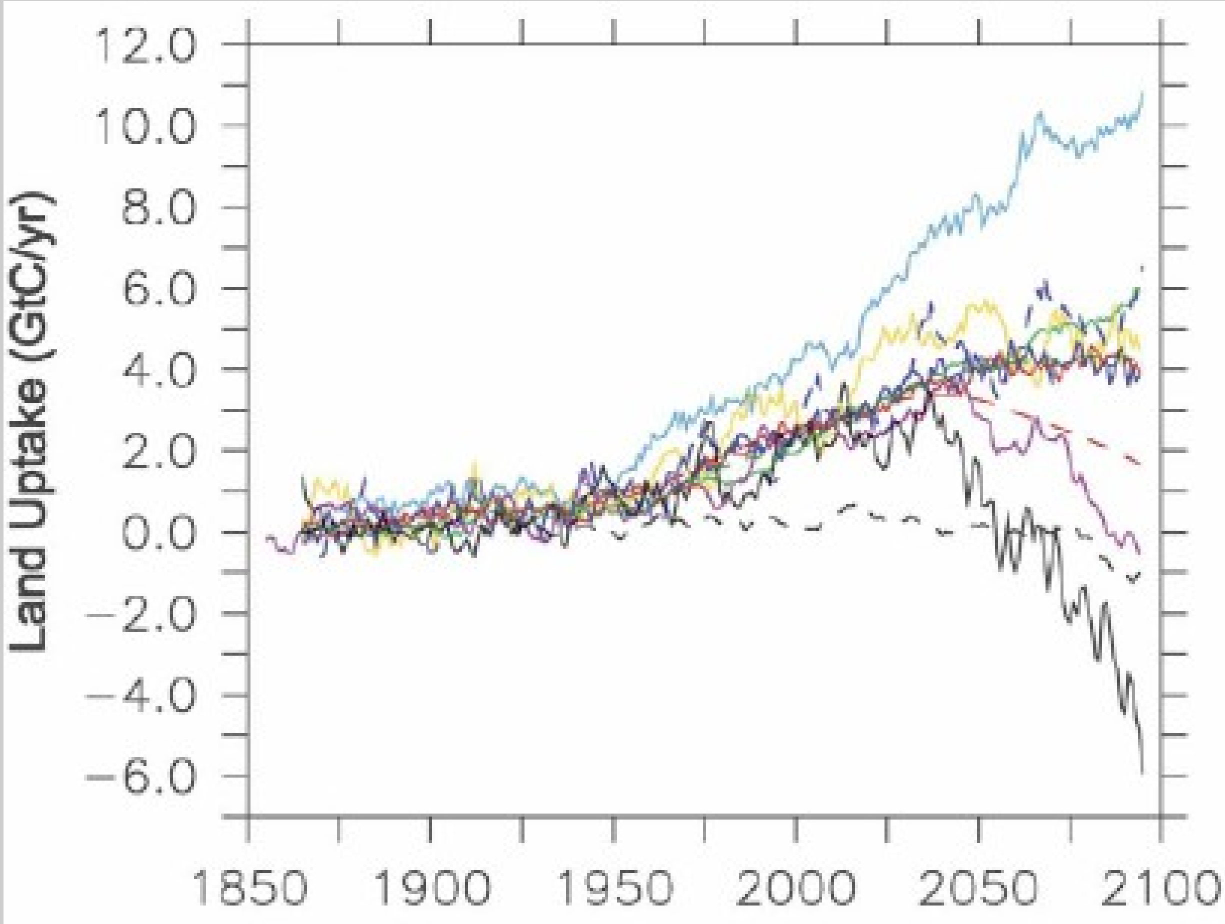
AN INTERACTIVE TOOL TO ANALYSE THE BENEFIT OF SPACE MISSIONS SENSING THE TERRESTRIAL VEGETATION

Thomas Kaminski (1), Wolfgang Knorr (2), Marko Scholze (2),
Bernard Pinty (3), Nadine Gobron (3), Ralf Giering (1), and Pierre-Philippe Mathieu (4)

(1) FastOpt GmbH, Hamburg, Germany, (2) Dept of Earth Science, University of Bristol, UK, (3) European Commission, DG Joint Research Centre, Institute for Environment and Sustainability, Global Environment Monitoring Unit, Italy, (4) European Space Agency, ESRIN, Frascati, Italy

Motivation



Land uptake - C4MIP results (Friedlingstein et al. 2006)

Objective

General Objective:

Exploit observational information to reduce uncertainty in terrestrial model simulation on climate time scales, through data assimilation

Specific Objective:

Quantify the benefit of particular data streams, including hypothetical observations; here: FAPAR and (in-situ) atmospheric CO2

Uncertainty in a terrestrial model simulation from:

