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USE OF REMOTE SENSING MEASUREMENTS AND DATA ASSIMILATION TECHNIQUES TO IMPROVE ESTIMATES OF LANDSCAPE DRYNESS

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ABSTRACT

Fire intensity, spread rate and ignition are very sensitive to the fuel dryness which in turn is strongly linked to soil moisture deficit. Though the value of soil moisture deficit in predicting fire danger has been long established, very few fire danger rating systems employ a comprehensive methodology to estimate it. Most fire danger rating systems use very simple empirical water balance models which are found to have errors. Hence they are poor drivers of the sophisticated fire models used operationally to manage and warn for dangerous fire conditions and spread. With advances in the science of measurement, in the form of satellite remote sensing, and in prediction, in the form of physically based land surface models, soil moisture can now be better analysed and predicted. Neither observations nor models give a complete picture of the soil moisture state in isolation, however. Data assimilation combines observational and model information optimally, yielding increasingly consistent and complete estimates of soil moisture. In this paper, we touch on the various operational satellite observations available. We also discuss land surface data assimilation methods used widely in soil moisture research and operations. This report is prepared for those with very limited technical and scientific background in satellite remote sensing or data assimilation. Hence complex mathematical and physical formulations are carefully omitted. However, the problems discussed here are highly non-trivial and inter-desciplinary, with much progress made in recent decades. Hence some technicalities are unavoidable. Also, the discussion is not intended to be complete. Our intention is to highlight, especially to the emergency management community, soil moisture estimation methods that may not be well known outside the scientific community.

1. INTRODUCTION

Fire danger rating systems are devised to evaluate and integrate the individual and combined factors influencing fire danger. The ignition and spread of fire together with short temporal variations in fire danger depend on fuel availability and prevalent weather conditions [Chandler *et al.,* 1983]. Fuel availability is the proportion of fuel which will burn in a fire [Luke and McArthur, 1978]. Because fuel availability measures are themselves not always readily available, fire danger rating systems include sub-models to estimate these quantities from weather observations. The McArthur Forest Fire Danger Index (FFDI) [McArthur 1967] used in Australia, for instance, has a component representing fuel availability called the Drought Factor, which in turn is partly based on soil moisture deficit, commonly calculated in Australia as either the Keetch–Byram Drought Index (KBDI) [Keetch and Byram, 1968] or Soil Dryness Index (SDI) [Mount 1972]. Soil moisture deficit therefore becomes a key variable in the FFDI calculations performed operationally in Australia, and accurate estimates and forecasts of soil moisture are crucial for effective fire danger calculations for fire weather forecasts and warnings, and for fire management.

The KBDI and SDI are simplified, empirical water balance models that do not comprehensively account for the majority of physical factors which affect soil moisture dynamics such as soil type, vegetation type, terrain or aspect. They over-simplify evapotranspiration and runoff processes, potentially leading to large errors in estimated soil moisture state. Studies have shown that soil moisture outputs from land surface models are more accurate than these indices [Vinodkumar et al., 2017]. With advances in the science of measurement — in the form of satellite remote sensing, and in prediction — in the form of physically based land surface models and advanced data assimilation schemes, soil moisture can now be better analysed and predicted. This report, as a basis for such research, describes the potential sources of remote sensing observations and data assimilation methods that can be used to estimate more accurate soil moisture deficit state for application in Australian fire danger rating systems.

2. REMOTE SENSING OF SOIL MOISTURE

In situ soil moisture measurements, though highly reliable, are cost-prohibitive for extended spatial mapping. Since soil moisture exhibits spatial variability that depends on the topography of an area and the soil characteristics, methods to characterize it on a regional scale without the necessity for exhaustive field measurements would be beneficial for applications like fire and flood forecasting. Remote sensing using satellites provides unique capability for the measurement of soil moisture at regional and global scales which satisfy the science and application needs of hydrology. The theory behind soil moisture remote sensing stems from the fact that the electromagnetic response of the land surface is modified by its soil moisture content. The dielectric constant (or equivantly relative permittivity) of soil increases as its moisture content increases. Dielectric constant measures a substance's ability to store electric energy. The dielectric constants for water is about 80 for frequencies below 5 GHz, where as that of dry soil is about 3.5. This large contrast between the dielectric constants of water and that of dry soil translate into difference of up to 100 K or more in brightness temperature between very dry and wet soils [Wang and Choudhury, 1995].

