data assimilation

Assimilating EO data into JULES

Tristan Quaife, Phil Brown,
Emily Black & Jane Lewis

University of Reading

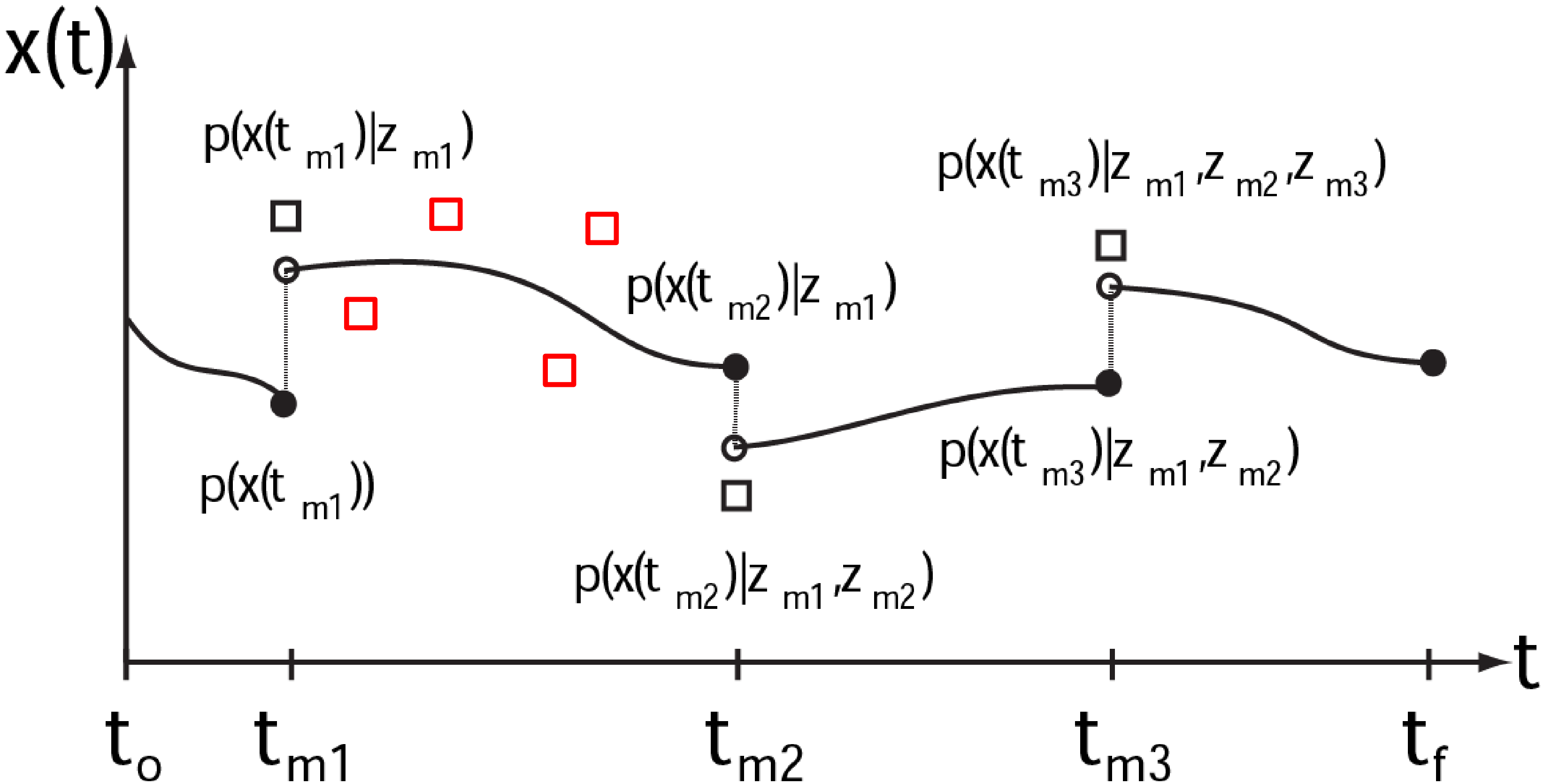
esa

National Centre for Earth Observation
NATURAL ENVIRONMENT RESEARCH COUNCIL

Sequential ensemble DA

- Start of a number of model runs
- Add independent stochastic forcing to state vector of each run at predefined intervals
  - represents model error
- When observations are available, resample the ensemble according to some algorithm
  - e.g. Ensemble Kalman Filter, Sequential Importance Resampling *etc.*