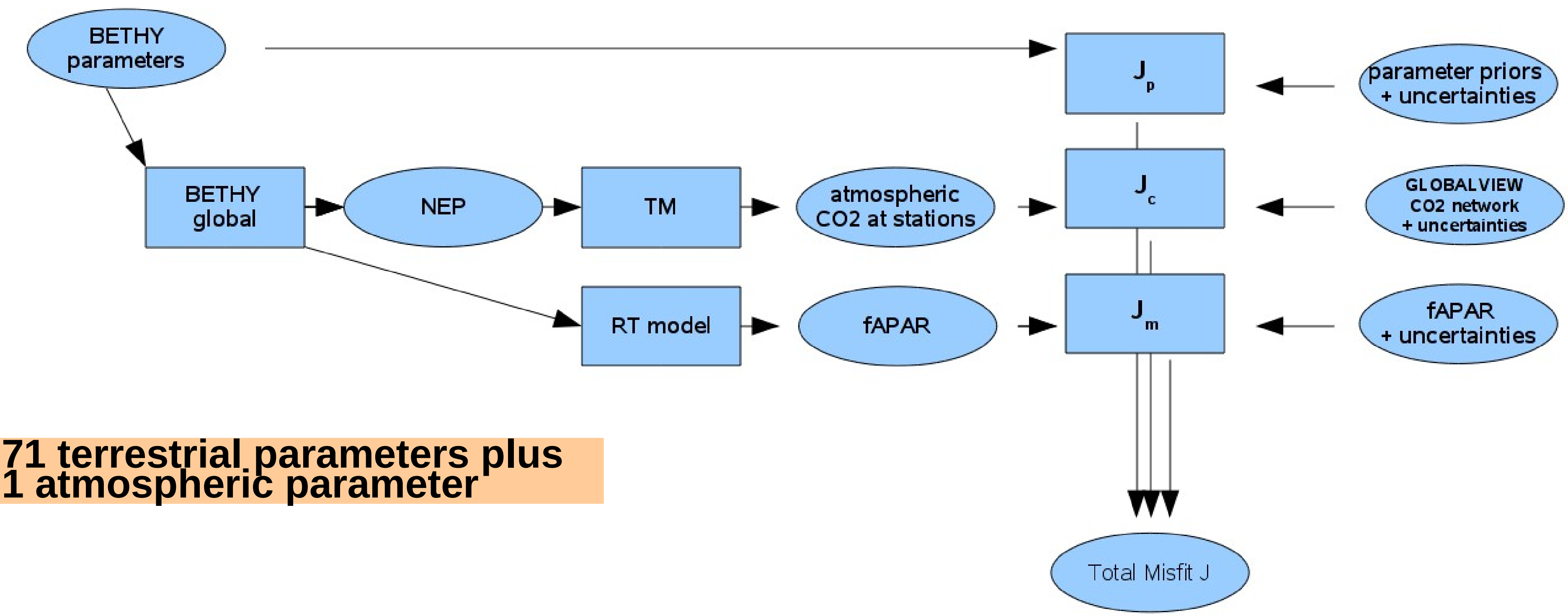
Driving data

Relevant processes and their implementation (structural)

Process parameters (parametric)

