Representing uncertainty in land surface hydrology: fully coupled simulations with the ECMWF land surface scheme

Hannah Cloke[1,2], Antje Weisheimer[2] and Florian Pappenberger[2]

[1] Department of Geography,
King's College London, London, WC2R 2LS, UK
[2] ECMWF

Abstract

The representation of soil moisture physics in land surface schemes is subject to uncertainty in parametrization as well as uncertainties in model structure and in initial and boundary conditions. Assessing parameter sensitivity in land surface schemes is vital for determining the dominant components of the predictive uncertainty in forecasts. Several techniques, that are routinely used in hydrological modelling, are applicable to land surface schemes. Here a first examination of the impact of perturbing soil physics parameters of the HTESSEL land surface scheme is tested using the IFS seasonal forecast system. Significant sensitivity is found to two typically dominant soil parameters, the van Genuchten α and the soil hydraulic conductivity, *K* and an improvement in 2m temperature forecast skill can be identified for summer months over Southern European land points. An assessment of parameter sensitivity of land surface schemes is seen as a precursor to stochastic paramaterization of land surface equations, and perspectives of application are discussed.

1. Introduction

Modern land surface schemes provide much more than a boundary condition to atmospheric models. These models include an often complex suite of hydrological equations to represent mass and energy flux at the surface and in the subsurface (Overgaard et al., 2006). Land surface modelling is a hot topic for research (a few examples selected from over the last two decades include: Balsamo et al., 2010; Boone et al, 2009; Famiglietti & Wood, 1995; Gedney et al, 1999; Gupta et al., 1999; Koster et al., 2010; Pitman et al., 1993, Pitman, 2003). Although, the physical representation of soil moisture in land surface schemes is known to have an influence on the quality of atmospheric predictions (e.g. Williams & Maxwell, 2011; Koster et al., 2010), the parametrization of the processes of soil moisture physics in land surface schemes is not straightforward and the uncertainties in the parameters selected are little researched, and thus there is very little understanding of the direct quantitative links between soil hydrology and atmospheric predictions. Representation of the relevant hydrological processes in land surface schemes, such as infiltration into the soil, overland flow and subsurface vertical and lateral flow, are now on a par with such representation in hydrological catchment models that are used to predict river flow, soil moisture and other hydrological variables (Cloke & Hannah, 2011). This is also true of the spatial and temporal scales used; i.e. the atmospheric and hydrological communities are beginning to work on similar scales. This paper draws on current practice in large scale catchment hydrology modelling on parameter uncertainty and adapts this for application to land surface schemes. A soil physics parameter perturbation experiment is undertaken with the ECMWF IFS seasonal forecasts coupled to the land surface scheme, HTESSEL (Balsamo et al., 2010) to explore the quantitative effects of the soil physics parameters on atmospheric predictions. The potential benefits of using a stochastic approach to soil physics parametrization is discussed.

2. Uncertainty in Hydrological Modelling

Hydrological models that predict river discharge and related hydrological variables such as soil moisture are used in research and practice together with sensitivity and uncertainty analysis techniques in recognition of the fundamental uncertainties in parameterisation, initial and boundary conditions and model structure/process representation, (often collectively known as model *factors*) (Beven, 1989; 2001a; 2006). It is well known that such distributed, physics based models are *overparameterised*, in that there are more parameters than can be estimated from the data, and even quite robust parameter calibration (or *tuning*) exercises do not guarantee good predictions. Hydrological processes are notorious for being difficult to represent because of their non-linearity, complexity and spatiotemporal variability. Thus the parameters in hydrological models are *effective*, in that they compensate for errors such as subgrid variability, inadequacy of equations in representing the processes, lack of knowledge about input and boundary conditions (in hydrology a typical input would be precipitation and a typical boundary condition would be groundwater pore pressure distribution in the subsurface) and inadequate observational data at the local scale in order to characterise the parameters and the errors. Of course, this is also true for all environmental models including atmospheric models (Järvinen et al, 2011). Several alternative approaches to modelling hydrological variables at the catchment scale have been proposed in order to counter some of the problems of purely physics based approaches, for example the Representative Elementary Watershed (REW) approach (Reggiani & Schellekens, 2003) or the hybrid physically based-conceptual approach used in the Lisflood model (van der Knijff et al., 2010) . What is certainly clear is that adding explanatory depth (representating more physical processes with new equations) or higher spatial resolution to a hydrological model is not always the only answer to improving predictions (Beven 1989; Beven & Cloke, in press).