Sequential ensemble DA

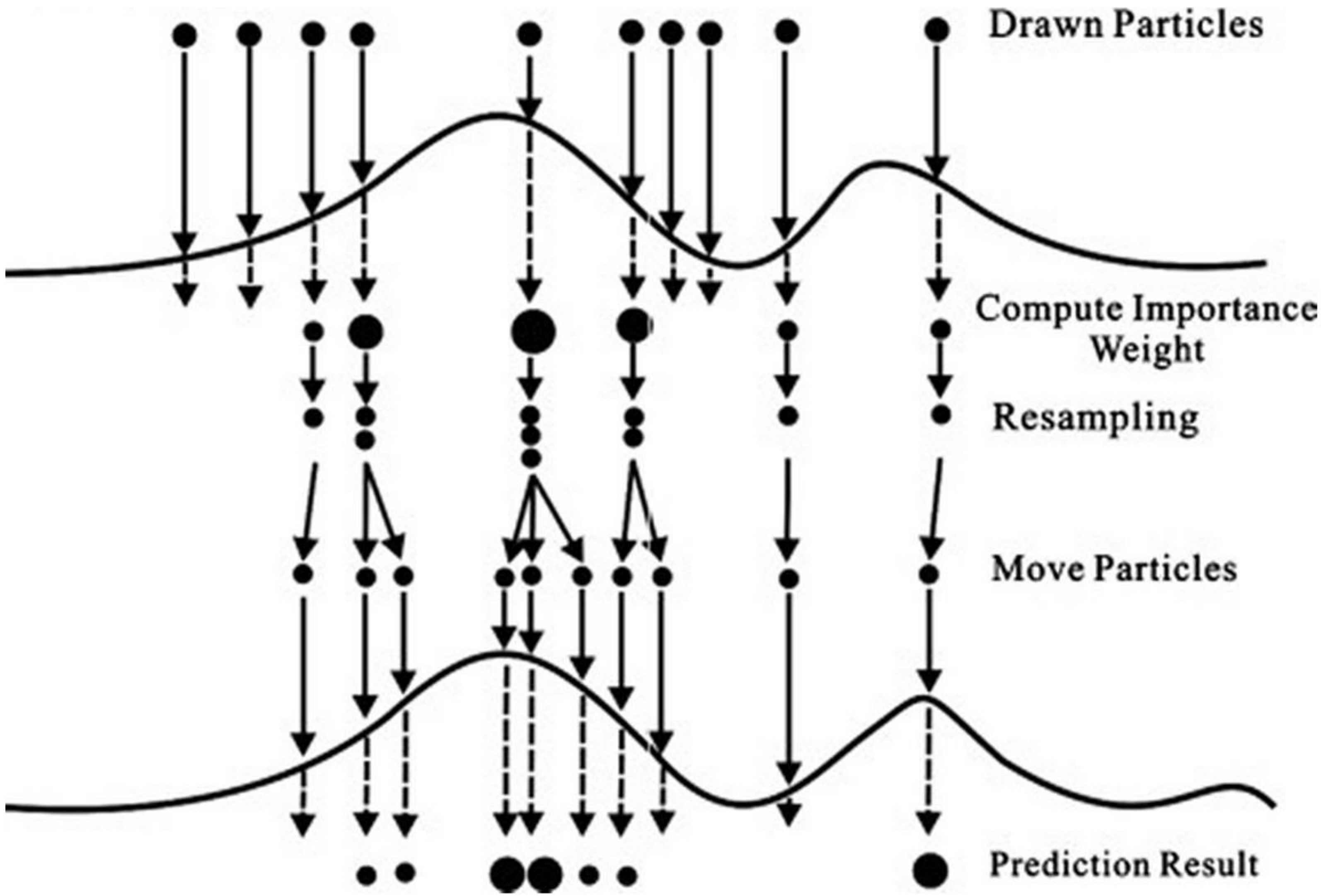


http://terpconnect.umd.edu/~baforman/

Particle filter

- Leaves individual model state vectors intact (i.e. no statistical "blending")
- Analysis step makes no assumption about probability distribution of ensemble
  - Fully Bayesian solution to sequential DA problem
- Suitable for extremely non-linear models
- Easily implemented…

Resampling Particle Filter



Wahyu Caesarendra, Gang Niu, Bo-Suk Yang, *Machine condition prognosis based on sequential Monte Carlo method,* Expert Systems with Applications, Volume 37, Issue 3, 15 March 2010, Pages 2412-2420.

