# Use of satellite information in land data assimilation to support operational NWP

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## 1 Introduction: The purpose of land data assimilation for NWP

Land parameters such as soil moisture, soil temperature and snow cover exhibit a strong influence on boundary layer forecasts of atmospheric variables such as temperature and humidity. For instance the spatial distribution of soil moisture has been shown to affect the distribution of convective precipitation (Taylor et al., 2012). Unsurprisingly therefore Land Surface Models (LSMs) have become an important component of NWP modelling systems and improvements to LSMs, including initialisation of land parameters, have been shown to strongly influence the accuracy of atmospheric forecasts, both at the regional (Di Giuseppe et al., 2011) and global level (Balsamo et al., 2011). Constraining the land state through the assimilation of observations is now performed in near real time by many operational centres and typically includes the following key variables:

- Soil moisture (both surface layer and at depth)
- Soil temperature (as above)
- Snow Extent (and amount)

There is a need then for land surface observations, but sites that monitor the soil state directly, via buried transducers for example, are limited to discrete regional networks, very few of which are available to the meteorological community with the timeliness required for operational ingest. For instance of the observations available in the International Soil Moisture Network (Dorigo et al., 2011) most are limited to mid-latitudes; there are almost no stations in Africa, for example. In addition to this the land surface is very heterogeneous in nature, encompassing a wide range of soil and vegetation types. An observation made at a site may not be representative of the locale, or indeed an area encompassing a model grid box. Consequently satellite data has the potential to provide global coverage of the key land variables and in this paper techniques to do this, used both in operational systems and those under development, are reviewed. Forecast impacts from assimilating the satellite data will also be highlighted.

Although the focus of this paper is the application of land observations to NWP, it is worth noting that there is a wider range of uses for the satellite techniques reviewed here. Examples that require soil moisture estimates include: drought monitoring for agriculture, fire risk monitoring and flood forecasting (Wanders et al., 2014). In concert with the NWP community these applications require data that is timely and at high spatial resolution. There may also be an aspiration to convert or use the data indirectly, for instance to give an indication of sub soil conditions.

## 2 Example land data assimilation systems

The progression of analysis methods for soil moisture over the past decade illustrates the increasing dependence on remote sensing data. Initially NWP soil moisture values were constrained to climatological values (these were typically derived by driving the LSM in offline mode via an atmospheric forcing dataset of known quality – e.g. the WATCH forcing dataset (Weedon et al., 2014). The next step was to diagnose the error in the soil moisture through the mismatch between observations of near surface parameters and the forecast model equivalent. An example of this was the nudging scheme developed at the Met Office (Best & Maisey, 2002). More recently operational NWP centres, such as ECMWF and the Met Office, have developed specific land assimilation schemes based on the Kalman Filter methodology. (e.g. de Rosnay et al., 2012) The main motivation here was to start to incorporate soil moisture observations from microwave instruments (both passive and active). In addition to this there is also the potential for using other remote sensing observations which contain indirect information about the surface moisture. An example of this is infra-red skin temperature (e.g. Ghent et al., 2010). Table 1 shows that many operational centres are using some form of optimal analysis scheme for analysing the land state, with either current or planned use to incorporate remote sensing information.

| **Centre** | **Scheme** | **Observation Usage** | |
|---|---|---|---|
| | | **In Situ** | **Remote Sensing** |
| ECMWF | Extended Kalman Filter | Y | Y [active] R&D [passive] |
| Météo-France | Optimal Interpolation | Y | R&D |
| Bureau of Meteorology | Nudging | Y | R&D |
| NCEP GFS | Relax towards Climate | | R&D |
| Environment Canada | Ensemble Kalman Filter | Y | R&D |
| Met Office | Extended Kalman Filter | Y | Y [active] |
| HIRLAM | Optimal Interpolation | Y | R&D |

*Table 1: The current operational and planned configuration of operational land data assimilation schemes at NWP centres.*

A brief illustrative description of one scheme follows. An Extended Kalman Filter has been used in operations since early 2013 at the Met Office over a global model domain. An analysis of soil moisture and temperature is performed every six hours for each model grid point at four soil layers whose thicknesses are 0.1, 0.25, 0.65 & 2.0 m. The observations assimilated are atmospheric observations of screen temperature and humidity (typically representing a height of 1.5 m). In addition to this satellite estimates of surface soil moisture are used from an active microwave sensor. Appropriate observation errors are used: these are determined through triple collocations following the methodology of O'Carroll et al. (2008). Within the Kalman Filter methodology Jacobians representing the sensitivity between the analysis variables and the observations are required. These are computed at every execution of the Kalman Filter via offline runs of the JULES LSM (Best et al., 2011) in which the analysis variables have been perturbed by a small amount. The Jacobians are then computed via finite difference. No updates to the analysis variables are performed for grid points containing snow cover or with surface soil temperatures below freezing point. Finally in order to simplify the computations to a manageable level, model grid points are assumed to have negligible horizontal error correlations, which appears reasonable for a model with a horizontal resolution of ~20 km.