Although many optimisation strategies exist for parameterisation of hydrological models (e.g. Feyen et al., 2007, Vrugt, 2003), realistically multiple <u>sets</u> of parameter values may be seen as *equally likely* as simulators of the land surface, within the limitations of a given model structure and errors in boundary conditions and observations (Beven & Binley, 1992). A common approach to deal with such parameter uncertainty (see e.g. Cloke et al., 2010) is that of first assessing the dominant sensitivities of these factors, through global sensitivity analysis and use these results to inform an uncertainty analysis, such as the Generalized Likelihood Uncertainty Estimation, or GLUE (Beven & Binley, 1992), in order to use the model in predictive mode. Parameter sets are selected randomly from specified distributions and many Monte Carlo simulations are undertaken. Those parameter sets that lead to a good model (forecast) performance are noted as 'behavioural' and retained for the prediction. Thus for predictions (forecasts) an ensemble of simulations is undertaken and for each member a *set* of parameters is stochastically selected from the behavioural sets (see also table 1). This procedure can be very computationally expensive for models with many equations and parameters, however, it is increasingly possible to use these or similar techniques for complex models (Pappenberger & Beven, 2006; Pappenberger et al., 2010; Cloke et al., 2008; Jackson et al., 2003). In this paper the first parts of this process are instigated (section 4).

1. Take a large random sample of models (structures and parameter sets)
2. Evaluate performance using one or more measures
3. Reject those that do not provide acceptable performance
4. Retain remaining behavioural models in prediction
5. Weight predictions according to performance from CDF of predicted variables
6. Parameter **SET** that gives the behavioural model

Table 1: Strategy for GLUE Uncertainy estimation (after Beven, 2001b)

3. Soil moisture physics and land surface schemes

There is a strong coupling between the land and the atmosphere which is inadequately understood (e.g. Fischer et al, 2007, Weisheimer et al., 2011). Recent research on land surface schemes has shown that the representation of soil hydrology can influence the variability of precipitation and air temperature. International projects such as PILP, GLACE2 and AMMA have improved understanding of the mechanisms and areas of strong coupling between the land surface and the atmosphere (Agusti-Panareda et al., 2010; Balsamo et al., 2010). Generally representations that lead to higher soil moisture will lead to higher evaporation and greater cooling of the surface and the overlying air, however the soil moisture effects on precipitation are more complex. For example, in the GLACE2 multimodel experiment for the boreal summer, the subseasonal (out to two months) forecast skill for precipitation and air temperature was quantified derived from the realistic initialization of land surface states, notably soil moisture. It was shown that land surface intitial conditions impacts on skill increase dramatically when conditioned on the size of the initial local soil moisture anomaly (http://gmao.gsfc.nasa.gov/research/GLACE-2/). Thus clearly representing initial soil moisture conditions is very important. However, in particular for seasonal forecasting the influence of initial conditions will deteriorate through the forecast period, and here it is hypothesized, based on experience with hydrological modeling (e.g. Mertens et al., 2004), that soil physics parametrization may have as least as much if not more influence than the initialization of soil moisture and the spatial representation of soil types.

Many land surface schemes of atmospheric models (including ECMWF's HTESSEL scheme) are based on Richards equation for flow of water in the subsurface (Richards, 1931), which is a very popular representation in soil physics (Hillel, 1998):

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z}\left[K(\theta)\left(\frac{\partial \varphi}{\partial x} + 1 \right) \right]$$

Where K is the hydraulic conductivity, φ is the pressure head, z is the elevation above a vertical datum, θ is the water content and t is time. The non-linear relationship between φ and θ is decribed with a soil moisture release curve (also known as the soil moisture characteristic, see Hillel, 1998 for an excellent description), for example the van Genuchten (1980) representation:

$$\theta(\varphi) = \theta_r + \frac{\theta_s - \theta_r}{(1 + \alpha\varphi)^{1-1/n}}$$

Where θ_r is the residual soil moisture content, θ_s is the saturated soil moisture content and α and n are soil dependent soil texture parameters which describe the shape of the soil moisture release curve. Typically a land surface textural type map is allocated for the land surface scheme (figure 1) and a look-up table gives a specified value per soil textural type (table 2).

The hydraulic conductivity, K, describes the ease with which water can move through the soil pore spaces. It is well known to be difficult to allocate values to this parameter as it does not scale adequately and the effective parameter does not represent the subgrid variability. There has been much research into the uncertainty in hydrological predictions due to uncertainty in hydraulic conductivity [e.g. Schulze-Makuch et al., 1999; Christiaens & Feyen, 2002; Cloke et al., 2008] and initial recognition of its importance as a dominant parameter in land surface modelling (e.g. Williams