Metropolis Hastings

Loop over all particles, x

x* = random particle

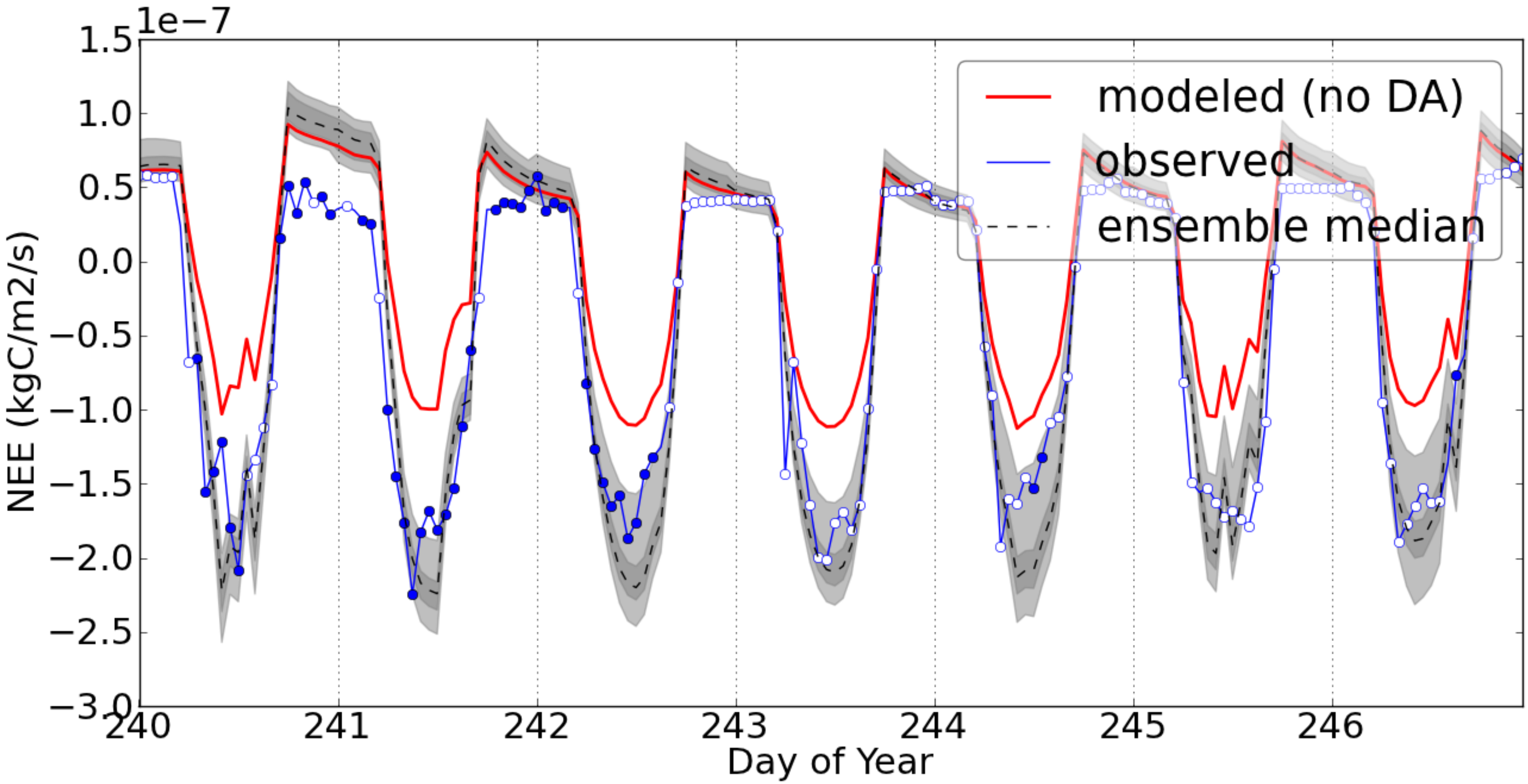
y = observations

$$\alpha = \min\left(1, \frac{L(y|x^*)}{L(y|x)}\right)$$

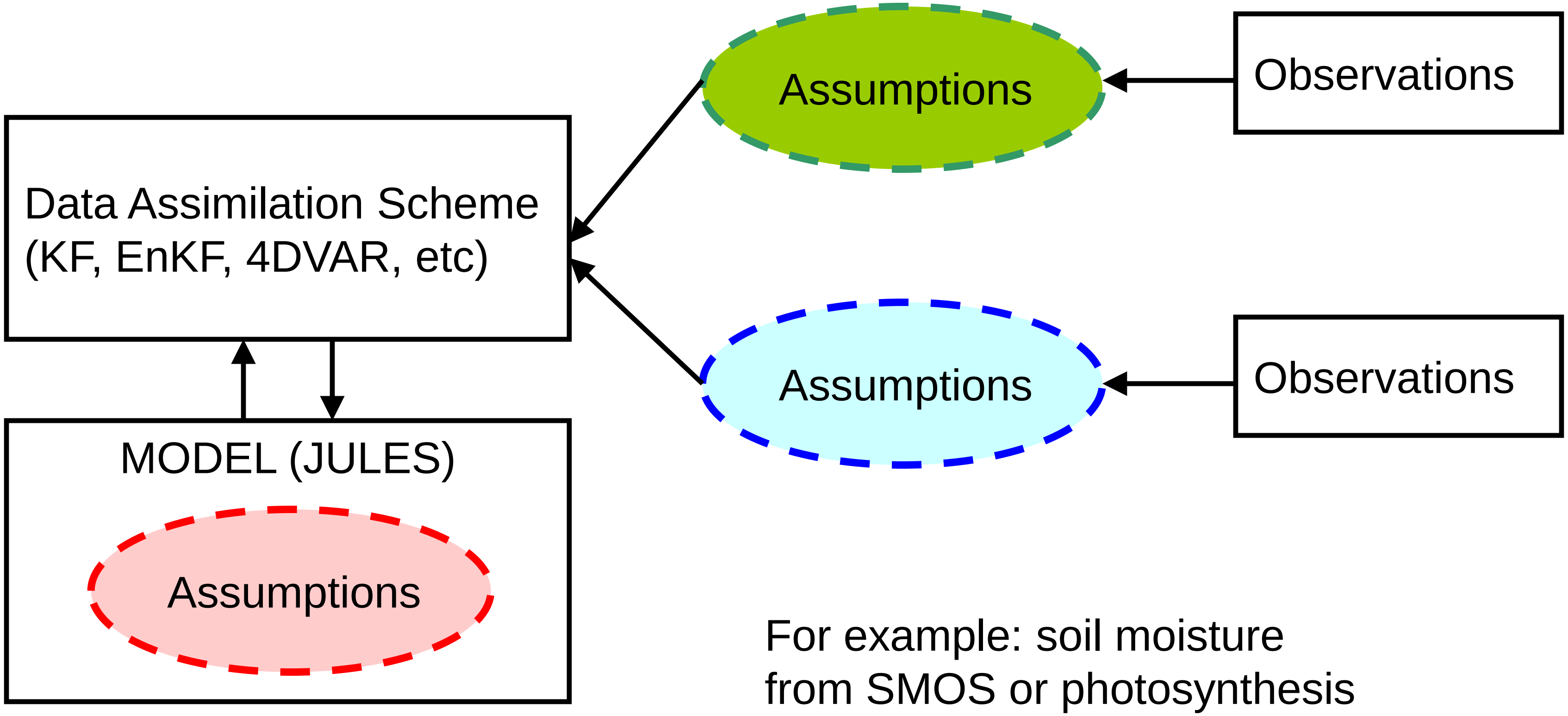
Draw *z* from U(0,1)

