Data assimilation into land surface models: the implications for climate feedbacks

D. Ghent*†, J. Kaduk†, J. Remedios‡, and H. Balzter†

†Department of Geography, University of Leicester, University Road, Leicester LE1 7RH, UK
‡Department of Physics and Astronomy, University of Leicester, University Road, Leicester LE1 7RH, UK

Abstract

Land surface models are integral components of General Circulation Models (GCMs), consisting of a complex framework of mathematical representations of coupled biophysical processes. Considerable variability exists between different models, with much uncertainty in their respective representations of processes, and their sensitivity to changes in key variables. Data assimilation is a powerful tool increasingly being employed to constrain land-surface model predictions with available observation data. The technique involves the adjustment of the model state at observation times with measurements of a predictable uncertainty, in order to minimize the uncertainties in the model simulations. By assimilating a single state variable into a sophisticated land surface model, this review investigates the effect this has on terrestrial feedbacks to the climate system; thereby taking a wider view on the process of data assimilation, and the implications for biogeochemical cycling, thus being of great relevance to the Intergovernmental Panel on Climate Change (IPCC) 5th Assessment Report.

Keywords: Soil moisture – climate feedbacks, land-surface temperature, data assimilation.

1. Introduction

Pioneering work such as Charney *et al*. (1975) on the link between vegetation loss in sub-Saharan Africa and drought persistence highlighted the role feedback mechanisms between the land-surface and atmosphere play in determining climate. Numerous studies since (Zeng *et al.* 1999; Friedlingstein *et al.* 2001) have reinforced our knowledge of how land-surface properties change in response to climatic forcing, the magnitude of which itself is influenced by the land-surface changes. Indeed, vegetation change is accompanied by soil moisture change; which can lead to changes in properties such as surface albedo and evaporation, resulting eventually in precipitation changes through the soil moisture feedback *(*Koster *et al.* 2004; Zhang *et al.* 2008; Liu *et al.* 2009*).* These complex feedbacks between the terrestrial ecosystem and climate have been extensively studied using land-surface models, but remain poorly understood.

Land surface models calculate the surface to atmosphere fluxes of heat, water and carbon; and update the state variable of the surface and sub-surface layers (Cox *et al.* 1999). They are crucial components of General Circulation Models (GCMs) influencing cloud cover, precipitation, and atmospheric chemistry, with these coupled systems representing key tools for predicting the likely future states of the Earth system under anthropogenic forcing (IPCC 2007). However, representation of highly complex biophysical processes in land-surface models over highly heterogeneous land surfaces with limited collections of mathematical equations, and the tendency of over-parameterisation, infers a degree of uncertainty in their predictions (Pipunic *et al.* 2008). Moreover, a substantial portion of this uncertainty may be attributed to the representation of land-surface feedbacks within coupled climate models (Notaro 2008).

Even if atmospheric greenhouse gas concentrations were stabilised, the long-memory effect associated with the climate system means anthropogenic warming would continue through future decades and centuries. However, large uncertainties remain with respect to our understanding of biogeochemical cycle feedbacks, diminishing our ability to accurately model climate forcing. Significant progress has been made in reducing uncertainties associated with atmospheric change, but further consideration of the long-term changes in atmospheric chemistry, and the consequences of the associated climate forcing, remains a priority (Dameris *et al*. 2005; Cracknell and Varotsos 2007; Varotsos *et al*. 2007). To this end improving the estimations in land-surface models of feedbacks to the climate system represents a pertinent objective. Data assimilation may be viewed as an optimum solution for such improvements.

Data assimilation is a method of minimising some of the uncertainties inherent in all land-surface models due to their approximation of the complexity in the terrestrial ecosystem. Observations, if available, from sources such as Earth Observation (EO) satellites, can be integrated into the model to update a quantity simulated by the model with the purpose of reducing the error in the model formulation. The correction applied is derived from the respective weightings of the uncertainties of both the model predictions and the observations. There has been much research focused on data assimilation into land-surface models in previous years. Particular attention has been paid to assimilation of land-surface temperature (LST) to constrain simulations of soil moisture and surface heat fluxes. These assimilation studies include the use of variational schemes (Caparrini *et al.* 2003); and variants of the Kalman Filter sequential scheme, such as the Ensemble Kalman Filter (EnKF) (Crosson *et al.* 2002; Huang *et al.* 2008; Pipunic *et al.* 2008; Quaife *et al.* 2008), first proposed by Evensen (1994).