# 3 Remote sensing techniques for soil moisture

## 3.1 Introduction

There is a strong relationship between soil moisture and the dielectric constant of the soil for wavelengths in the microwave range. For passive sensors this leads to a variation in observed brightness temperature, whilst for active systems the amount of surface backscatter will vary as a function of soil moisture. Modelling the emitted blackbody radiation from a range of natural surface scenes (forest, cropland, partial snow cover etc.) can be complex, however a simplified model highlights the issues concerning soil moisture retrieval. Following Kerr et al. (1990), the emission from the surface can be represented with an overlying vegetation layer as:

$$T_b = \tau_v \varepsilon T_s + (1-w)T_{can}(1-\tau_v) + (1-\varepsilon)(1-w)T_{can}(1-\tau_v)\tau_v \qquad (1)$$

Where ε represents the surface emissivity, $\tau_v$ the transmittance through the vegetation layer, $T_s$ the surface radiometric temperature and $T_{can}$ the canopy radiometric temperature. The emissivity can be modelled through applying dielectric models of soil-water mixture (e.g. Wang, 1980) into the Fresnel equations to yield the surface reflectivity. Bare soil is unlikely to be a smooth surface and so the reflectivity is typically modified by a semi-empirical term proposed by Choudhury et al. (1979) or similar. Finally some estimate of the transmittance through the vegetation is required. The model proposed by Schmugge et al. (1992) represents the vegetation optical depth as a linear function of the vegetation water content, with the constant of proportionality increasing as the frequency increases. Other more recent models have $\tau_v$ as a function of leaf area index, which is potentially easier to diagnose from other remote sensing measurements. If these terms are applied to (1) for a range of frequencies and soil moisture values over a bare soil surface then the response is shown in Figure 1a. There is a strong decrease in the observed brightness temperature as the soil moisture rises, which is consistent for each frequency. In Figure 1b a vegetation layer has been added, with a water content of 2 kgm$^{-2}$, typical for a mature crop. The sensitivity to soil moisture is reduced, particularly for the shorter wavelengths. This leads to the requirement for C-band (~5 GHz) or L-band (<2 GHz) systems in order to retrieve soil moisture over vegetated areas, but it should also be noted that there will be some regimes, notably thick forest where the sensitivity to soil moisture will be very low even for these lower frequencies.

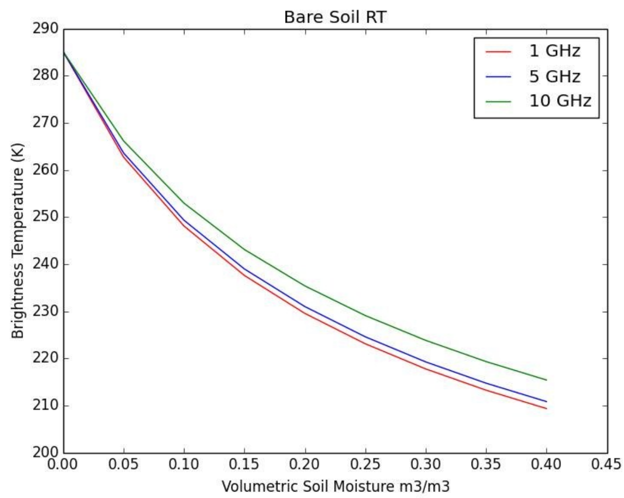


*Figure 1a: Modelled microwave brightness temperature emission from a bare soil surface for a selection of low frequencies. The model and parameters used are described in the text.*

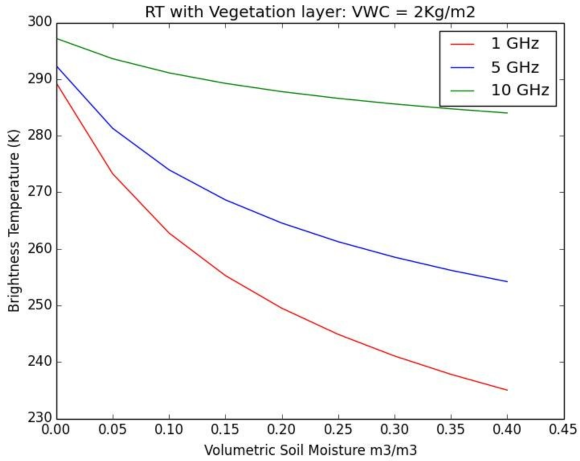


*Figure 1b. Modelled microwave brightness temperature emission for a selection of low frequencies from a surface containing a layer of vegetation. The model and parameters used are described in the text.*

The response to radar reflectivity can also be estimated starting with the dielectric mixing model. Ulaby et al. (1986) propose a two term backscatter model to incorporate the effect of a vegetation layer. As with the passive model, the sensitivity of the signal to surface soil moisture is reduced by the presence of a vegetation layer (noting that for the case of reflection the signal increases with increasing soil moisture).