$$x = \begin{cases} x^* & \text{if } z \leq \alpha \\ x & \text{if } z > \alpha \end{cases}$$

Assimilating site level data

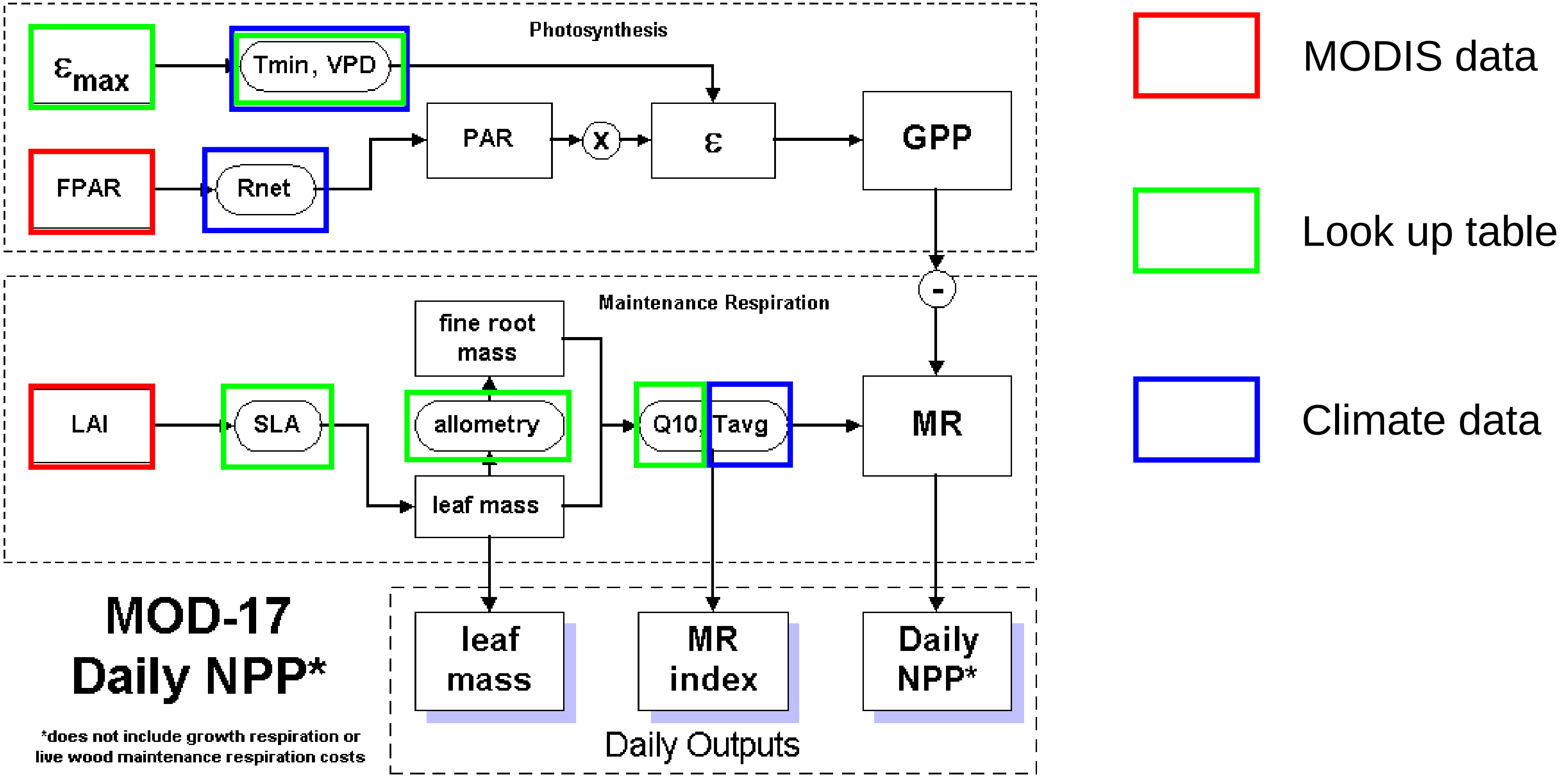


Assimilating EO products



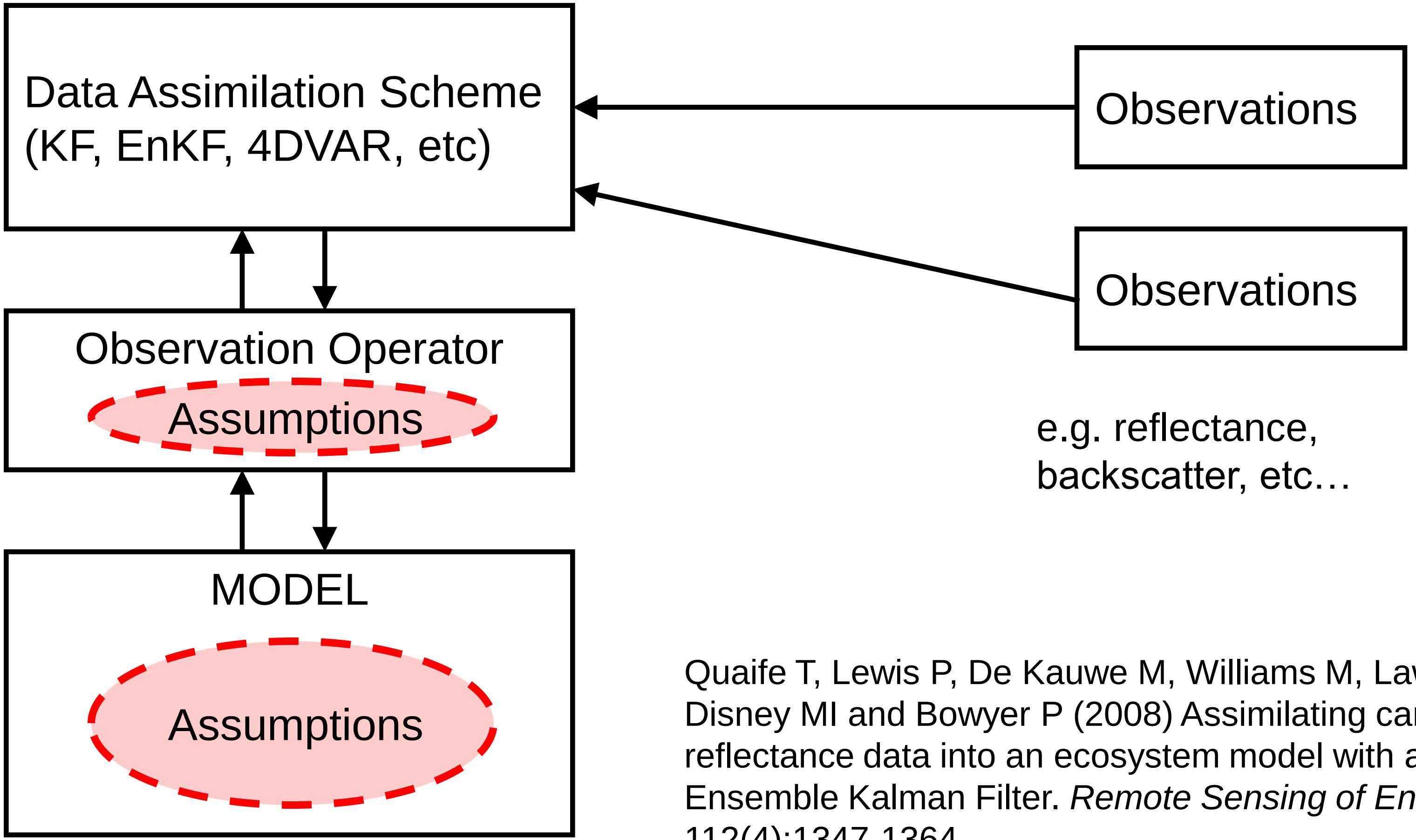
For example: soil moisture from SMOS or photosynthesis (GPP) from MODIS

MODIS GPP



http://www.ntsg.umt.edu/remote_sensing/netprimary/

Assimilating low level data



Quaife T, Lewis P, De Kauwe M, Williams M, Law BE, Disney MI and Bowyer P (2008) Assimilating canopy reflectance data into an ecosystem model with an Ensemble Kalman Filter. *Remote Sensing of Environment*. 112(4):1347-1364

What data to assimilate?

- Ideal data streams:
  - Energy incident at the satellite sensor.
  - Have previously used TOC BRFs.
  - But introduce lots of additional unknowns in the OO which also have to be estimated.
- Compromise:
  - Albedo, LST, brightness temperatures (long W/L)
  - Avoid conflicting assumptions as far as possible.