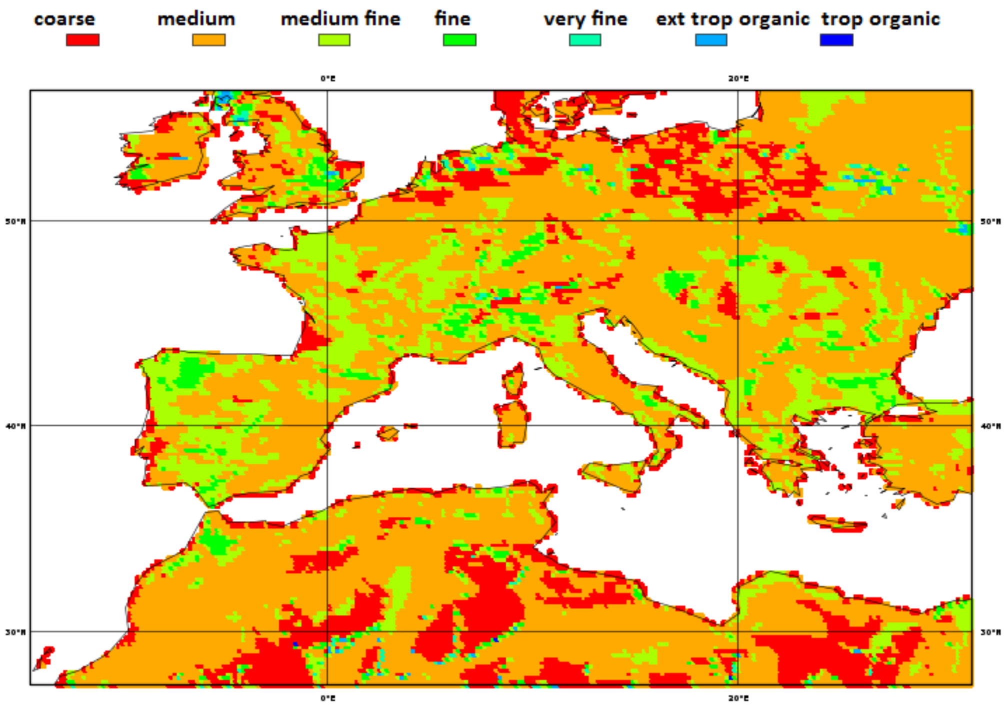

Figure 1: ECMWF soil distribution map built from the FAO database

Textural type	van Genuchten α (m^{-1})	van Genuchten n (-)	K (ms^{-1} x 10^{-6})
Coarse	3.83	1.38	6.94
Medium	3.14	1.28	1.16
Medium-Fine	0.83	1.25	0.26
Fine	3.67	1.10	2.87
Very Fine	2.65	1.10	1.74
Organic	1.30	1.20	0.93

Table 2: Subset of soil parameters used in the operational version of HTESSEL

and Maxwell, 2011). Other soil parameters, for example the van Genuchten α, also affect the movement of water in and through the soil and model predictions can be highly sensitive to the value allocated (Cloke et al., 2008). Thus, there is the compound problem of model sensitivity to these parameters and the fact that they may not represent values that can be physically measured (they are 'effective', a heterogeneous unsaturated zone will not average linearly in its parameters and the Richards equation is not representative of all processes such as preferential flow). Richards equation remains a useful tool for modelling subsurface flow if it is understood that the parameters used are only effective and not directly comparable to measurements and there remains a model structural problem in that it does not represent all water flow pathways (note that alternative hydrological approaches such as TOPMODEL may prove competitive to implement in this framework – Best et al, 2011). Here it is hypothesised here that sampling values from a possible distribution of values is a better approach as it may lead to better model performance. There has been little research into the prior distributions of the soil moisture physics parameters that may be valid to use at the scale of land surface schemes, however, Cloke et al (2008) note the descriptive statistics of the distributions of relevant soil moisture physics parameters applicable at a smaller scale, which is a starting point. Here we are not considering varying the soil map itself, which is another notable consideration for future work.

4. A soil parameterisation experiment with ECMWF seasonal forecasts

Using ECMWF's seasonal forecasting system in model cycle 36R4 and T159L62 resolution the following retrospective forecast experiments (reforecasts) were generated:

(i) a 25 member control forecast (**ffcf**)

(ii) a 25 Member perturbed soil physics experiment (**fi8x**)

(iii) a 25 member perturbed soil physics experiment WITHOUT the atmospheric stochastic physics scheme operating (**fjee**)

All reforecast experiments were run for 1st May start dates over the period 1989-2008. The forecast length is 4 months ensuring the full coverage of the meteorological boreal summer season June to August (JJA). The forecasts were compared to both ERA40 and ERA-interim data. The soil physics parameters that were varied were those that have been found to be sensitive in previous studies (Cloke et al., 2008): *K* (hydraulic conductivity) and α (van Genuchten parameter affecting shape of soil moisture release curve), and the soil becomes more hydrologically active as these parameter values increase. Ranges of possible parameters were inferred from distributions presented in Cloke et al. (2008). The reported parameter values of K and α reported in the look-up table (table 2) were used as a base and also perturbed by ±10% and ±20% in order to generate the 25 member parameter sets; this is a very conservative perturbation – well within the known range of uncertainty, but suitable for a first test. As an illustration of the effect of these parameters, figure 2 shows the soil moisture release curves generated by these perturbations (α). Focus is on Southern European land areas and the summer of 2003, as this region and time period is of particular interest for predictability as an extreme hot and dry summer (Weisheimer et al., 2011).