## 3.2 Active systems

The ASCAT instrument is a multi-beam radar operating in the C-Band and is present on board the MetOp series of operational satellites. ASCAT is an improved version of the successful AMI instrument which flew during the 1990s on board ERS 1&2. Originally designed for retrieving surface wind speed over the ocean, backscatter observations from these instruments are also used to retrieve surface soil moisture and are disseminated in near real time, making this dataset very attractive for operational assimilation. A change detection algorithm is used to extract information from the backscatter observations (further details see Naeimi et al., 2009). Assuming that there is a linear relationship between backscatter (dB) and the surface soil moisture, and also that the backscatter observations can be successfully corrected for the vegetation effects on the signal, then a measure of surface soil wetness can be derived in the following manner:

$$soil\ wetness = \frac{\sigma^o - \sigma^o_{dry}}{\sigma^o_{wet} - \sigma^o_{dry}} \qquad (2)$$

Where the reference values $\sigma^o_{wet}$ and $\sigma^o_{dry}$ are the highest and lowest corrected backscatters seen in a long time series of observations (noting that the ERS/ASCAT dataset now exceeds 20 years). Before this dataset can be assimilated quality control needs to be applied. At the Met Office the soil wetness observations are discarded in regions where the soil is frozen or snow covered, regions of inland water, complex surface topography and regions of significant vegetation (where the sensitivity to soil moisture is likely to be low). Nevertheless a useful amount of data remains as shown in Figure 2. Before assimilation a conversion must also be applied to transform the soil wetness value into equivalent model soil moisture. Since the satellite data typically represents a shallower layer ~1cm than the model top layer which can typically be ~10 cm, depending on the model, the preferred approach is to use CDF matching (e.g. Mahfouf, 2010) in which the satellite bias and standard comparisons of the resulting soil moisture analyses against in situ measurements of soil moisture and deviation at each grid point is adjusted to represent the model characteristics. Typically one year or more of model and satellite data is used to perform the conversion. Figure 3 shows an example of the cumulative distribution prior to matching for both the model and satellite at a grid point in the US. For the April period the satellite observations are drier, whereas they appear moister in July. It demonstrates that the CDF parameters need to be computed seasonally.

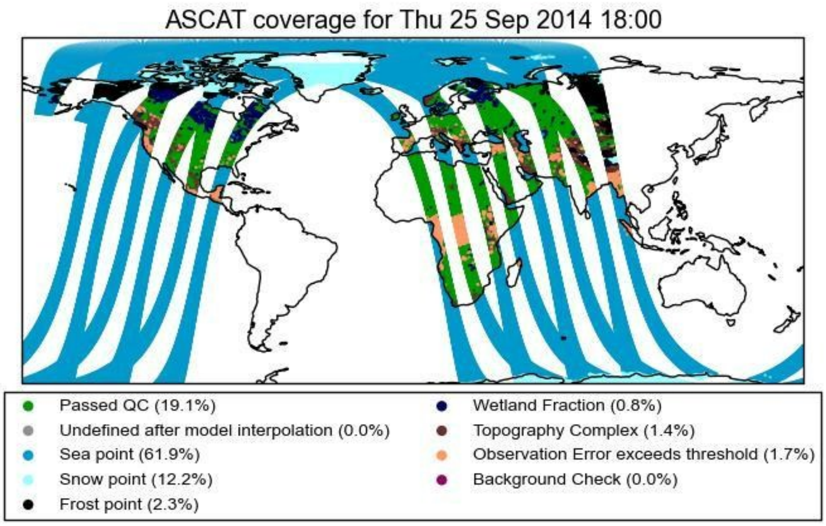


*Figure 2: Coverage of the ASCAT instrument on MetOp-A after quality control for 6 hours of observations.*