Coupled GCM land-atmosphere models are important tools for climate change prediction and for assessing climate feedbacks over future decades and centuries. However, due to large uncertainties with respect to these feedbacks - an example being cloud formation - a concerted effort is required to improve the modelling of water, energy and carbon exchanges in these coupled systems, by optimising prediction of key variables, such as soil moisture. The assimilation of observations to improve the quantification of soil moisture has long been an objective of the hydrological community (Crosson *et al*. 2002; Crow and Wood 2003; Huang *et al*. 2008). Margulis and Entekhabi (2003), for instance, assimilated skin and air temperature, plus relative humidity, to optimise the water and energy budgets of a coupled land surface-atmospheric boundary layer model. Pipunic *et al*. (2008) also demonstrated enhanced model estimates as a result of integrating EO observations into their land-surface scheme, with improved predictions of latent and sensible heat fluxes. This focus on the moisture states of models illustrates the importance attributed to the longer memory characteristics in coupled systems. Optimisation, as a result of data assimilation, thus presents an opportunity to improve our ability to predict water and energy fluxes from the land-surface to the atmosphere, with the prospect of reducing climate feedback uncertainty. Moreover, the application of data assimilation in understanding and quantifying feedbacks in the climate system is not just restricted to land-atmosphere interactions. The role of marine sediments and ocean biogeochemistry in the long-term regulation of atmospheric carbon has driven the development of data assimilation techniques in these systems; resulting in improved parameter estimation (Annan *et al*. 2005), and enhanced calibration of ocean-atmosphere models (Ridgwell *et al*. 2007) through, for example, the integration of phosphate and alkalinity observations. However, as in any coupled chaotic system, minor changes in a single characteristic can have far reaching effects.

This paper considers the sensitivity of related characteristics to the model update of a single variable, through the process of data assimilation. In section 2, LST over two regions of the African continent: an area of West Africa (17°W to 20°E longitude, 4°N to 20°N latitude); and an area of North Africa (10°W to 33°E longitude, 20°N to 30°N latitude); is integrated into the state-of-the-art land surface model JULES (Joint UK Land Environment Simulator), developed by the UK Met Office, during the period 1st January to 31st May 2007. The effect on soil moisture is discussed in section 3, whereby the model simulations are compared with European Remote Sensing Satellites (ERS-1 and ERS-2) scatterometer top soil moisture observations. Finally, in section 4, the implications of the data assimilation exercise on surface energy, water, and carbon fluxes are considered.

2. Land surface temperature

LST is the radiative skin temperature of the land, with wide-ranging influences on several biophysical processes of the terrestrial biosphere: such as the partitioning of energy into ground, sensible and latent heat fluxes (Sellers *et al.* 1997; Huang *et al.* 2008) and the emission of long-wave radiation from the surface (Rhoads *et al.* 2001; Trigo *et al.* 2008); the physiological activities of leaves (Sims *et al.* 2008); surface dryness (Sandholt *et al.* 2002; Snyder *et al.* 2006); and stomatal conductance (Sellers *et al.* 1997); and its reported response as an effect of El Niño Southern Oscillation (ENSO) (Manzo-Delgado *et al.* 2004). Sensible heat flux (H) is a function of the difference between surface and air temperature (Rhoads *et al.* 2001). Latent heat flux (LE), on the other hand, is a function of surface temperature due to the influence LST expends on vapour pressure deficit (Hashimoto *et al.* 2008). Within the surface balance equation, LE and H are tightly coupled, in which an increase in one is usually at the expense of the other.

LST also has a role to play in the hot topic of fire modelling within land surface models. For example, it is related to fuel moisture content (Chuvieco *et al.* 2004), and in combination with other environmental variables can be applied in predicting fire occurrence and propagation (Manzo-Delgado *et al.* 2004). This is particularly crucial for Africa, where climate scenarios remain highly uncertain (Williams *et al.* 2007), most notably in the fire dominated savannas. Here cloud-free LST pixels from the Spinning Enhanced Visible and InfraRed Imager (SEVIRI) instrument onboard the Meteosat Second Generation (MSG) geostationary satellites, centred over the equator at an altitude of 36000km, is integrated into the JULES model over two regions of the African continent - West Africa and North Africa - for a five month period of 2007.