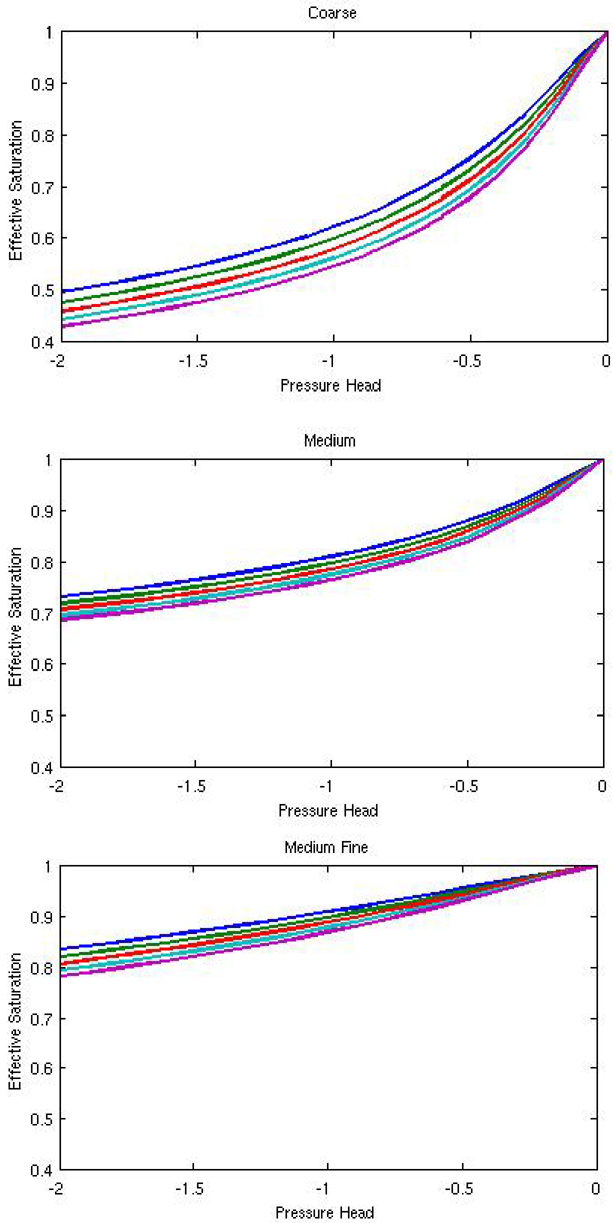

Figure 2: Soil moisture release curves for coarse, medium and medium-fine soils, examples selected to show the effects of perturbing the van Genuchten α parameter.

Figure 3 shows that there is variation in the ensemble mean performance of the 3 experiments compared to ERA-interim for 2m temperature anomalies of Southern European land surfaces during JJA over the 1989-2008 period. However, the two perturbed soil physics experiments with (fi8x) and without (fjee) the atmospheric stochastic physics do, in most places, outperform the control forecast (ffcf) for this case. In summer 1992, the perturbed soil physics experiment (fi8x) outperforms the others and interestingly in 1995-1997 and 2003 the perturbed soil physics without atmospheric physics (fjee) performs the best. However, it is clear from figure 4, showing the absolute temperatures, that there is a warm bias to this last experiment, fjee, although there is no such bias evident in the perturbed soil physics experiment, fi8x. The performance of the various experiments with respect to the control also varies widely over the years, and thus relative performance is likely to be dependent on the summer predictability. This rather complicated result does point to a possible increase in skill with the addition of soil physics perturbations, which should be explored further in future work.

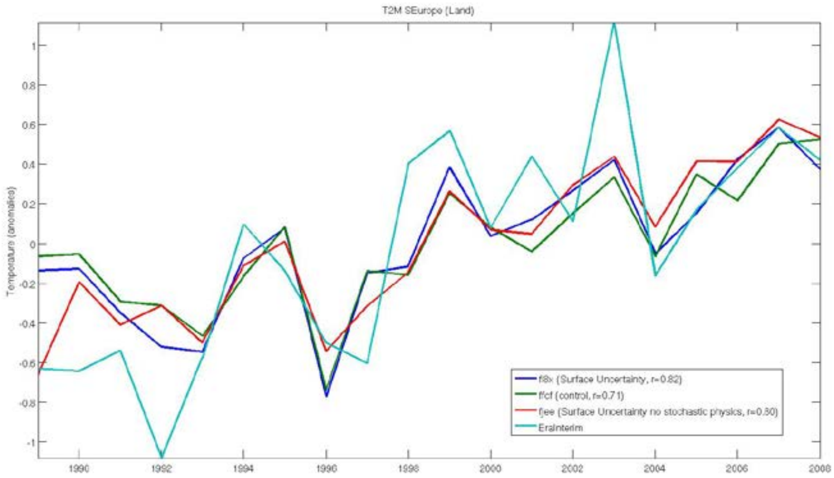

Figure 3: Ensemble mean 2m temperature anomalies for JJA over Southern European land for the 3 forecast experiments and ERA-interim.