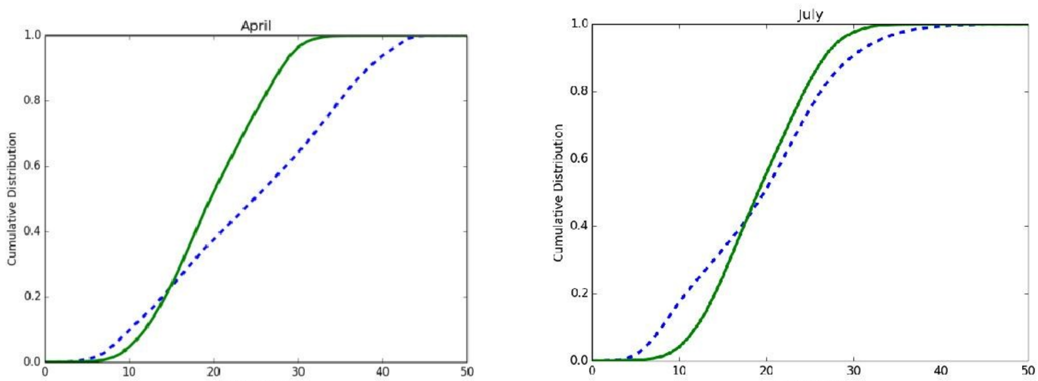


*Figure 3.An example of the cumulative distribution for satellite soil moisture estimates and the Met Office surface soil moisture at a point in the US Great Plains. Left panel: data accumulated over April, Right panel: over July. In each case the solid line represents the satellite data.*

The impacts of assimilating ASCAT data have been examined in both regional and global NWP models. Mahfouf (2010) looked at the response of assimilating ASCAT in the Météo-France ALADIN regional model via an Extended Kalman Filter. For a region containing a high density of screen observations which also contribute to the soil moisture analysis, a small improvement in short range forecast of humidity was observed. At the Met Office, Dharssi et al. (2011) examined the impact of using ASCAT in the then operational soil moisture nudging scheme. Although the satellite data was only limited to influencing the top soil layer, important positive benefits were found, both in comparisons of the resulting soil moisture analyses against in situ measurements of soil moisture and in the atmospheric forecasts. In a northern hemisphere summer period, large (~10%) improvements to the screen humidity forecast error were seen in the tropics across the the forecast range out to five days. Positive impacts also observed over Australia and North America. The above experiments were performed with data from the ASCAT instrument on MetOp-A. In 2012 MetOp-B was launched. Recent comparisons at the Met Office show that the bias characteristics of this new instrument versus the model soil moisture are very close to MetOp-A. Consequently forecast impact trials have been performed using observations from both instruments, which due to their relative orbits, increases the number of grid points containing satellite data by ~20% in each assimilation cycle. The additional observations appear to yield a small, but positive improvement to humidity forecasts over Australia and so use of the second satellite in operational assimilation is intended to commence in spring 2015.

### 3.3 Passive systems

There have been several successful demonstrations of assimilating soil moisture products from the passive AMSR-E instrument which operates in the C and X-band (e.g. Draper et al., 2009). However, instruments operating in the L-band are expected to be of the greatest benefit since the longer wavelength potentially allows information on soil moisture over a wider variety of vegetation cover. L-band poses a significant technical challenge to deliver observations with sufficient horizontal resolution from a practical antenna system. The Soil Moisture and Ocean Salinity (SMOS) mission provides observations at a resolution of 50 km at a frequency of 1.4 GHz. This horizontal resolution is achieved through aperture synthesis; a network of 69 conventional radiometers are linked together to act as one large antenna. SMOS provides a full measure of the emitted radiation (V, H polarisation and their relative phase) and has been operating since 2009. Soil moisture is estimated from this data using a physically based retrieval driven via an L-band radiative transfer model (Kerr et al., 2012). Additionally, there are plans to disseminate a fast delivery product for near real time applications using a neural net based approach. The brightness temperatures are also available in near real time and a comprehensive research project is underway at ECMWF to exploit this data with the aim of operational use. Arising from the instrument mode of operation, up to 150 observations can be made at each point on the earth at a range of incidence angles. This can lead to a large amount of SMOS data, typically 8 GB per day. To deal with this superobbing of the brightness temperatures are performed, binning the data as a function of incidence angle, typically around the values of 30, 40, 50 degrees. In addition to this data is pre-screened for radio frequency interference (RFI) using a quality flag supplied with the data. At the current time (see http://www.cesbio.ups-tlse.fr) significant sources of RFI sources mainly exist over Asia and parts of the Middle East.