Albedo

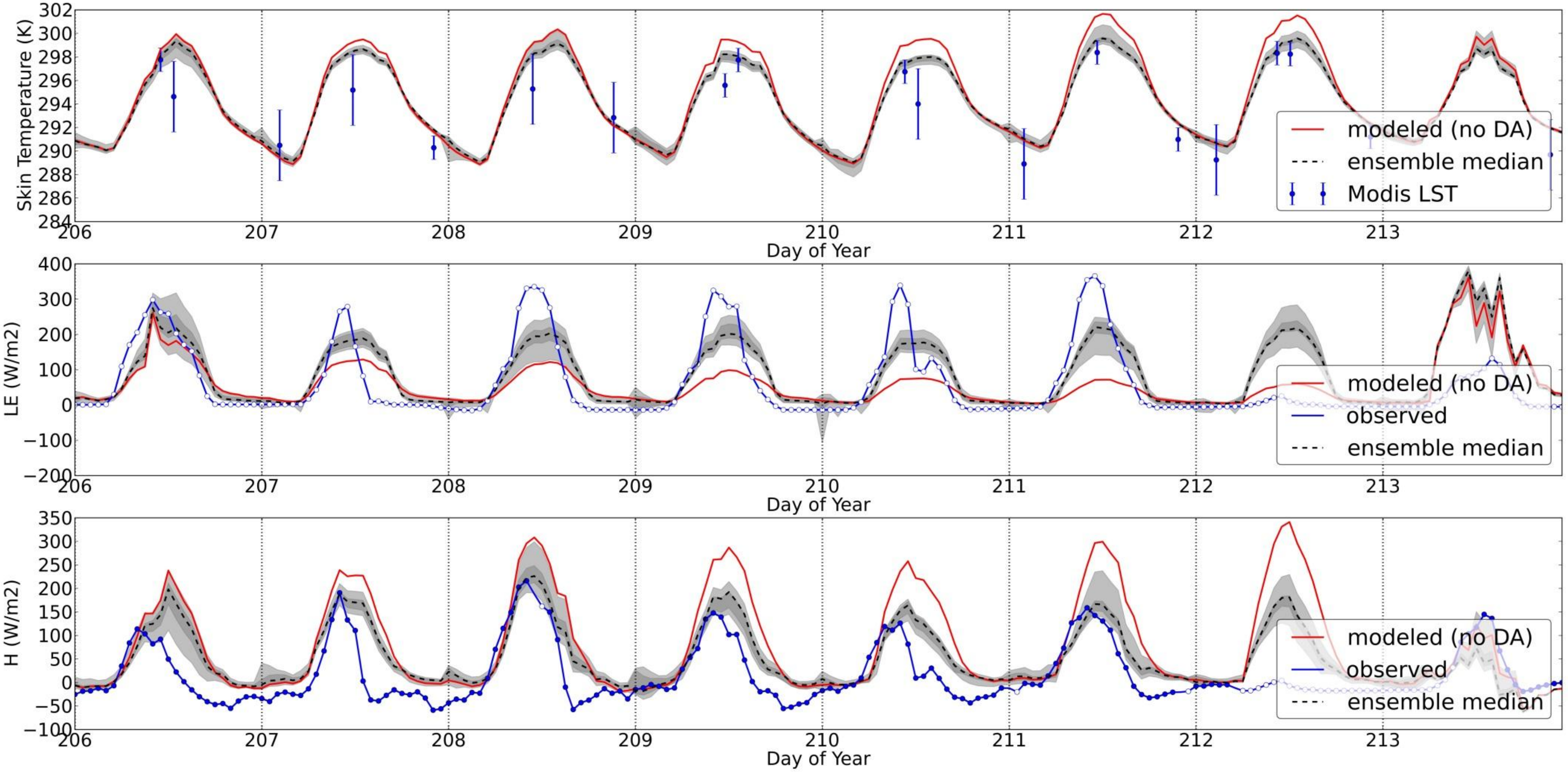
- JULES uses a Sellers two-stream model
  - Predicts spectral and direct/diffuse albedos
  - This is estimated by EO albedo products (MCD43)
- Two options:
  - Off-line/on-line assimilation
- Also implementing a sun angle implement a structure factor after Pinty *et al.* (2006):

$$LAI_{eff} = LAI \times \zeta(\mu)$$

Land surface temperature

- JULES models a per tile skin temperature
- Currently we assume that this can be compared directly with MODIS LST data
- Use MODIS QA to set uncertainties
- Future work will investigate angular dependency of the LST observations and potential to estimate surface emissivity (currently a user defined parameter).

Assimilating LST & albedo

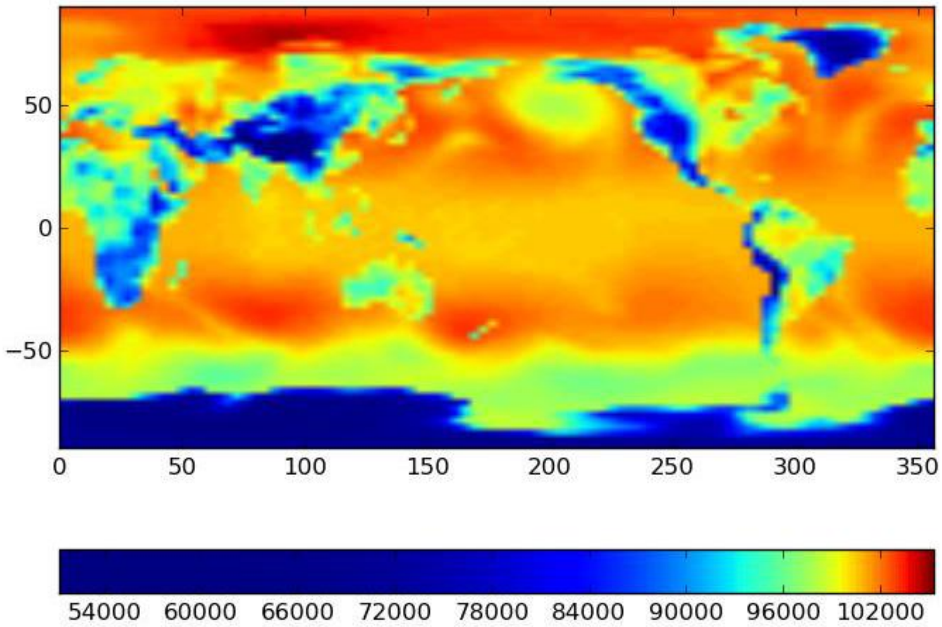


Where next?