2.1. MSG-SEVIRI data

SEVIRI acquires an image every 15 minutes, at a spatial resolution of between 3km and 5km for the African continent. LST is generated by the Satellite Application Facility on Land Surface Analysis (LandSAF) using a Generalized Split Window (GSW) algorithm (Madeira 2002) for channels IR10.8 and IR12.0, as a linear function of clear-sky top-of-the-atmosphere (TOA) brightness temperatures. Within each scene, bareground and vegetation emissivities, previously assigned to land cover classes (Peres and DaCamara 2005) are averaged, and weighted with the fraction of vegetation cover retrieved by the LandSAF (Garcia-Haro *et al.* 2005) to estimate channel surface emissivity.

Independent data assessment of the GWS algorithm against a set of radiative transfer simulations indicated a bias free algorithm, with random errors increasing in response to increasing viewing zenith angle (Trigo *et al.* 2008), with a reported accuracy of 1.5K (Sobrino and Romaguera 2004) for most simulations between nadir and 50°. Since clouds scatter and absorb infra-red radiance, LST retrieval requires identification of cloudy / part cloudy pixels. Clear sky pixels are identified by the LandSAF through the application of a cloud mask which makes use of software developed in support to Nowcasting and Very Short-Range Forecasting Satellite Application (NWC SAF; http://nwcsaf.inm.es); with this information being represented in quality control flags. A complete description of the LST retrieval algorithms can be found in the LandSAF product user manual (available at http://landsaf.meteo.pt/).

2.2. Model description and data assimilation

The JULES land surface model, which has been described elsewhere (Cox *et al.* 1999; Alton *et al.* 2007) in considerable detail, is the community version of MOSES (Met Office Surface Exchange System). It is becoming increasing important to the UK ecological modelling community since it can be coupled to the Hadley Centre GCM or driven by its output. Briefly, JULES is terrestrial gridbox model of a fine temporal resolution, in which each gridbox is composed of nine surface tiles: five plant functional types (PFTs) - broadleaf trees, needleleaf trees, C_3 grasses, C_4 grasses, and shrubs; and four non-vegetation types - urban, inland water, bare soil and ice. Each gridbox is profiled into four soil layers, which are homogeneous over the gridbox, with soil thermal characteristics being functions of soil moisture. Prognostic soil fields are updated from values for the previous time step using the mean heat and water fluxes over the time step; whereby the total soil moisture content within each soil layer is incremented by the evapotranspiration extracted directly from the layer by plant roots, the diffusive water flux flowing in from the layer above, and the diffusive flux flowing out to the layer below (Cox *et al.*, 1999). Furthermore, the Clapp and Hornberger (1978) relations for hydraulic conductivity and soil water suction are applied in the model.

The physical processes are driven by meteorological data, which update the state variables typically every 30 or 60 minutes; whereas the biophysical parameters remain constant over the duration of each model run. The output from JULES includes numerous variables depicting the state of the land-surface surface in terms of water, energy and carbon fluxes. At each timestep the grid box LST is derived from the sum of the individual tile surface temperatures multiplied by their respective fractional covers within the grid box. Whereby the surface energy balance equation for each tile, defined by Cox *et al*. (1999), is given by equation (1):

$$SW_N + LW_\downarrow - \sigma T_s^{\,4} = H + LE + G_0 \tag{1}$$

Where SW_N is the net downward short wave radiation, which is derived from the surface albedo, $LW_\downarrow$ is the downward long wave radiation, σ is the Stefan–Boltzmann constant, T_s is the surface temperature, H is the sensible heat flux, LE is the latent heat flux, and G_0 is the heat flux into the ground.