At ECMWF several experiments have been performed assimilating the brightness temperatures directly. To do this a land surface model, CMEM (Muñoz-Sabater et al., 2011), has been coupled to the ECMWF land Kalman Filter. As with the ASCAT assimilation experiments SMOS data is also bias corrected using CDF matching and after this has been applied there is low residual bias between observations and model, except for regions of known RFI. Figure 4 shows the SMOS Jacobians for both summer and winter periods. The values represent the change in brightness temperature due to a change in surface soil moisture. Values are generally negative which would be expected due to the responses modelled in Section 2, except for some desert areas. Larger values over the western US, Sahel and Australia suggest that the impact of SMOS data may be significant in these regions. Note also that there is little sensitivity in regions of dense tropical forest (e.g. Congo). A series of experiments assimilating SMOS brightness temperatures have been performed and these demonstrate (Figure 5) widespread changes to the soil moisture in the surface layer, with a general feature that the new data source is attempting to dry the model. There is also evidence (Figure 5, right panel ) that adjustments are also being made in some regions to deeper soil layers. Comparisons between the resulting soil moisture analyses and in situ observations from US and Australian networks have revealed that the effect of SMOS is to improve the fit to these independent data as measured by correlation and RMS error, consistent with expectation based on the Jacobian analysis. At the time of writing a second L-band mission is ready for launch, SMAP, which brings the prospect of assimilation tests with two passive sensors.

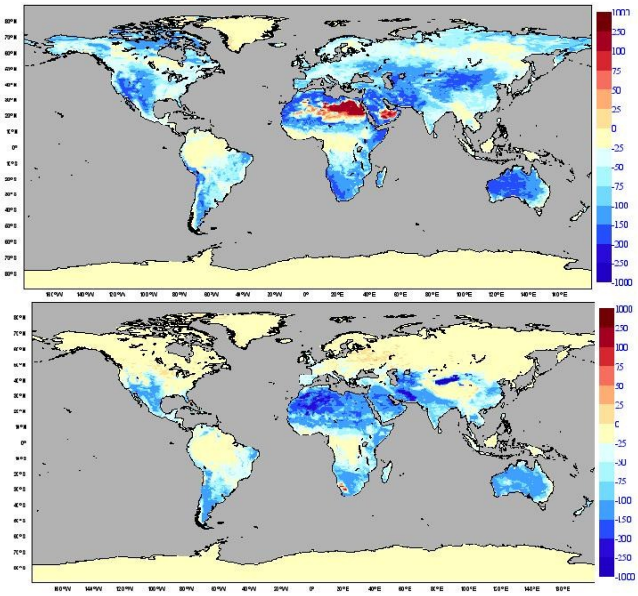

*Figure 4:Jacobians showing the sensitivity of hpol brightness temperatures with respect to changes in surface soil moisture for (top panel) summer and (bottom panel) winter. Results generated at ECMWF courtesy of J. Muñoz-Sabater.*

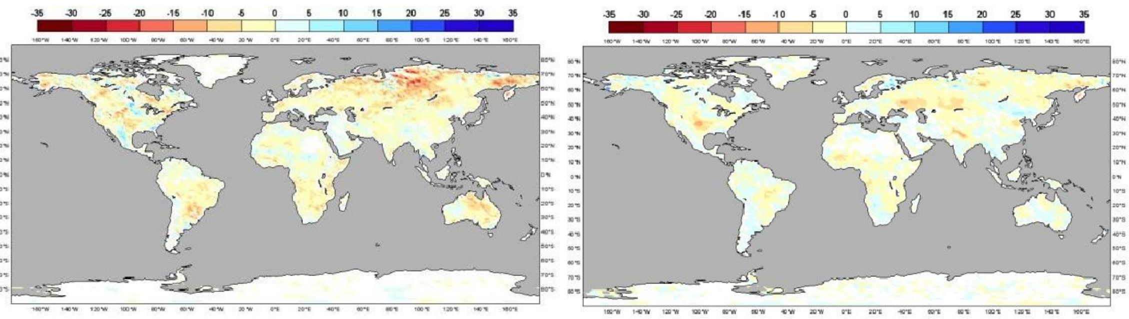

*Figure 5: Differences in mean analysis increments (mm) arising from the SMOS assimilation experiment and control run using screen observations for a period in summer 2012. Left Panel level 1 soil moisture; right panel level 2. Results generated at ECMWF courtesy of J. Muñoz-Sabater.*