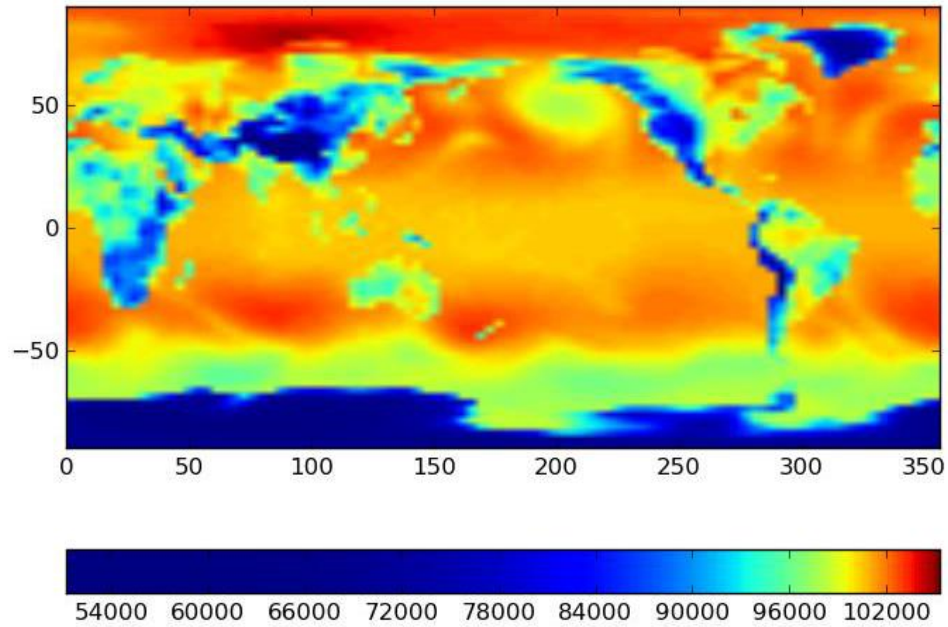
- Current Python implementation is slow
- Needs to be much faster for large scale work
- EMPIRE
  - Employing Message Passing Interface for Researching Ensembles
  - Uses MPI framework
  - Already implemented with HadCM3

EMPIRE: HadCM3

Surface air pressure



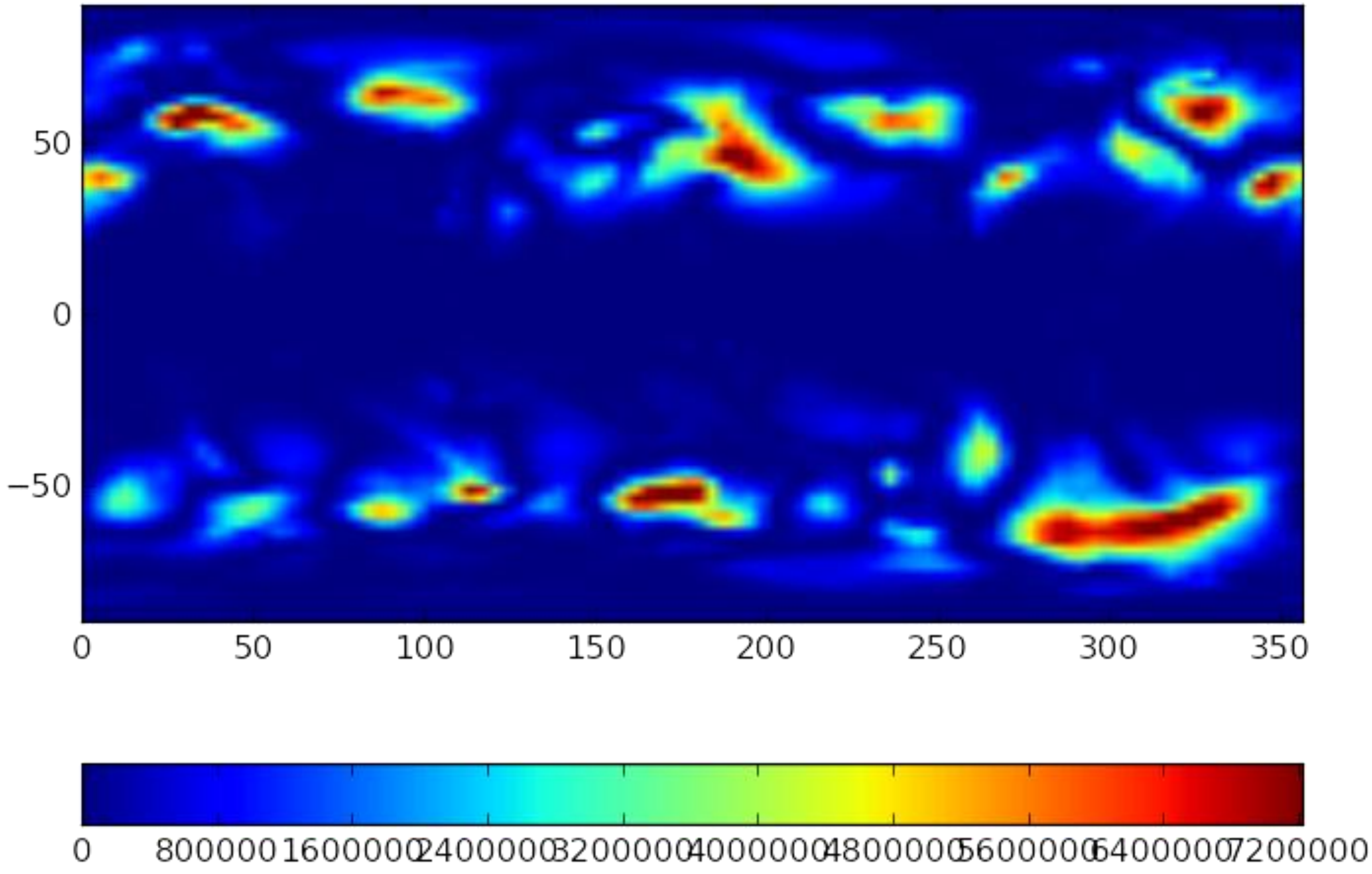
“truth”