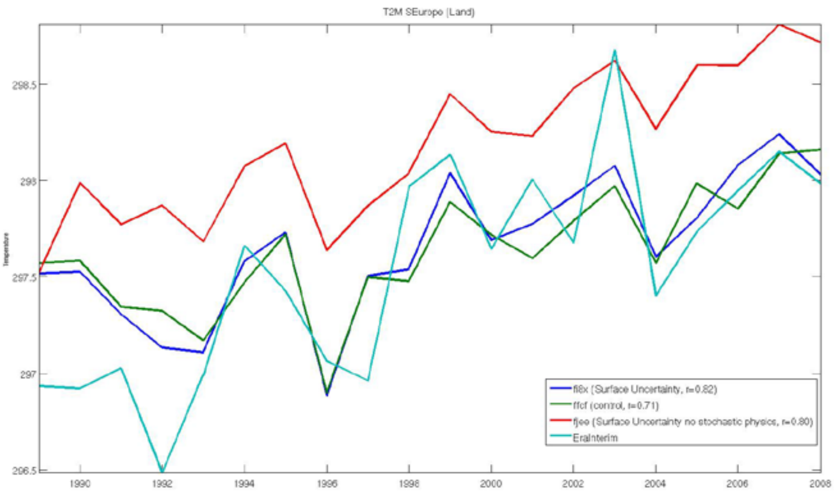

Figure 4: 2m absolute temperature over Southern European land for the 3 forecast experiments and ERA-interim.

Figure 5 shows the 2m temperature RMS errors and anomaly correlations for Southern European land points against ERA40 (extended with operational analysis). Comparing the RMS errors and the ensemble standard deviations, the perturbed soil physics experiment (fi8x) shows an improvement on the control (ffcf) (closer lines and lower RMS error) in the first month. The ensemble standard deviation of fi8x in fact mostly tracks the control line (ffcf). Although this picture is not free from variability there is some indication from these initial results that for Southern European land points there is an improved performance when soil physics perturbations are included.

For the soil physics experiment without atmospheric stochastic physics (fjee), the RMS error is only slightly lower than the control (ffcf). Again, these initial results suggest that for Southern European land points there is an improved performance when soil physics perturbations are included and good performance is seen even without the atmospheric stochastic physics operating (noting warm bias).

The anomaly correlations (bottom panels of figure 5) are particularly encouraging. They show that for the soil physics perturbation experiment (fi8x) the anomaly correlation is noticeably higher than the control (ffcf) and importantly that this is not just an improvement over the first months, but that the effect is maintained until month 4.