Here LST was assimilated into JULES for a five month period from 1st January to 31st May 2007, by applying EnKF sequential data assimilation, which applies a Monte Carlo approach. The exact methodology, which has been applied previously (Ghent *et al.* 2009a; Ghent *et al.* 2009b), is described comprehensively in Ghent *et al.* (2009b), with the EnKF approach implemented according to Evensen (2003). To give a brief overview though, at each timestep, model estimates are nudged towards the observations based on the respective state and observation error covariance matrices, **P** and **R**. The correction to the forecast state vector is determined by the Kalman gain matrix **K** defined by equation 2:

$$\mathbf{K} = \mathbf{P}^{\mathrm{f}}\mathbf{H}^{\mathrm{T}} [\ \mathbf{H}\ \mathbf{P}^{\mathrm{f}}\mathbf{H}^{\mathrm{T}} + \mathbf{R}\ ]^{-1} \tag{2}$$

Where **H** is the observation operator relating the true model state to the observations, taking into account the observation uncertainty. The Kalman gain matrix is applied to the difference between the model estimates and the observations according to equation 3:

$$\boldsymbol{\psi}^{\mathrm{a}} = \boldsymbol{\psi}^{\mathrm{f}} + \mathbf{K}\,(\mathbf{H}\boldsymbol{\psi}^{\mathrm{t}} - \mathbf{H}\boldsymbol{\psi}^{\mathrm{f}} + \boldsymbol{\varepsilon}) \tag{3}$$

Where $\boldsymbol{\psi}^{\mathrm{a}}$ is the updated model estimate, $\boldsymbol{\psi}^{\mathrm{f}}$ is the forecast state vector, $\boldsymbol{\psi}^{\mathrm{t}}$ is the true model state, and $\boldsymbol{\varepsilon}$ is the observation uncertainty. The estimate of the model state following the update is taken as the mean of the ensemble members, with the uncertainty indicated from the variance around the mean. The observation error covariance matrix is a measure of the ensemble spread of observations, with randomly generated perturbations constructed using the observation uncertainty of 1.5K for SEVIRI LST (Sobrino and Romaguera 2004). The distribution of the model ensemble spread, from an ensemble size of 50 in this case, determines the state error covariance matrix, thereby avoiding the expensive integration of the standard Kalman Filter. In this study, only perturbations to the meteorological forcing data, generated from normally distributed random number perturbations with zero mean and unit variance, following the Box-Muller transform method (Box and Muller 1958), and scaled to each variable were considered. Uncertainties in model parameterisation or initial conditions were not taken into account.

Meteorological forcing variables were taken from generated 6-hourly National Centers for Environmental Prediction (NCEP) reanalysis datasets (Kalnay *et al.* 1996); with precipitation data calibrated from monthly Tropical Rainfall Measuring Mission (TRMM) precipitation data (Kummerow *et al.* 1998). The model itself was run at an hourly timestep over the five month assimilation period, with a spatial resolution of 1° x 1°. Land-cover change was not considered in this experiment, so the fractional coverage of the surface tiles were derived from International Geosphere-Biosphere Programme (IGBP) land-cover classes and mapped onto JULES according to Dunderdale *et al.* (1999). Initial conditions were set from an equilibrium state following a 200-year spin-up cycle; with soil parameters derived from the International Satellite Land-Surface Climatology Project (ISLSCP) II soil data set (Global Soil Data Task 2000). To quantify the influence LST assimilation has on the state of the modelled land surface the changes in several variables were examined: soil moisture; evapotranspiration (ET); and net primary productivity (NPP).

3. Soil moisture

The partitioning of available energy into sensible heat (H) and latent heat (LE), driven by changes in the surface temperature, is influenced by the vegetative cover and the available soil moisture (Smith *et al.* 2006). Temperature change in soil is dependent on thermal conductivity and heat capacity. A dry soil heats up more rapidly than wet soil, since the heat capacity of water is higher than that of air, which occupies a much greater percentage of the volume in dry soil. A wet soil surface loses more LE, whereas a dry soil surface loses more H.

Soil moisture exhibits a significant memory, which can persist for many months, prolonging and intensifying pluvial and drought events (Notaro 2008). Moreover, soil moisture feedbacks can regulate climate change and increase our predictability of seasonal climate, yet the strength and regional significance of this feedback remains poorly understood (Zhang *et al.* 2008). Evidence for soil moisture – climate feedbacks includes the relationship between soil moisture and precipitation; evaporation; air temperature; and cloud cover (Findell and Eltahir 1997; Zhang *et al.* 2008).