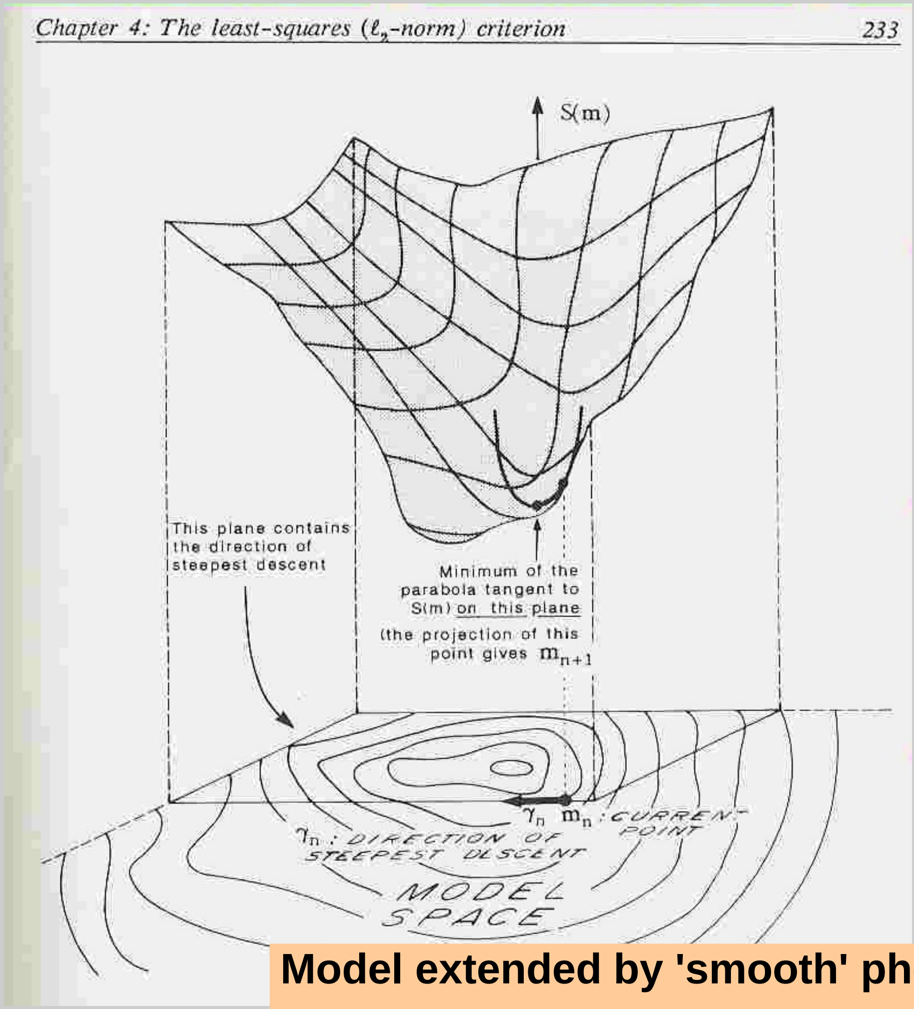
Initial state

Flow of Information in forward sense



71 terrestrial parameters plus 1 atmospheric parameter

Carbon Cycle Data Assimilation System



- Iterative minimisation of **J(x)**

$$J(x) = ½ \, [\, (x-x_{pr})^T C_{pr}^{-1}(x-x_{pr}) + (M(x)-d)^T C_d^{-1}(M(x)-d) \,]$$

- Uses gradient of J with respect to parameters
- Second derivatives (Hessian) at minimum $\mathbf{x_{po}}$ provide approximation of parameter uncertainties (error bars)

$$C_{po}^{-1} = \partial^2 J(x_{po}) \, / \, \partial x^2$$

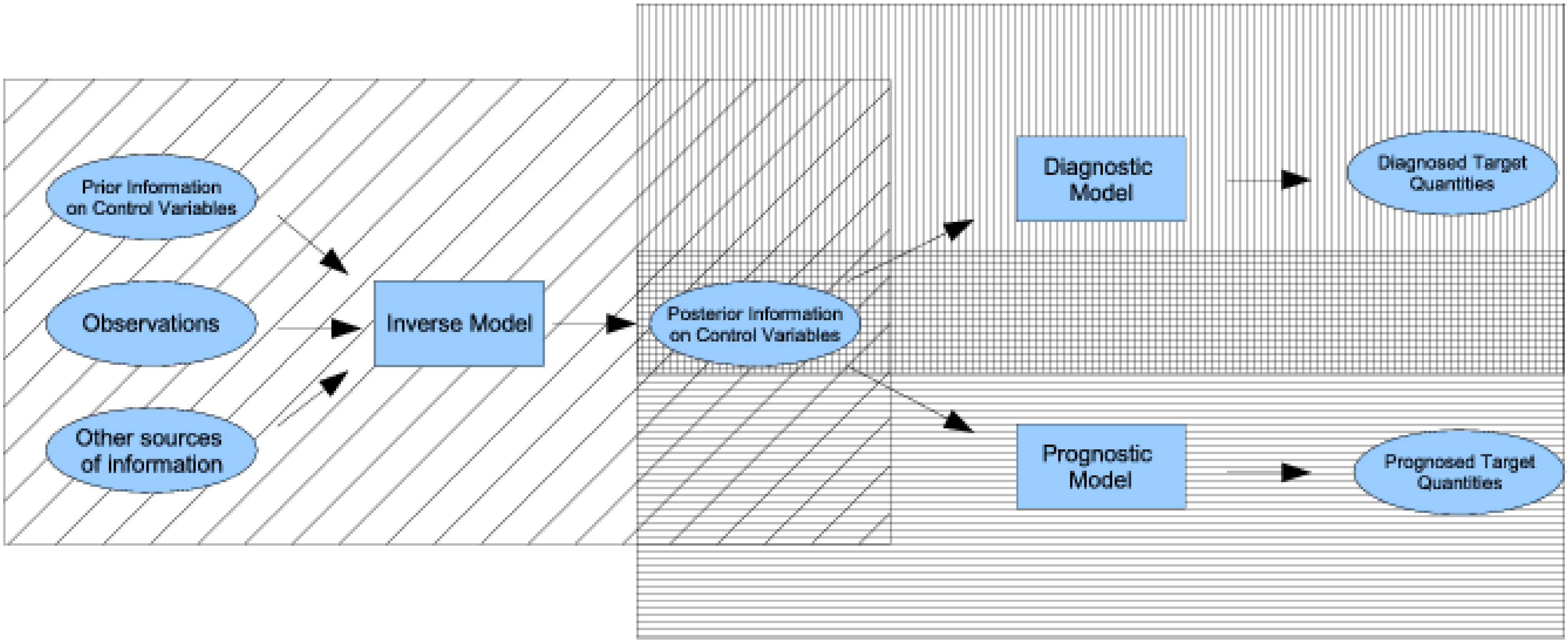
- Uncertainties on current of future target quantities (e.g. net flux, NEP) via linearisation of model (Jacobian matrix)

$$C_{NEP} = \partial M / \partial x \; C_{po} \; \partial M / \partial x^T$$

- All derivatives provided via automatic differentiation of model code (TAF), see Kaminski et al. (2003)
- Figure taken from Tarantola (1987)