Various regions of the electromagnetic spectrum have been used to estimate soil moisture, including gamma [Carroll, 1981], thermal infrared [Price, 1982], and microwave [Jackson *et al.*, 2005] radiation. Many factors modulate the radiation reaching the sensor; for example surface temperature, surface roughness, vegetation, atmospheric effects etc. However, these effects are negligible at low frequencies of the microwave spectrum (roughly 1 – 5 GHz). Further, longer wavelengths have a higher capacity to measure deeper (2 – 5 cm) soil moisture layers, the penetration depth being of the order of one tenth of the wavelength [Lakshmi, 2013]. These are significant advantages of microwave remote sensing and hence there has been considerable amount of research done to determine soil moisture in low-frequency microwave spectra [Jackson and Schmugge, 1995; Jackson et al., 1999]. Microwave instruments may make either passive or active measurements [Jackson, 2005]. Active instruments transmit electromagnetic pulses towards the Earth and measure the reflected and scattered energy back from the earth's surface. Passive instruments measure radiation emitted by the Earth's surface. Thus, for passive instruments, the energy source is the target itself. The earliest efforts to determine soil moisture from space-borne microwave sensors for large spatial scale hydrological studies started with the availability of Scanning Multi-channel Microwave Radiometer (SMMR; Njoku *et al.*, 1998) and Special Sensor Microwave Imager (SSM/I; Hollinger *et al.*, 1990) data sets. Figure 1 depicts a schematic overview of the past, present and future soil moisture remote sensing missions. Table 1 summarises the results of some important validation studies done on historical and current satellite soil moisture datasets. For the present study, we focus only on the current and future soil moisture remote sensing instruments. The following sub-sections give a short description of each of these space-borne data sets.

2.1 ASCAT

The Advanced Scatterometer (ASCAT; Wagner et al., 2013) instrument on board EUMETSAT's MetOp-A and B satellites is an active microwave instrument. Retrieved ASCAT surface soil wetness products are disseminated within 135 minutes of measurements. Daily coverage is about 80% of the globe. MetOp-A was launched in

2006 and MetOp-B was launched 2012. A third mission MetOp-C is expected to be launched in 2018, thus maintaining the service until at least 2020. Albergel *et al.* (2012) compared the ASCAT surface soil wetness products against ground based observations and concluded that ASCAT data is of very good quality, especially for Australia.