The most extensive study on soil moisture effects - the Global Land-Atmosphere Coupling Experiment (GLACE) (Koster *et al.* 2004; Guo *et al.* 2006) – involved a 12 Atmospheric General Circulation model (AGCM) intercomparison illustrated that the strong land-atmosphere coupling lies mainly in the ability of soil moisture to affect evaporation in the transition zones between dry and wet climates (Zhang *et al.* 2008). Identified hotspots include, the Sahel, the northern United States, and southern Europe. Furthermore, the feedback among Intergovernmental Panel on Climate Change (IPCC) AR4 models was assessed over Europe (Seneviratne *et al.* 2006), with a positive correlation between soil moisture and precipitation. In other words, high soil moisture will support enhanced evaporation, increasing atmospheric water content and eventually leading to increased rainfall; although this temporal response depends on sub-grid condensation processes within global models, and therefore can vary substantially (Koster *et al.* 2004). Moreover, the strength and impact of soil moisture feedbacks are likely to differ between El Niño and La Niña events (Seneviratne *et al.* 2006; Notaro 2008); with vegetation interactions also being a substantial influence (Sellers *et al.* 1997).

Future climate change, driven by increased greenhouse gas concentrations, are likely to enhance hydrological responses in these hotspots of strong positive soil moisture feedback (Notaro 2008). In respect of this, the importance of global soil moisture retrieval, and assimilation into hydrological and biophysical models, has received much recent recognition (Crow *et al.* 2005; Reichle and Koster 2005; Parajka *et al.* 2006; Parajka *et al.* 2009). Here modelled and assimilated soil moisture estimations and are compared with ERS scatterometer top soil moisture observations.

3.1. ERS-Scatterometer data

The ERS-1 and ERS-2 scatterometers are active C-band (5.6 GHz) microwave instruments, providing backscatter measurements sensitive to the surface soil water content without being affected by cloud cover. The surface soil moisture data (SSM) are retrieved, in a discrete

12.5km global grid, from the radar backscattering coefficients using a change detection method, developed at the Institute of Photogrammetry and Remote Sensing at the Vienna University of Technology. Scatterometer estimates are used to model the incidence angle dependency of the radar backscattering signal. Backscattering coefficients are normalised to a reference incidence angle of 40°, with these coefficients scaled between the driest and wettest observations over the long-term to produce relative SSM data ranging between 0% and 100%; with uncertainty detailed with a soil moisture noise model (Naeimi *et al.* 2009).

The ERS scatterometer (ESCAT) soil moisture dataset used here has undergone previous validation experiments. Wagner *et al.* (1999) tested the SSM dataset with gravimetric soil moisture measurements over field sites in the Ukraine and found mean correlations of 0.45 (0–20 cm profile) and 0.41 (0-100 cm profile). Furthermore, Ceballos *et al*. (2005) performed a more extensive validation using a network of 20 soil moisture stations located in western Spain. They found a correlation of 0.75; with a root mean square error (RMSE) (0–100cm profile) between the scatterometer data and the average soil moisture of 2.2%. However, use of this dataset comes with the caveat that in extreme climates, such as desert regions, biased estimates may be derived, with azimuthal viewing geometry not taken into account during retrieval (Bartalis *et al.* 2006).

3.2. Comparison Model-ESCAT

In this study modelled soil moisture from the JULES model is compared with SSM scatterometer values in the top 5cm of the soil from two separate ERS receiving stations generating SSM 'observations' for northern hemisphere Africa: Maspalomas, covering West Africa; and Matera, covering North Africa. Since 2001, coverage of southern hemisphere Africa did not begin until mid-July 2008, and therefore is not considered during our assimilation period. Figure 1(*a)* and figure 1(*b*) illustrate the comparison for both the modelled state and the assimilated state carried out over the five month assimilation period. The SSM 'observations' derived from ERS scatterometers for both West Africa and North Africa are lower than the equivalent modelled by the JULES land-surface model. It is clear following assimilation that the updated model estimates are closer to the 'observation' values. Indeed, for West Africa a 27.4% reduction in RMSE, from 16.8vol% to 12.2vol% between the model soil moisture estimates and the ERS scatterometer SSM 'observations' resulted from the assimilation process. For North Africa, the reduction in RMSE between the model soil moisture estimates and the ERS scatterometer SSM 'observations' as a result of the assimilation process was 32.2%, from 14.6vol% to 9.9vol%. The modelled and assimilated runs were repeated 50 times over each region respectively; and paired *t*-tests performed on the mean RMSEs showed that these reductions in RMSE were significant at the 99% confidence level.