Model extended by 'smooth' phenology module (Knorr et al., 2010)

CCDAS scheme



Scholze et al. (2007)

Mission Benefit Analysis Tool

x: Parameters

x_{pr}: Priors

C_{pr}: Uncertainties

$M(x)$: Model

d: Observations

C_d: Their uncertainties

σ_{d_i}: Uncorrelated!

$J(x)$: Cost function

$\frac{d^2J(x)}{dx^2}$: Hessian

x_{po}: Posterior parameters

C_{po}: Posterior uncertainties

$y(x)$: Target quantity

σ_y: Its uncertainty

$$J(x) = \frac{1}{2}\left(x - x_{pr}\right)^T {C_{pr}}^{-1}\left(x - x_{pr}\right) + \frac{1}{2}\sum_{i=1,nd}\left(\frac{M_i(x) - d_i}{\sigma_{d_i}}\right)^2$$

$$\frac{d^2J(x)}{dx^2} = {C_{pr}}^{-1} + \sum_{i=1,nd}\frac{1}{\sigma^2_{d_i}}\left(\frac{dM_i(x)}{dx}^T\frac{dM_i(x)}{dx} + \frac{d^2M_i(x)}{dx^2}^T\left(M_i(x) - d_i\right)\right)$$

uncertainty in observations AND model

- Hessian independent of x for linear model
- For synthetic data use $d = M(x)$.
- Decomposes nicely, can precompute model contribution

$$C_{po} \approx \frac{d^2J(x_{po})}{dx^2}^{-1}$$

$$\sigma_y^2 \approx \frac{dy(x_{po})}{dx}C_{po}\frac{dy(x_{po})}{dx}^T \approx \frac{dy(x_{po})}{dx}\frac{d^2J(x_{po})}{dx^2}^{-1}\frac{dy(x_{po})}{dx}^T$$

Kaminski and Rayner (2008)

Implementation

Uses pre-computed model sensitivities, coarse global resolution (8 x 10 deg.)

Just need linear algebra, can be fast, interactive

Can vary:

- Data uncertainty for FAPAR
- In/Exclusion of atmospheric CO_2 (two sites: MLO and SPO)
- Mission length

Provides

- Uncertainties in target quanties: NEP, NPP, evapotranspiration, plant available soil moisture, 5 year average annual mean values per region
- Uncertainties reflect uncertainty in process parameters, other sources of uncertainty are neglected (e.g. driving data, process formulation)