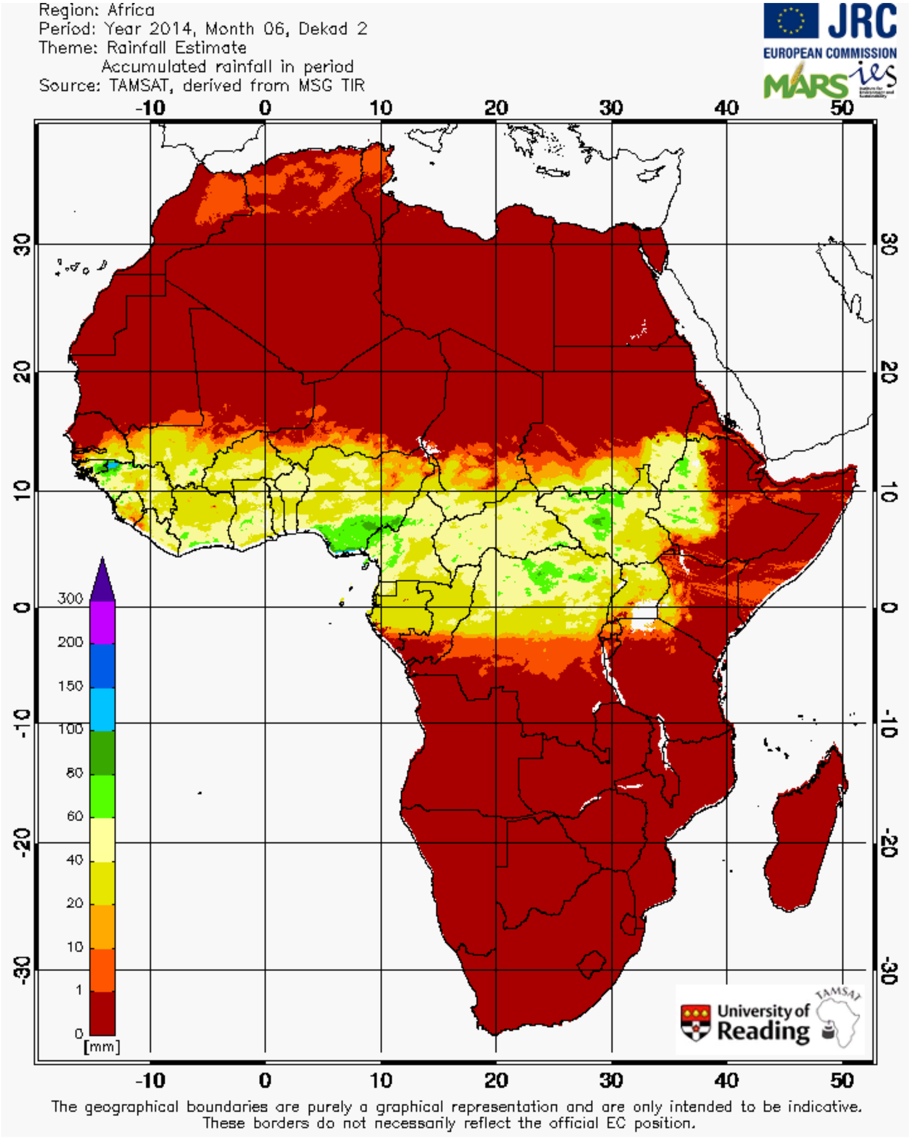
Ensemble mean

EMPIRE: HadCM3

Surface air pressure



Work with TAMSAT



- Rainfall ensembles
- ESA SM CCI data
- Aim to provide full column soil water
- Feeds into to insurance algorithms

Conclusions

- Implemented non-linear DA scheme for JULES
- Demonstrated it for various EO data streams
- Currently working on:
  - MPI framework
  - African soil moisture DA system

- Questions?

esa-da.org

Passive microwave

- Sensitive to soil moisture and temperature
- SM *products* make assumptions about soil type which may not be consistent with JULES
- Have implemented a microwave emission model and coupled the JULES
- Has not been used in the DA scheme yet
  - Issues of spatial scale and depth of emission

Passive microwave

$$I^{+}\left(\tau_0^*, \mu\right) = T_B^p e^{-\tau_0^*/\mu} + \left(1-\omega^*\right) T_c \left(1 - e^{-\tau_0^*/\mu}\right) + R_p \left(1-\omega^*\right) T_c \left(1 - e^{-\tau_0^*/\mu}\right) e^{-\tau_0^*/\mu}$$