It is therefore evident that the process of data assimilation has produced a systematic reduction in the model predictions of soil moisture over both West Africa and North Africa for the period 1st January – 31st May 2007. The implication is that this reduction may affect the predictions of heat, water, and carbon fluxes from the land-surface to atmosphere. When coupled to the Hadley Centre GCM this altered change in the strength of the soil moisture – climate feedback could influence the predictions of seasonal and interannual climate.

4. Biogeochemical cycles

The main aim of this investigation is to understand and quantify the impact a change in LST has on the water, heat, and carbon fluxes from the surface to the atmosphere. It has been shown that integrating SEVIRI LST into the JULES land-surface model for the first five months of 2007 over much of northern hemisphere Africa resulted in a mean reduction in surface soil moisture during this period. We now consider the effect this integration, taking the case of West Africa as an example, has on further key fluxes of the water and carbon cycles respectively - ET (figure 2) and NPP (figure 3). Unmistakeable mean reductions are observed for both these fluxes over the assimilation period.

LST and the partitioning of surface energy into H and LE is a function of varying surface soil moisture and vegetation cover. Predominantly vegetated surfaces are associated with lower maximum LST values than bare soil (Weng *et al.* 2004), with surface roughness a factor (Sandholt *et al.* 2002). This is because increases in surface temperatures are associated with increases in H, and due to the surface balance equation more energy is partitioned into LE for higher vegetative cover; whereas higher H exchange is more typical of sparsely vegetated surfaces. LE is enhanced with increased ET, which is controlled by stomatal conductance (Essery *et al.* 2003). Stomatal conductance is affected by the quantity of photosynthetically active radiation (PAR), but is also critically linked to the availability of moisture in the soil. A reduction in soil moisture below a critical value causes a partial closing of stomata on the underside of leaves to reduce water loss. The subsequent decrease in ET results in a decrease in LE, since the drop in humidity reduces the humidity gradient between the surface and atmosphere, reducing the evaporative cooling causing an increase in H and thus surface temperature (Crucifix *et al.* 2005).

ET is an important climate system feedback between the land-surface and the atmosphere in that soil moisture anomalies can translate into precipitation anomalies through the ET rate (Shukla and Mintz 1982). This feedback on the precipitation regime could significantly influence the occurrence and persistence of pluvial and drought conditions, which in turn influences the distribution of vegetation and thus surface albedo, subsequent surface evaporation and the terrestrial carbon stocks. The terrestrial carbon cycle feedback may be an important component of future climate change (Melillo *et al.* 2002), with experiments such as Cox *et al*. (2000) inferring that these feedbacks could significantly influence climate change over the course of the next few decades. A reduction in soil moisture and associated reduction in ET impacts upon the carbon balance, leading to a reduction in NPP as suggested by Rosenzweig (1968) who postulated, in general, a positive relationship between ET and NPP. With interannual variability of NPP greater than that of heterotrophic respiration over Africa (Weber *et al.* 2009), the implication of a reduction in NPP over a region would be a corresponding reduction in net ecosystem productivity, and hence an altered carbon balance. However, large uncertainties in both the sign and magnitude of the carbon cycle feedbacks remain, because of model simplification of the complex terrestrial system.

Data assimilation is an exciting field of research offering significant benefits to land surface modelling. The rationale behind this technique is that although both sources of information – model and EO – are associated with uncertainty, the combination of the two sources is expected to reduce the resultant uncertainty. For highly changeable variables in time a land-surface model may produce more comprehensive coverage than an EO product, which can suffer from missing data or occasional instrumentation problems. However, since validated EO products can be shown to produce more realistic representations of the ground measurements, the integration of these into land-surface models may provide the best possible compromise. Furthermore, data assimilation is reliant on the accurate prediction of uncertainty in observations. EO products are generated using implicit or explicit assumptions, which may not be consistent with the assumptions made in a land-surface model, whereby biased observations will cause the model to depart from the correct state (Quaife *et al.* 2008). If remote sensing products are to be integrated more comprehensively into land surface models, then further validation work needs to be undertaken, with the accurate reporting of measurement uncertainty a priority.