Benefit per data stream: Carbon Cycle

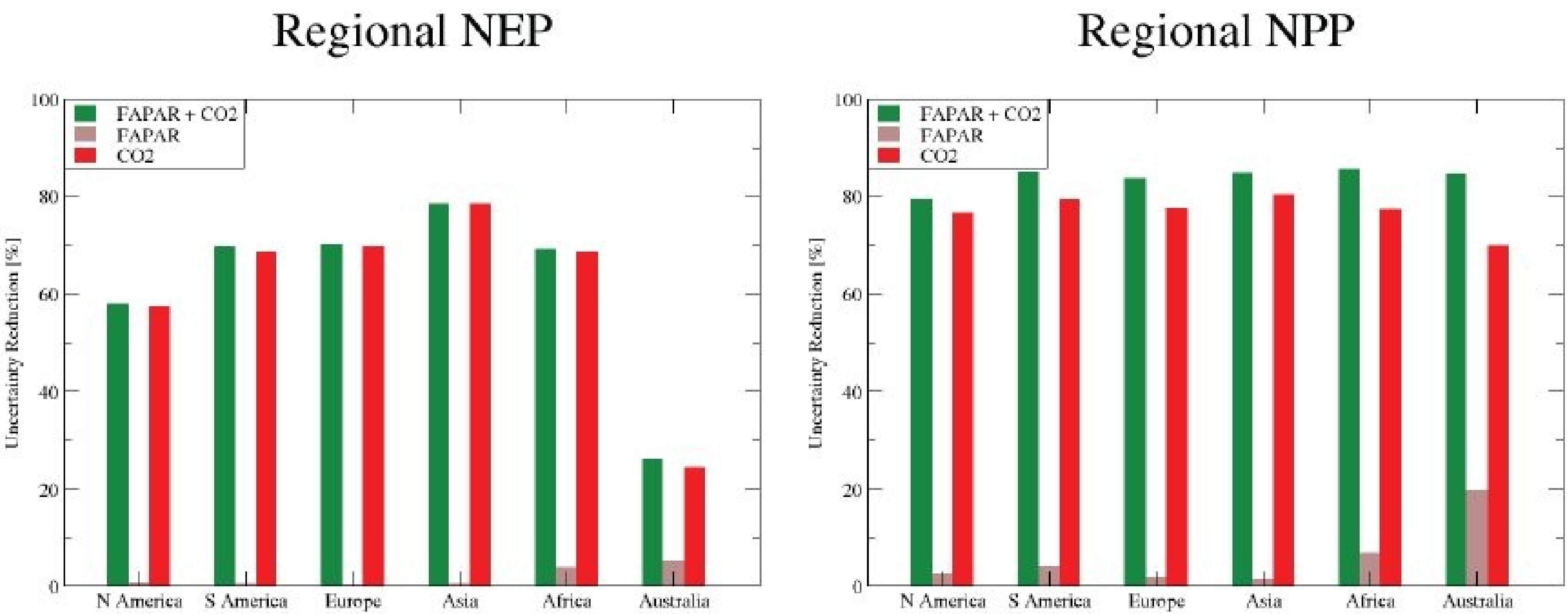


Fig. 7. Reduction in uncertainty in NEP (left hand panel) and NPP (right hand panel) over six regions from MERIS sensor for a 14-yr mission. For assimilation of CO_2 (red) and FAPAR (brown) separately and jointly (green).

Benefit per data stream: Hydrological Cycle

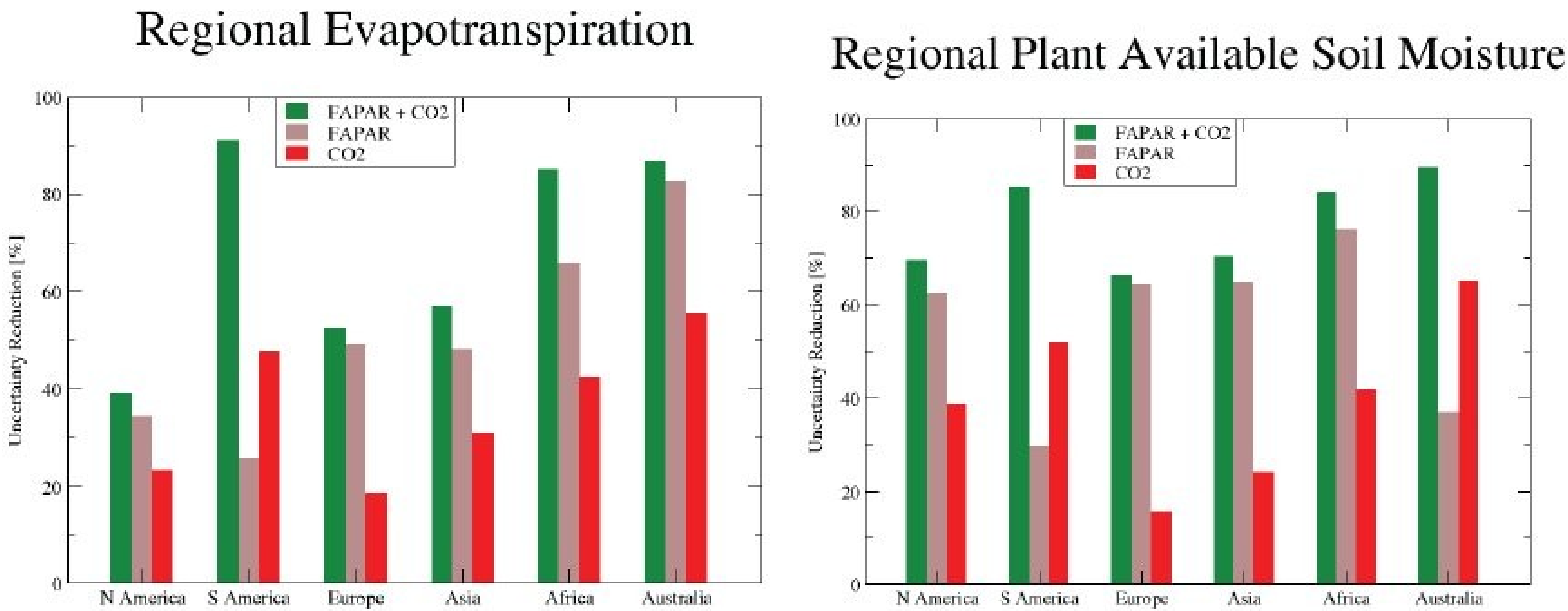
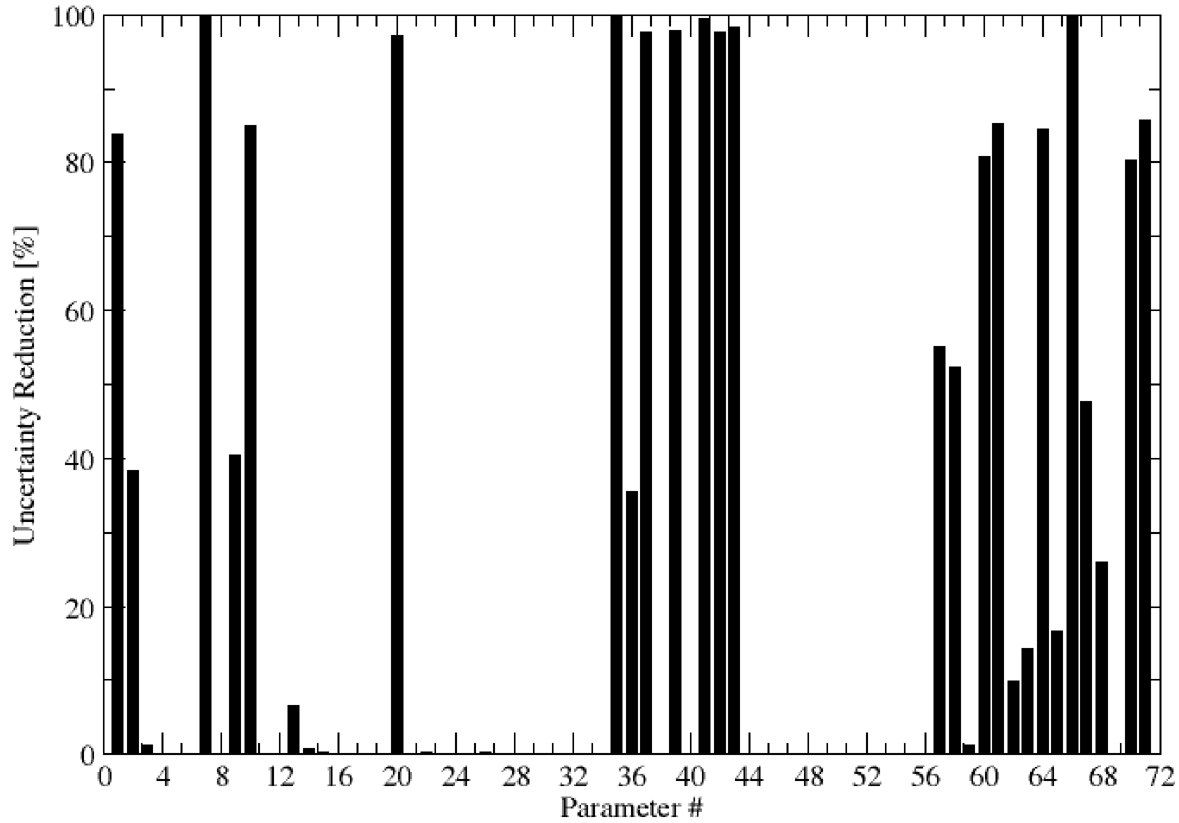