## 4 Snow

An accurate model representation of snow extent and snow amount results in, amongst other effects, improved specification of the radiative fluxes at the surface. This leads to the expectation that a snow analysis will improve near surface temperature forecasts, for example. Estimates of snow coverage from satellite are the principle component of such analyses, with a range of instrumentation (infra-red and visible from geostationary and polar orbits) being employed. The ESA funded GlobSnow project (www.globsnow.info) has produced a 15 year record of snow extent based on reflectivity measurements from the ATSR series of satellites, which is useful for model assessment or reanalyses. For operational centres the principle product used for a number of years now is the NESDIS Interactive Multi Sensor Snow and Ice Mapping System (IMS). This is a daily merged product based on a range of sensors, including microwave data. Resolution of the product is 4 km, and it is available for both northern and southern hemispheres. Forecast models require snow amount at each grid point and one example to update this variable in a global model via the IMS snow extent is described by Pullen et al. (2010). The IMS data is mapped to model grid points as an equivalent fractional cover. For those snow-covered model points where the IMS data is snow free, the snow amount is set to zero. Adding snow to the model where the model background is snow free, but the IMS is not, is trickier. In the Pullen Scheme snow amount is added via an empirical relationship based on the IMS fractional cover on the coarser model grid. Figure 6 shows the effect of this analysis on the model snow cover over Europe. The percentage of model points in agreement with independent station reports of snow are shown. A small improvement in the winter period is observed, and a large improvement in the agreement during the spring melt. The model tendency is to melt the snow out early, an effect that is also noted to occur over North America and in other models.

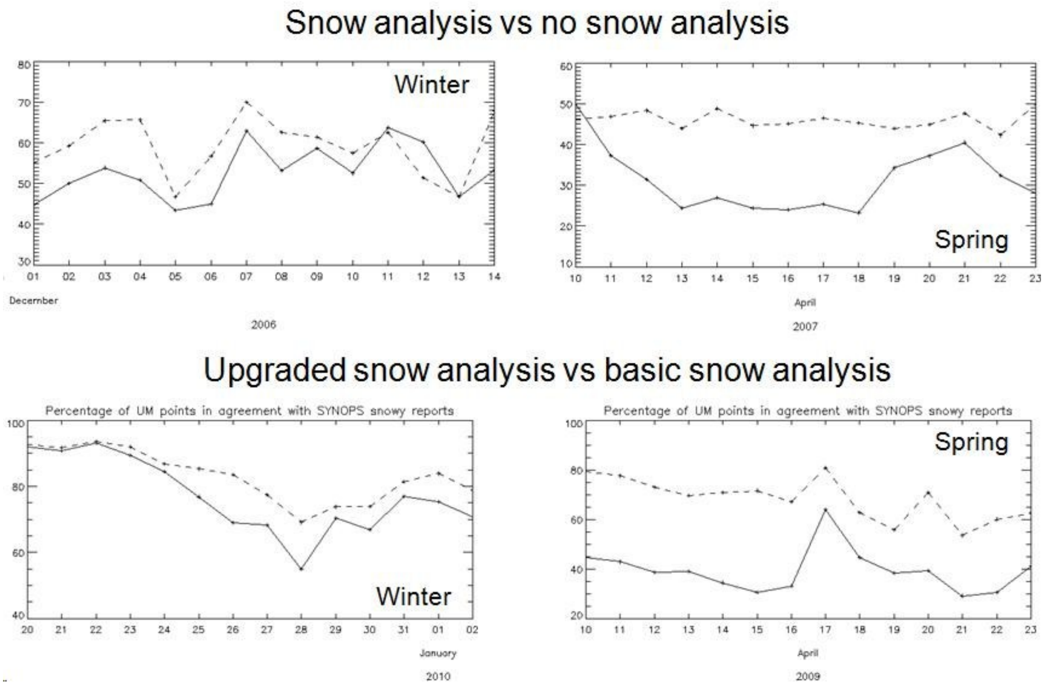


*Figure 6. Percentage of model grid points in Europe in agreement with station reports of snow. Data from the Met Office snow analysis scheme courtesy of S. Pullen.*

Planned improvements to the IMS expected in 2015 include a increase in horizontal resolution and information on the age of the oldest observation used. The latter is useful because, as noted by Pullen, older observations may miss a recent snow event leading to erroneous reduction in the analysed snow cover Other centres, notably ECMWF, combine the IMS product with in situ reports of snow depth within Optimal Interpolation schemes. For limited area models over Europe additional high resolution observations of snow cover are available from Meteosat observations generated by the Hydrology SAF (www.hsaf.meteoam.it). Finally there is also wide spread interest in high resolution SAR based products, particularly detection of wet snow.

# 5 Leaf area index & albedo

Both leaf area index (LAI, a measure of the one-sided leaf area per unit ground area) and snow free albedo are important factors in specifying the correct fluxes of moisture and energy between the land and atmosphere. Some LSMs may fix these variables as a function of surface type, but a description of the temporal variation, particularly through the seasonal vegetation cycle, has been shown to reduce model biases. This variation can be described through constructing climatologies from multiple satellite observations; both LAI and albedo may be determined from visible reflectance measurements on polar orbiting platforms. Albedo observations for instance are derived from MODIS observations in 10 wavelength bands from 0.3 to 5 µm. An in-filling technique has been developed to include missing grid points in regions of semi-permanent cloud cover. This technique uses the temporal variation of albedo for clear grid points nearby with similar vegetation (Moody et al., 2005). The GlobAlbedo project uses a multi sensor approach (AATSR, MERIS, SPOT-VEGETATION) and aims to produce a 15 year dataset. Aggregation of such data into monthly climatologies has been found to improve model temperature biases at the Met Office, particularly over the continental United States.