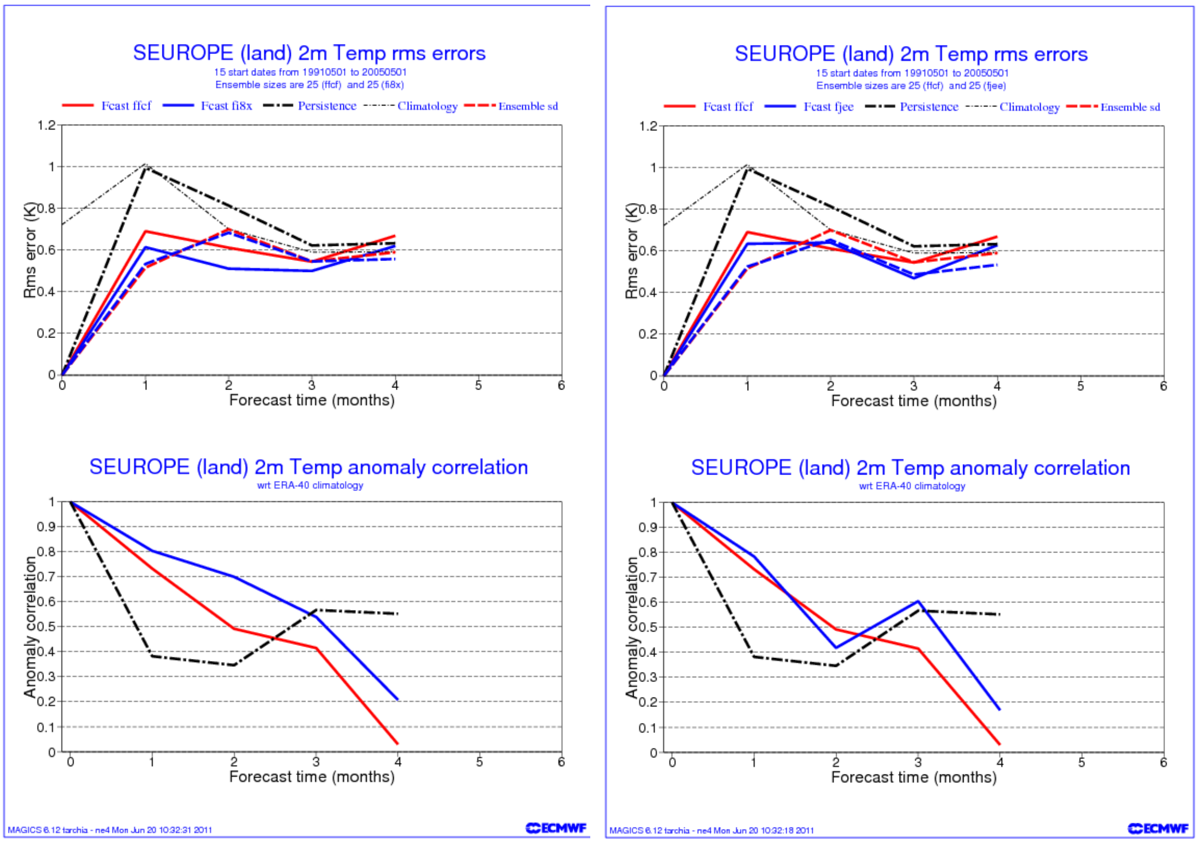

Figure 5: 2m temperature RMS errors and anomaly correlations for Southern European Land points during JJA. Left: control (ffcf) against perturbed soil physics (fi8x). Right: control (ffcf) against perturbed soil physics without atmospheric stochastic physics (fjee).

Figure 6 shows PDFs of Summer 2m temperature anomaly over Southern European land points for the experiments. Solid lines represent the climatology over the verification period and stars represent the 2003 anomaly ensemble. The dashed vertical line represents the verifying anomaly. Study of the left panel of the figure shows that the overall climatology of the experiments does not change the distributions with the addition of the soil physics perturbations which gives us confidence that the climatic processes are being correctly represented overall. Compared to the control, for 2003 (stars), the perturbed soil physics experiment is closer to the extended ERA40 than the control experiment (noting that the ensemble size of 25 is still relatively small for representing the full distribution). The right panel shows that the combination of atmospheric stochastic physics and soil physics perturbations leads to a relatively higher peak in the distribution and a very slight shift towards the verifying anomaly. Figure 7 as a summary shows that the perturbed soil physics experiment (fi8x) does overall show an improved probabilistic skill (measured as the Brier Skill Score for upper tercile temperature events) for southern European land points in JJA.

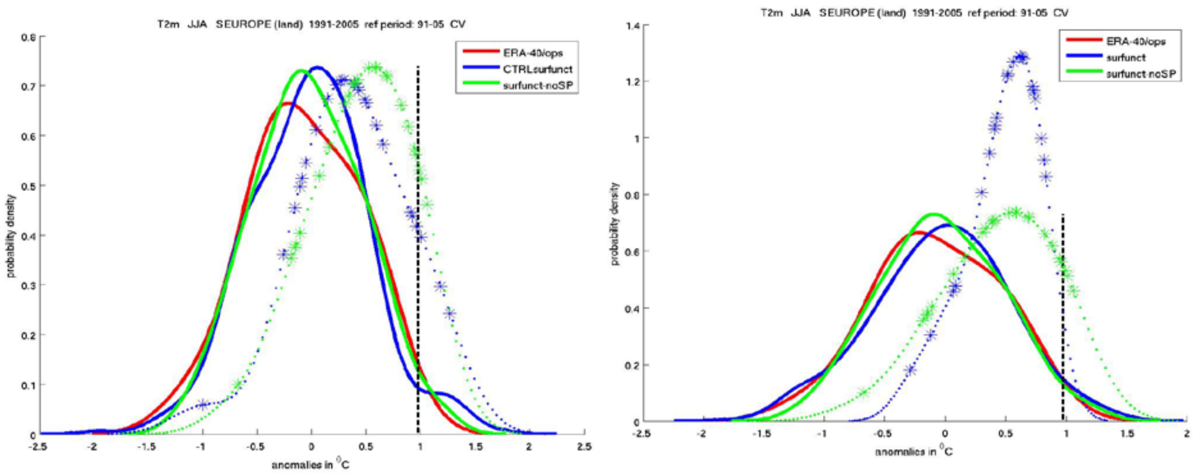

Figure 6: PDFs of JJA 2m temperature anomalies over Southern European land points for LEFT: soil physics perturbation without atmospheric stochastic physics (fjee) against control (ffcf) and ERA40-extended with operational analysis, and RIGHT: soil physics perturbation without atmospheric stochastic physics (fjee) against soil physics perturbation (fi8x) and ERA40 (extended with operational analysis). Solid lines represent the climatology over the verification period and stars represent the 2003 anomaly ensemble. The dashed vertical line represents the verifying anomaly.