Fig. 8. Reduction in uncertainty in evapotranspiration (left hand panel) and plant available soil moisture (right hand panel) over six regions from MERIS sensor for a 14-yr mission. For assimilation of CO_2 (red) and FAPAR (brown) separately and jointly (green).

Benefit from FAPAR: MERIS (Unc. 0.1)



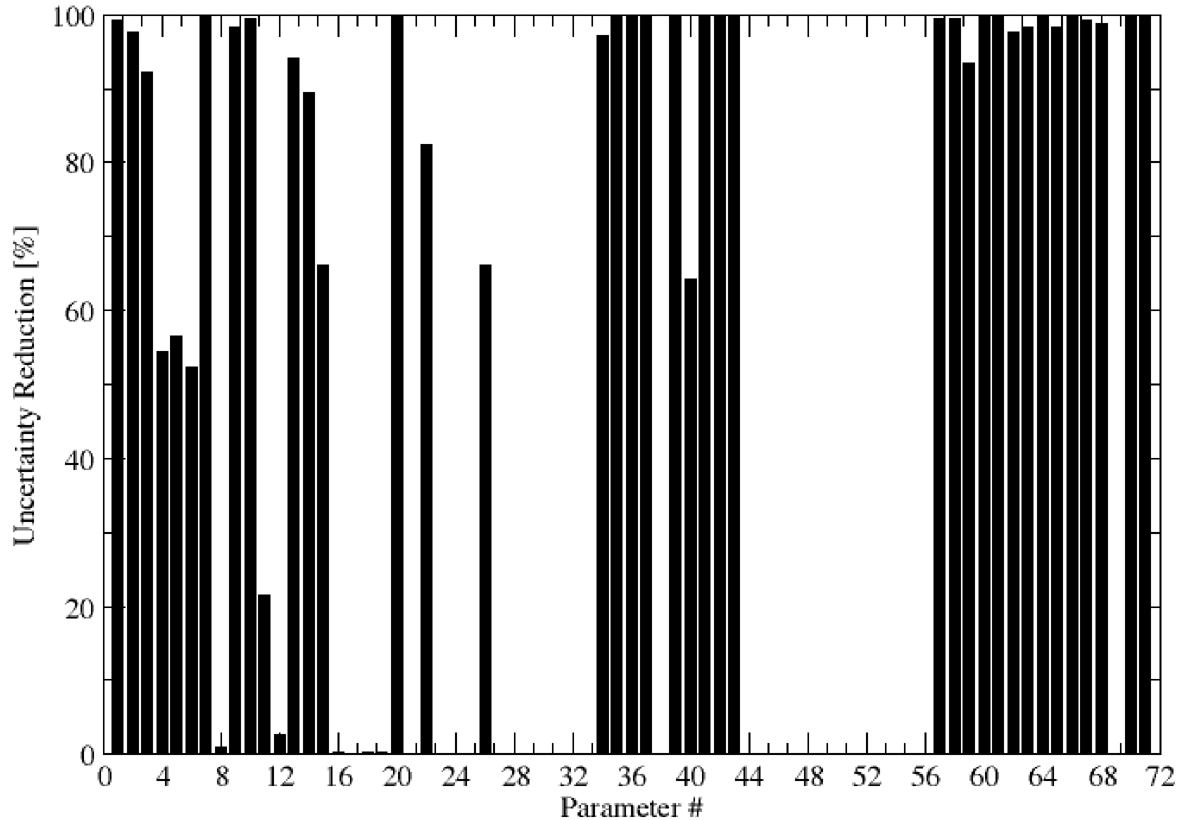
Institute for Environment and Sustainability