A daily albedo is generated over Europe via the Land SAF and the impact of this data in a regional model (Cedilnik et al., 2012) has also been investigated. The observations were optimally combined with a climatology via a Kalman Filter. For this the *a priori* or background estimate was taken as persistence. Results based on one year of model runs showed that the analysed albedo was higher than the reference values used in the control run and this led to a notable reduction in near surface model temperature and in the strength of convective precipitation. This work demonstrates that in areas where the frequency of albedo observations is sufficient, data assimilation of this quantity could yield improvements beyond a seasonal climatology.

# 6 Conclusions and Outlook

Increasing use is being made of microwave information in soil moisture analyses. Several centres now use active microwave data in operations, whilst others plan to move to operations in the near future. The Kalman Filter is the preferred method to assimilate this soil moisture information with other sources such as screen (low level atmospheric) data; either via the ensemble or extended schemes. There is now evidence that the use of multiple instruments (e.g. ASCAT on the Metop satellite series) yields additional forecast benefit. A major step forward recently is the assimilation of L-band SMOS data in a global model, with resulting measured improvements to quality of the soil moisture analysis. Before satellite soil moisture datasets can be assimilated some form of conversion is required from the satellite climatology to the model equivalent. At the current time CDF matching is the most popular method to do this. Future research directions are likely to include investigating the combined assimilation of active and passive systems and improved treatment of observation and background errors. Such improvements on the specification of errors may help to efficiently project the satellite information into the deeper soil layers, particularly the root zone. This latter goal is of improving the root zone soil moisture analysis has benefits beyond NWP, for example agricultural production. To aid assessment of improvements to analysis schemes and also to understand the characteristics of satellite retrievals it is very important that networks of independent in situ soil moisture data are maintained. Initiatives such as the International Soil Moisture Network help to facilitate access to this data.

The IMS multi sensor product remains the principle satellite dataset for the analysis of snow extent. Higher resolution products such as those from the H-SAF are increasingly of interest for convective scale modelling, as are observations of wet snow available from microwave SAR systems.

Several NWP centres make use of monthly climatologies for parameters that are strongly influenced by the vegetation cycle, principally Leaf Area Index and surface Albedo. These make use of the long time series of instruments such as MODIS. There is also now evidence that daily assimilation of surface Albedo can yield additional forecast benefits, principally to near surface temperature and convective scale precipitation.

## Acknowledgements

The author is grateful to the input from the following people, for their help in creating the seminar and this associated paper: Wouter Dorigo, Sebastian Hahn (both TUWien), Julia Figa-Saldana (EUMETSAT), Stephane Belair (Environment Canada), Jean-Francois Mahfouf (Météo-France), Weizhong Zheng (NOAA) , Tomas Landelius (SMHI) & Emma Kendall (University of Leeds). Joaquin Muñoz-Sabater and Patricia de Rosnay have kindly discussed their innovative work on SMOS assimilation. Finally the author would like to thank colleagues Keir Bovis, Sam Pullen, Malcolm Brooks and Imtiaz Dharssi (now at CAWCR) for discussions concerning land surface data assimilation at the Met Office, especially during the creation of the Extended Kalman Filter.

## References

Balsamo, G., S.Boussetta, E. Dutra, A. Beljaars, P. Viterbo & B. Van Den Hurk, 2011: Evolution of land-surface processes in the IFS. *ECMWF Newsletter No. 127*, 17–22.

Best, M.J. et al., 2011: The Joint UK Land Environment Simulator (JULES), Model Description – Part 1: Energy and Water Fluxes. *Geosci. Model. Dev. Discuss.,***4**, 595–640.

Best, M. & P. Maisey, 2002: A Physically Based Soil Moisture Nudging Scheme. *Hadley Centre Technical Note No. 35,* Available from the Met Office, UK.

Cedilnik, J., D. Carrer, J.-F. Mahfouf & J.-L. Roujean, 2012: Impact Assessment of Daily Satellite-Derived Surface Albedo in a Limited Area NWP Model. *J. Appl. Meterol. Clim.,***51**, 1835–1854

Choudhury, B.J., T.J. Schmugge, A. Chang & R.W. Newton, 1979: Effect of Surface Roughness on the Microwave Emission From Soils. *J. Geophy. Res.,***84(C9)**, 5699–5706.

