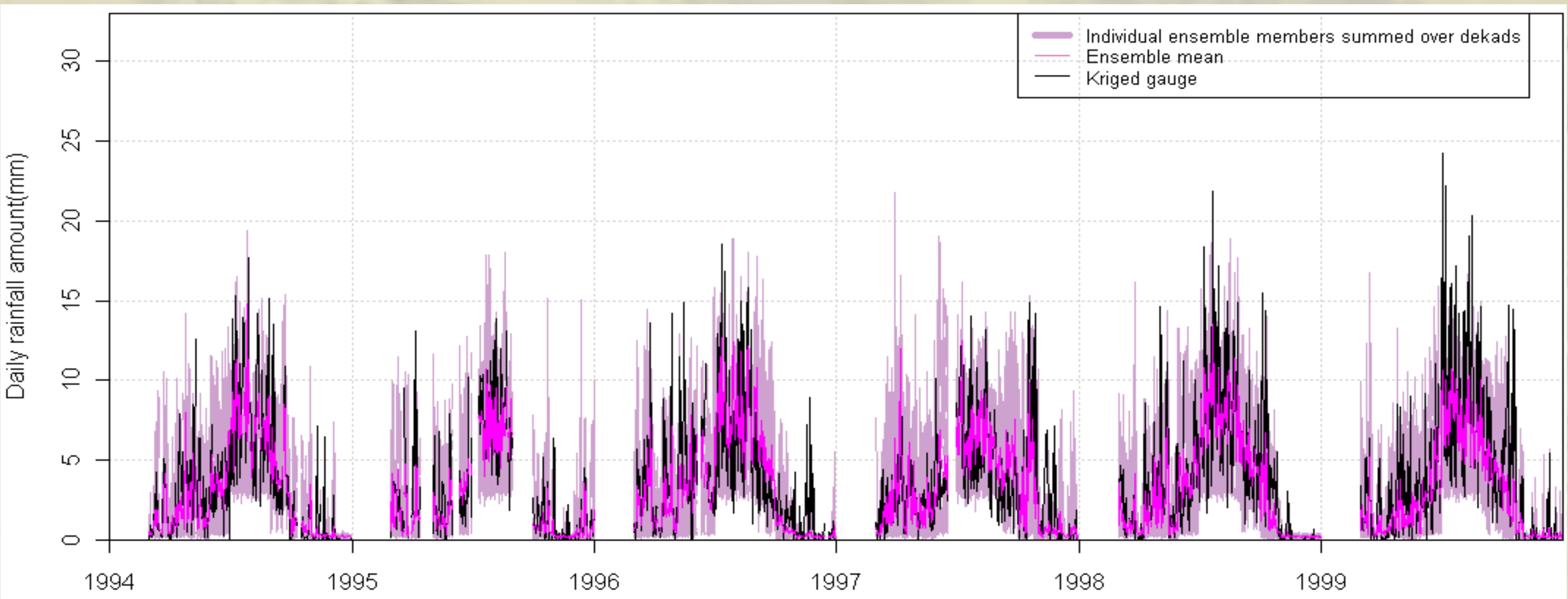


Ensemble validation









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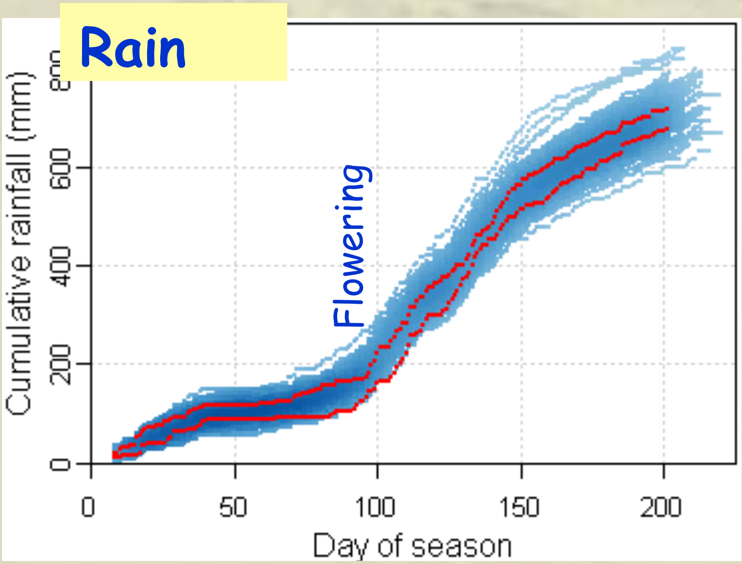
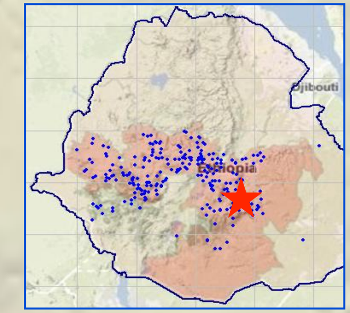
Crop yield monitoring in Ethiopia

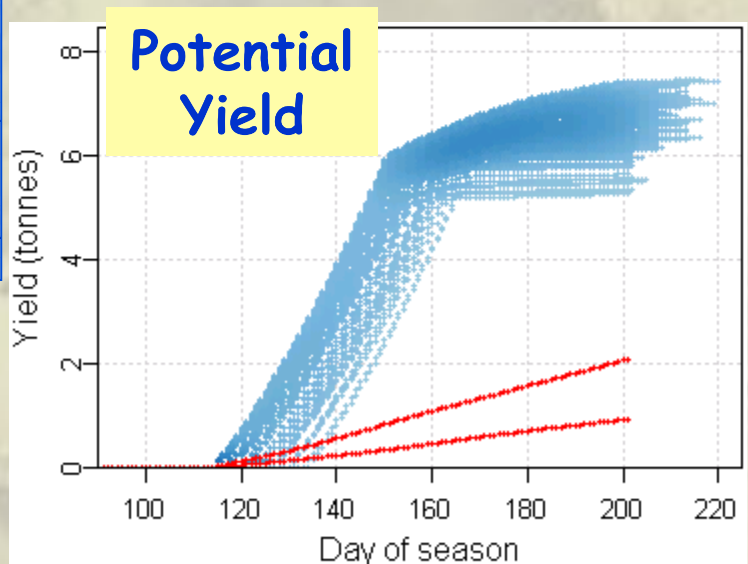
Ensemble of observed rainfall from TAMSAT satellite observations

GLAMmaize crop model

Ensemble of crop yield







Ensemble member

Ensemble members where there was water stress between silking and tasselling (flowering)

Conclusions

- Use of satellite data is vital for successful monitoring of rainfall in Africa;
- For convective rainfall, locally calibrated TIR methods do as well as (or better than) more sophisticated methods;
- In collaboration with African NMSs, TAMSAT algorithm is being used to build temporally homogeneous, 29 year, high resolution time series for Africa;
- Satellite imagery can be used to derive an ensemble of daily rainfall maps with correct spatial correlation;
- Ensembles can be used to drive crop yield models such as GLAM to estimate rain-related uncertainty.

University of Reading

Crops and Climate Group

TAMSAT