University of BRISTOL

esa

FastOpt

Benefit from FAPAR: Ideal (Unc. 0.001)



Benefit from FAPAR: Impact of product unc.

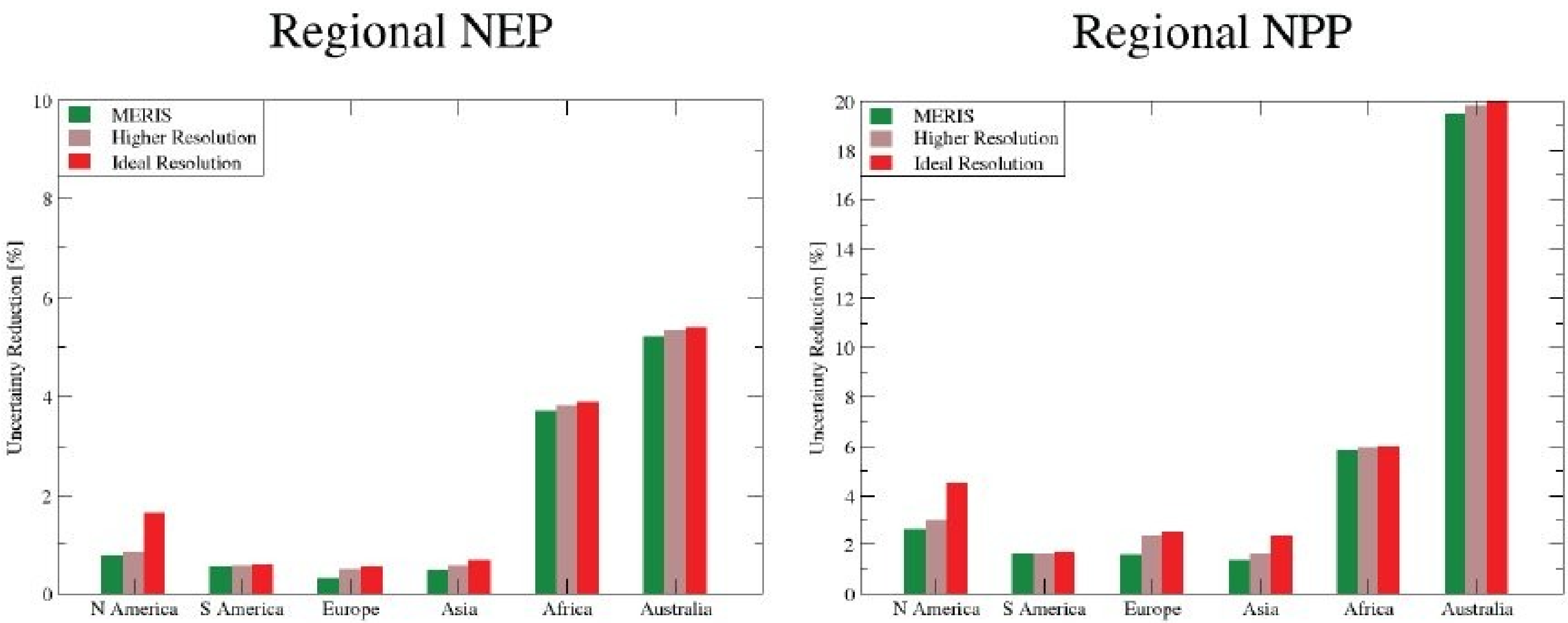


Fig. 10. Reduction in uncertainty in NEP (left hand panel) and NPP (right hand panel) over six regions from three sensor concepts: the MERIS sensor (green), the higher resolution sensor (brown), and the ideal resolution sensor (red).