As highlighted in Pinheiro *et al*. (2006), to demonstrate how a small change can be influential: Brutsaert *et al*. (1993) report a 10% error in sensible heat flux as a result of an error of 0.5 K in LST; Moran and Jackson (1991) report a 10% error in ET as a result of a 1 K error in LST; and Kustas and Norman (1996) suggest a LST error of between 1 to 3 K can lead to errors of up to $100Wm^{-2}$ in surface fluxes to the atmosphere. Due to the feedbacks between the land surface and the atmosphere it is clear how these comparatively minor uncertainties can produce significantly different climatic conditions. Climate change can lead to both positive and negative feedbacks to the climate system. It is therefore essential that we accurately represent these feedbacks in coupled land-surface model - general circulation model frameworks if we are to successfully predict future climate change.

5. Concluding remarks

These relationships, among others, suggest that the potential is there for LST to act as surrogate for assimilating other state variables into a land surface scheme. Indeed, demand for LST observations is increasing due to its importance in regional and global ecosystem studies, particularly its sensitivity to surface moisture conditions. Remotely sensed data from EO satellites offers the most feasible source of data to constrain and validate land surface models over large geographical regions, as this overcomes the limitation of sparsely available ground measurements. The significance of model predictions as a resource in climate policy decision making ensures the validation of increasingly employed data assimilation methods a priority. Moreover, care should be taken to quantify the changes in the entire ecosystem dynamics through updating of key variables.

While assimilation of EO data into land-surface models offers the prospect of optimising estimates of key biogeochemical states, herein the danger lies. Unless a thorough understanding and validation of the model output is performed the possibility of the model being improved in one sense, in terms of reduced RMSEs against validation observations, but degraded elsewhere remains a distinct likelihood. In terms of the predictions of biogeochemical fluxes, the acknowledgement of the influence data assimilation of EO data has on the feedback from land-surface models to AGCMs is of great relevance to the IPCC 5th Assessment Report.

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Figures

Figure 1(*a*): Time series of modelled vs. assimilated mean daily soil moisture from the JULES land-surface model in the top 5cm of the soil profile over West Africa (17°W to 20°E longitude, 4°N to 20°N latitude) from 1st January – 31st May 2007. ERS scatterometer surface soil moisture observations from the top 20cm of the soil profile are plotted for comparison.

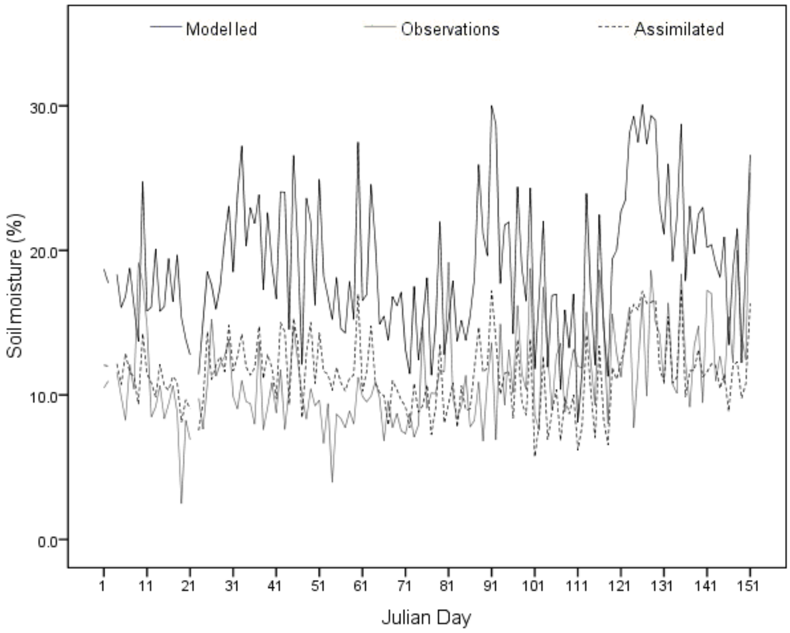

Figure 1(*b*): Time series of modelled vs. assimilated mean daily soil moisture from the JULES land-surface model in the top 5cm of the soil profile over North Africa (10°W to 33°E longitude, 20°N to 30°N latitude) from 1st January – 31st May 2007. ERS scatterometer surface soil moisture observations from the top 20cm of the soil profile are plotted for comparison.