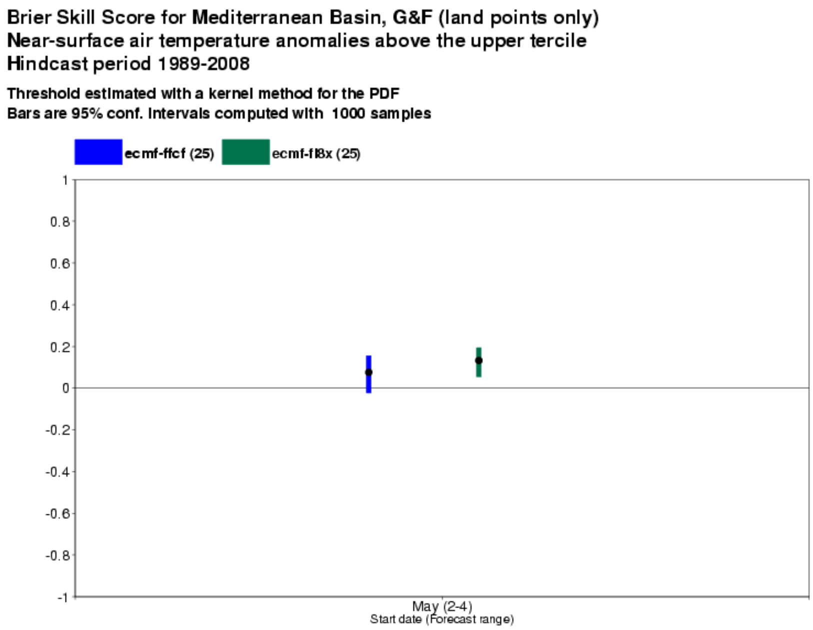

Figure 7: Brier Skill Score for Southern European land points for JJA 2m temperature anomalies. Perturbed soil physics (fi8x) against control (ffcf).

5. Conclusions

Parameterisation of soil moisture physics equations in land surface schemes (LSS) is not straightforward. The land surface is extremely heterogeneous and difficult to parameterise. There are many realistic parameter sets none of which necessarily represent the 'true' or 'measurable' parameter value. Experience in hydrological modelling has demonstrated that a modelling strategy that selects parameter sets from the range of well performing models can improve predictive ability and can quantify uncertainty in predictions.

A simple soil physic perturbation experiment was undertaken to test the sensitivity of seasonal forecast predictions to two soil parameters. Focus was for Southern European land points in JJA. *Initial results* show that just by taking account of some of the uncertainty in two of the most sensitive soil parameters 2m Temp skill in seasonal forecasts for S Europe in ECMWF seasonal forecasts can be improved. However, results require confirmation and are affected by sample size and are dependent on summer type. Ongoing work is testing the tendencies found in initial results on other regions and time periods. This methodology could be expanded to test parameter sensitivity of land surface schemes and to implement stochastic paramaterization of land surface equations.

Acknowledgements

Many thanks to Tim Stockdale at ECMWF for his assistance with seasonal forecast simulations and to Gianpaolo Balsamo, Emanuel Dutra and Tim Palmer also from ECMWF for their helpful discussions.

References

Agusti-Panareda A, Balsamo G & Beljaars A (2010) Impact of improved soil moisture on the ECMWF precipitation forecast in West Africa. *Geophysical Research Letters* **37** L20808, doi:10.1029/2010GL044748

Balsamo G, Dutra E, Bousstta S, Beljaars A, Viterbo P, van den Hurk B (2010) Recent advances in land surface modelling at ECMWF. *ECMWF/GLASS workshop on Land Surface Modelling*, 9-12 November 2010

Best MJ, Pryor M, Clark DB, Rooney GG, Essery RLH, Menard CB, Edwards JM, Hendry MA, Porson A, Gedney N, Mercado LM, Sitch S, Blyth E, Boucher O, Cox PM, Grimmond CSB & Harding RJ (2011) The Joint UK Land Environment Simulator (JULES), Model description – Part 1: Energy and water fluxes. *Geoscientific Model Development Discussions* **4** 595-640.

Beven KJ (1989) Changing Ideas in Hydrology: the case of physically based models *Journal of Hydrology* **105**, 157-172.

Beven KJ & Binley AM (1992) The future of distributed models: model calibration and uncertainty prediction. *Hydrological Processes,* **6**, 279-298.

Beven KJ (2001a) How far can we go in distributed hydrological modelling? The Dalton Lecture. *Hydrology and Earth System Sciences,* **5** (1) 1-12.

Beven KJ (2001b) *Rainfall Runoff Modelling: The Primer*. Wiley.

Beven KJ (2006) A manifesto for the equifinality thesis. Journal of hydrology 320 (1-2) 18-36.

Beven KJ & Cloke HL (in review) Hyperresolved ignorance: A comment on Wood et al (2011) Hyperresolution global land surface modelling: Meeting a grand challenge for monitoring Earth's terrestrial water. *Water Resources Research*.

Boone A et al (2009) The AMMA land surface model intercomparison project (ALMIP). *Bull. Amer. Meteor. Soc.*, **90**, 1865–1880.

Christiaens, K. and Feyen, J. (2002), Constraining soil hydraulic parameter and output uncertainty of the distributed hydrological MIKE SHE model using the GLUE framework. *Hydrological Processes*, **16**: 373–391. doi: 10.1002/hyp.335

Cloke HL & Hannah DM (2011) Large-scale hydrology: advances in understanding processes, dynamics and models from beyond river basin to global scale. *Hydrological Processes*, Doi: 10.1002/hyp.8059.