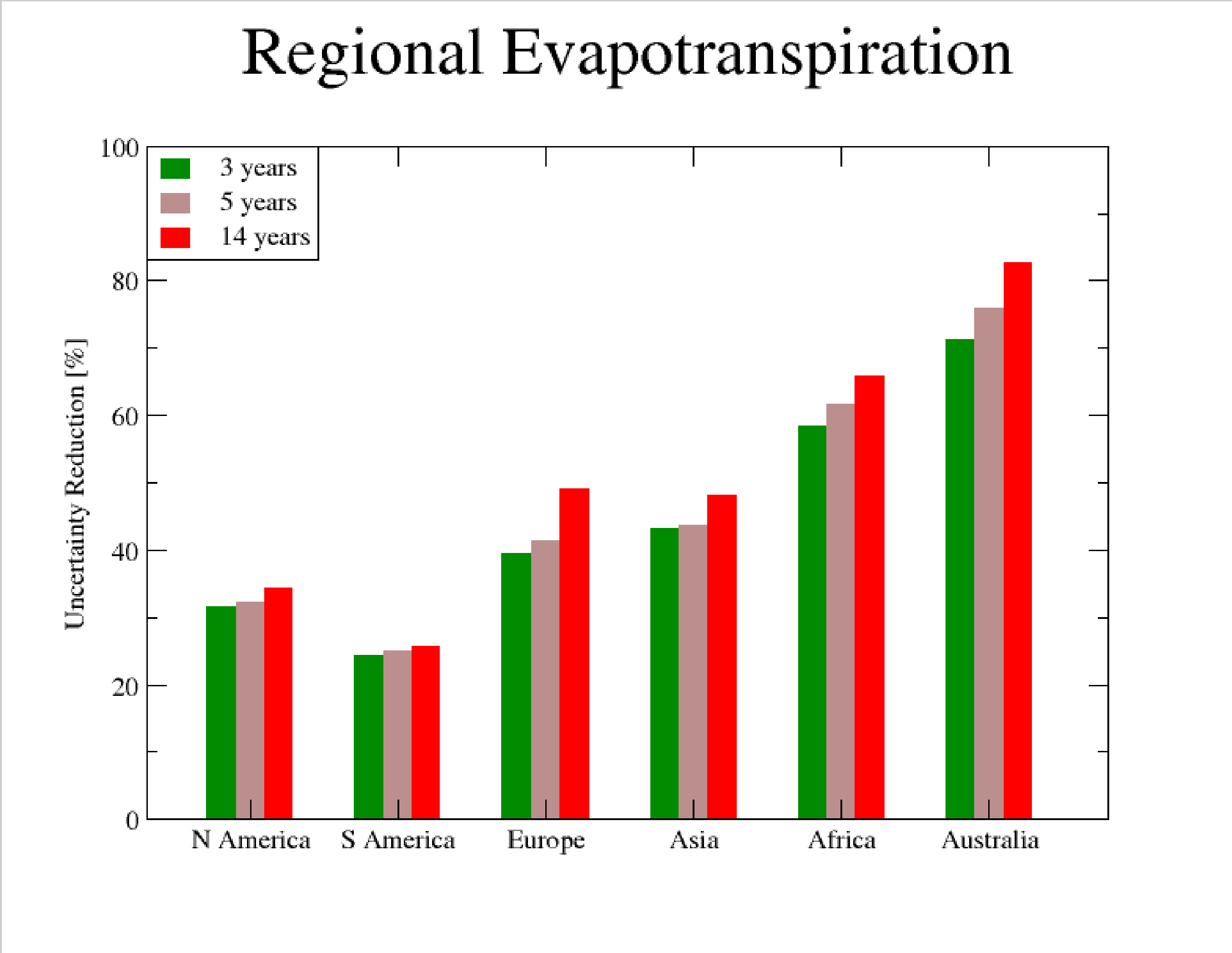
Institute for Environment and Sustainability

University of BRISTOL

esa

FastOpt

Impact of mission length



Summary

- Constructed and demonstrated MBA tool
- Can evaluate indirect constraints of observations on simulated fluxes
- Fast: suited to support decisions within meetings
- FAPAR most useful to constrain hydrological fluxes, in some regions adding CO2 yields considerable improvement
- Atmospheric CO2 most useful to constrain carbon fluxes, adding FAPAR yields only minor improvements
- Extending mission from 3 to 14 years yields only small improvement
- Concept can be extended to include further (also multiple) sensor concepts, also beyond optical
- Acknowledgement: Study supported by ESA
- More info: http://rs.ccdas.org
- Kaminski et al., BG, in press