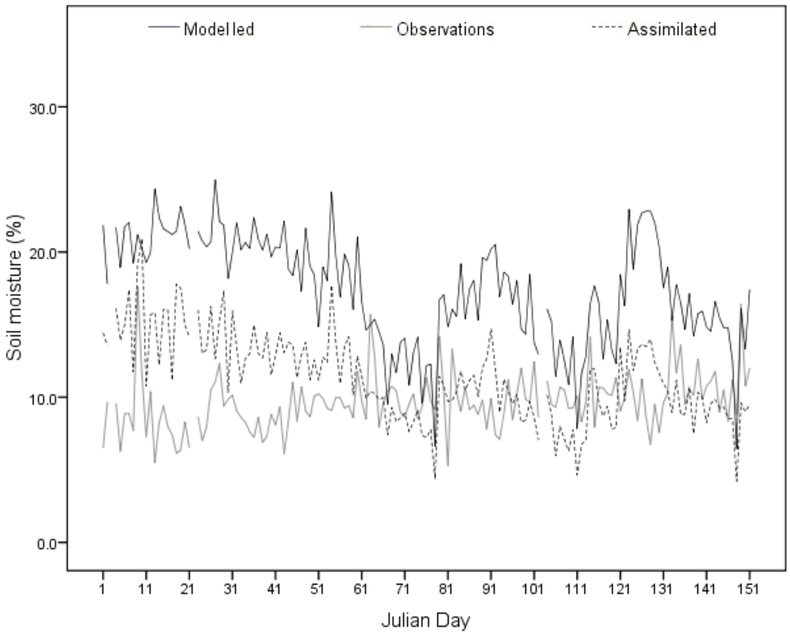

Figure 2: Time series of modelled vs. assimilated values of mean daily evapotranspiration (ET) from the JULES land-surface model over West Africa (17°W to 20°E longitude, 4°N to 20°N latitude) from 1st January – 31st May 2007.

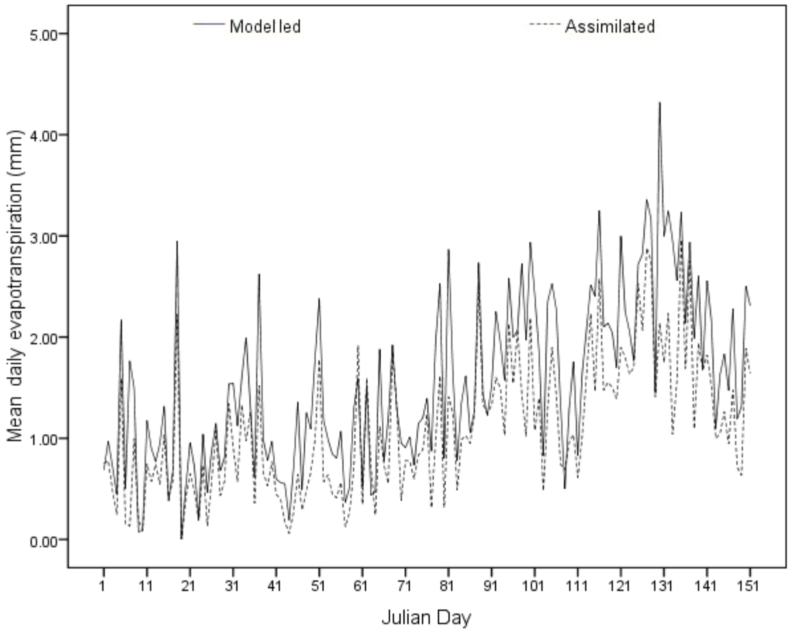

Figure 3: Time series of modelled vs. assimilated values of mean daily net primary productivity (NPP) from the JULES land-surface model over West Africa (17°W to 20°E longitude, 4°N to 20°N latitude) from 1st January – 31st May 2007.