Dorigo, W.A., W. Wagner, R. Hohensinn, S. Hahn, C. Paulik, A .Xaver, A. Gruber, M. Drusch, S. Mecklenburg, P. van Oevelen, A. Robock & T. Jackson, 2011: The International Soil Moisture Network: a data hosting facility for global in situ soil moisture measurements. *Hydrol. Earth Syst. Sci.***15**, 1675–1698.

Draper, C.S., J.-F. Mahfouf & J.P. Walker, 2009: An EKF assimilation of AMSR-E Soil Moisture into the ISBA land surface scheme. *J. Geophys. Res.,***114**, D20104, doi:10.1029/2008JD011650

Dharss, I., K. Bovis, B. Macpherson & C. Jones, 2010: Assimilation of ASCAT Surface Soil Wetness. *Forecasting Tech. Report No. 545*, The Met Office.

Ghent, D., J. Kaduk, J. Remedios, J. Ard & H. Balzter, 2010: Assimilation of land surface temperature into the land surface model JULES with an ensemble Kalman Filter. *J. Geophys. Res.,* 115:D19112.

Kerr, Y.H. et al., 2012: The SMOS Soil Moisture Retrieval Algorithm. *IEEE Trans. Geosci. Remote Sensing,* **50,** 1384–1399.

Kerr, Y.H. & E.G. Njoku, 1990: A semiempirical model for interpreting microwave emission from semiarid land surfaces as seen from space. *IEEE Trans. Geosci. Remote Sensing,* **28,** 384–393.

Di Giuseppe, F., D. Cesari & G. Bonafe, 2011: Soil Initialization Strategy for Use in Limited-Area Weather Prediction Systems. *Mon. Wea. Rev.*, **139**, 1844–1860.

Mahfouf, J.F., 2010: Assimilation of satellite derived soil moisture from ASCAT in a limited area NWP model. *Q. J. R. Meteorol. Soc.,* **136**, 784–798.

Moody, E.G. et al., 2005: Spatially Complete Global Spectral Surface Albedos: Value-Added Datasets Derived From Terra MODIS Land Products. *IEEE Trans. Geosci. Remote Sensing,* **43,** 144–158.

Muñoz-Sabater, J., P. de Rosnay & A. Fouilloux, 2011: Use of SMOS at ECMWF. *ECMWF Newsletter No. 127,* 23–27

Naeimi, V., K. Scipal, Z. Bartalis, S. Hasenauer & W. Wagner, 2009: An Improved Soil Moisture Retrieval Algorithm for ERS and METOP Scatterometer Observations. *IEEE Trans. Geosci. Remote Sensing,* **47,** 1999–2013.

O'Carroll, A.G., J.R. Eyre & R.W. Saunders, 2008: Three-Way Error Analysis between AATSR, AMSR-E, and In Situ Sea Surface Temperature Observations. *J. Atmos. Oceanic Technol.*, **25**, 1197–1207.

Pullen, S., C. Jones & G. Rooney, 2010: Using Satellite Derived Snow Cover Data to Implement a Snow Analysis in the Met Office Global NWP Model. *J. Appl. Meterol. Clim.,***50**, 958–973.

deRosnay, P., M. Drusch, D. Vasiljevic, G. Balsamo, C. Albergel & L. Isaksen, 2012: A simplified Extended Kalman Filter for the global operational soil moisture analysis at ECMWF. *ECMWF Tech. Memo. No. 662.*

Schmugge, T.J. & T.J. Jackson, 1992: A Dielectric Model of the Vegetation Effects on the Microwave Emission from Soils. *IEEE Trans. Geosci. Remote Sensing,* **30,** 757–760.

Taylor, C.M., R.A.M de Jeu, F. Guichard, P.P. Harris & W.A. Dorigo, 2012: Afternoon rain more likely over drier soils. *Nature*, **489**, 423–426.

Ulaby, F.T., R.K. Moore & A.K. Fung 1986: *Microwave Remote Sensing: Active and Passive*, *Vol II*. Artech House, ISBN 0-89006-191-2.

Wanders, N., D. Karssenberg, A. de Roo, S.M. de Jong & M.F.P. Bierkens, 2014: The suitability of remotely sensed soil moisture for improving operational flood forecasting. *Hydrol. Earth Syst. Sci.*, **18**, 2343–2357.

Wang, J.R., 1980: The dielectric properties of soil-water mixtures at microwave frequencies. *Radio Science,* **15,** 977–985.

Weedon, G.P., G. Balsamo, N. Bellouin, S. Gomes, M.J. Best & P. Viterbo, 2014: The WFDEI meteorological forcing data set: WATCH Forcing Data methodology applied to ERA-Interim reanalysis data. *Water Resources Research*, **50**, doi:10.1002/2014WR015638.