Cloke HL, Jeffers C, Wetterhall F, Pappenberger F, Byrne T, Lowe J (2010) Climate impacts on river flow: projections for the Medway catchment UK with UKCP09 and CATCHMOD. *Hydrological Processes,* **24** (24) 3476–3489

Cloke HL, Pappenberger F & Renaud JP (2008) Multi-method Global Sensitivity Analysis (MMGSA) for Modelling Floodplain Hydrological Processes. *Hydrological Processes*, **22**((11) 1660-1667.

Famiglietti JS & Wood EF (1995) Effects of Spatial Variability and Scale on Areally Averaged Evapotranspiration. *Water Resources Research*, **31** 699-712.

Feyen L, Vrugt J, O Nuallain B, van der Knijff J, de Roo A (2007) Parameter optimisation and uncertainty assessment for large-scale streamflow simulation with the LISFLOOD model. *Journal of Hydrology*, **332**(3-4) 276-289

Fischer EM, Seneviratne SI, Luthi D and Schar C (2007) Contribution of land-atmosphere coupling to recent European summer heat waves, *Geophysical Research Letters*, **34** L06707

Gedney N, Cox PM, Douville H, Polcher J & Valdes PJ (1999) Characterising GCM land surface schemes to understand their response to climate change, *Hadley Centre Technical Note* HCTN 4, UK Met Office.

Hillel D (1998) *Environmental soil physics*. Academic Press. 771 pages.

Jackson, C., Y. Xia, M. K. Sen, and P. L. Stoffa (2003), Optimal parameter and uncertainty estimation of a land surface model: A case study using data from Cabauw, Netherlands, *J. Geophys. Res.*, **108**(D18), 4583, doi:10.1029/2002JD002991.

Järvinen H, Laine M, Solonen A and Haario H (2011) Ensemble prediction and parameter estimation system: the concept. *Q.J.R.Meterol.Soc.*, DOI:10.1002/qj.923

Mertens J, Madsen H, Feyen L, Jacques D & Feyen J (2004) Including prior information in the estimation of effective soil parameters in unsaturated zone modelling. *Journal of Hydrology*, **294** (4) 251-269.

Overgaard J, Rosbjerg D & Butts MB (2006) Land-surface modelling in hydrological perspective – a review. *Biogeosciences*, **3** 229-241.

Pappenberger F and Beven KJ (2006) Ignorance is bliss: Or seven reasons not to use uncertainty analysis. *Water Resources Research*, **42**, W05302 doi:10.1029/2005WR004820

Pappenberger F, Cloke HL, Balsamo G, Oki P, Ngo-Duc T (2010) Global routing of surface and subsurface runoff produced by the hydrological component of the ECMWF NWP system, *International Journal of Climatology*, **30**(4) 2155-2174.

Pitman AJ (2003) The evolution of, and revolution in, land surface schemes designed for climate models. *International Journal of Climatology*, **23** 479-510.

Pitman AJ, Henderson-Sellers et al. (1999) Key results and implications from phase 1(c) of the Project for Intercomparison of Land-surface parameterization schemes. *Climate Dynamics* **15** (9) 673-684.

Reggiani P and Schellekens J (2003) Modelling of hydrological responses: the representative elementary watershed approach as an alternative blueprint for watershed modelling. Hydrol*ogical Processes*, **17**: 3785-3789.

Richards LA (1931) Capillary conduction of liquids through porous mediums. *Physics*, **1** (5) 318-333.

Schulze-Makuch, D., Carlson, D. A., Cherkauer, D. S. and Malik, P. (1999), Scale Dependency of Hydraulic Conductivity in Heterogeneous Media. *Ground Water*, **37**: 904–919. doi: 10.1111/j.1745-6584.1999.tb01190.x

Shao and Henderson-Sellers (1996): Modelling soil moisture, PILPS phase2, (the Intercomparison of Land-surface Parameterization Schemes) http://www.pilps.mq.edu.au/ (GLASS)

van der Knijff JM, Younis J and de Roo APJ (2010) LISFLOOD: A GIS-based distributed model for river-basin scale water balance and flood simulation. *International Journal of Geographical Information Science*, **24** (2) 189-212.

van Genuchten M Th (1980) A closed-form equation for predicting the hydraulic conductivity of unsaturated soils. *Soil Science Society of America Journal* **44** 892-898.

Vrugt JA. (2003) Effective and efficient algorithm for multiobjective optimization of hydrologic models. *Water Resources Research*, **39**, No. 8, 1214, doi:10.1029/2002WR001746

Weisheimer A, Doblas-Reyes FJ, Jung T and Palmer TN (2011) On the predictability of the extreme summer 2003 over Europe. *Geophysical Research Letters*, **38**, L05704. Doi:10.1029/2010GL046455

Williams JL and Maxwell RM (2011) Propagating Subsurface Uncertainty to the Atmosphere Using Fully Coupled Stochastic Simulations. *Journal of Hydrometeorology*, **12**, 690-701. DOI: 10.1175/2011JHM1363.1