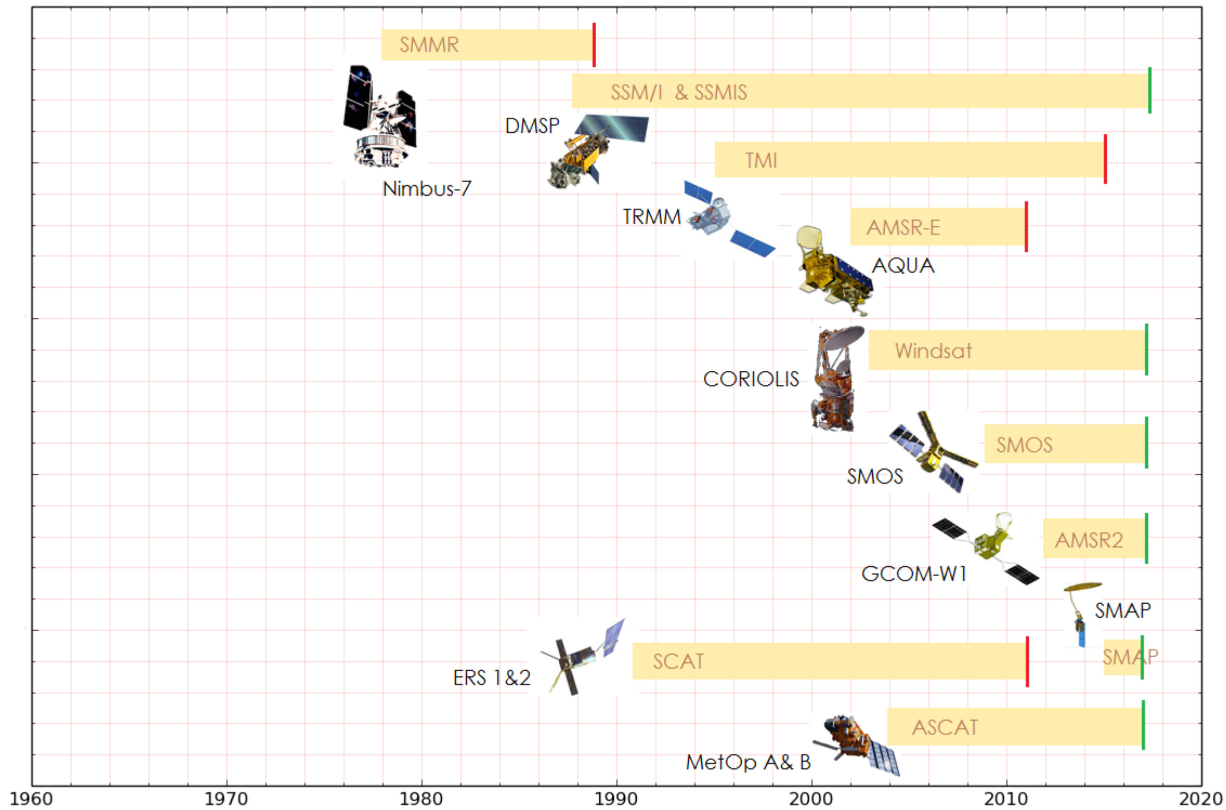

Figure 1. Overview of soil moisture remote sensing from space – missions and their timelines.

2.2 SMOS

The Soil Moisture Ocean Salinity (SMOS; Kerr et al., 2010) is the first satellite mission dedicated to the global mapping of surface soil moisture. SMOS was launched in 2009 and measures brightness temperatures in the L-band. Albergel *et al.* (2012) have compared SMOS retrieved surface soil moisture against ground based observations and found good agreement between the two data sets. However, ASCAT appears to provide more accurate estimates of soil moisture than SMOS over Australia. This was observed in other studies as well (e.g. Holgate et al., 2016). Al Yaari et al., 2014 suggest that i) the contamination of SMOS signal by Radio Frequency Intereference, ii) higher order surface-vegetation interaction effects that may increase the sensitivity of active systems (like ASCAT) to surface soil moisture and, ii) sensitivity of ASCAT to seaonal vegetation dynamics as few possible reasons for the relatively high skill of ASCAT compared to SMOS. Figure 2 shows typical time averaged soil moisture products retrieved in early October 2013 from ASCAT and SMOS missions over Australia.

Instrument	**Resolution**	**Study Area**	**Literature Source**	**Validation Metric**		
				Bias (m^3/m^3)	*RMSD (m^3/m^3)*	*Temporal Correlation*
TMI	40km	USA	Gao et al., 2006	—	—	0.59
WindSat	40km	France	Li et al., 2007	0.00	0.06	0.74
ERS	50km	Sahel	Gruhier *et al.*, 2010	0.04	0.05	0.52
AMSR-E[*]	60km	Australia	Draper *et al.*, 2009	0.0	0.03	0.83
AMSR-E[#]				-0.01 to 0.19	0.11	0.79
ASCAT[+]	25km	Australia	Abergel *et al.*, 2012	0.01	0.06	0.80
SMOS[+]	40km	Australia	Abergel *et al.*, 2012	-0.06	0.08	0.74
AMSR2	60km	Australia	Rudiger *et al.*, 2013	–0.01 to 0.05	0.04 to 0.09	—
SMAP	36km	Australia	Al-Yaari et al., 2017	0.02	0.09	0.85[@]

Table 1. Validation studies of sensors against the in situ observations. A single value for a metric implies a mean value.

*validation against smoothed and bias corrected AMSR-E data;

#validation against the original AMSR-E data.

+To enable a fair comparison, both in situ and remotely sensed soil moisture data sets are scaled between [0,1] using their own maximum and minimum values.

@ Median value. Normalised values are converted to units of m^3/m^3 assuming a dynamic range of 0.3 m^3/m^3.

2.3 AMSR2

The Global Change Observation Mission-Water (GCOM-W; Imaoka *et al.,* 2010) launched by the Japanese Space Agency is another instrument which provides microwave estimates of soil moisture. GCOM-W1 was launched in 2012. The Advanced Microwave Scanning Radiometer–2 (AMSR2) instrument on board the GCOM-W1 is a successor of the AMSR-E instrument on board EOS-Aqua satellite. AMSR2 contains some improvements in the calibration system and an additional 7.3 GHz channel to mitigate the radio frequency interference issues seen in some predecessors. An initial evaluation using *in situ* observations from OzNet show that the root means square difference is about 0.04 – 0.09 m^3/m^3 (Rüdiger *et al.,* 2013).

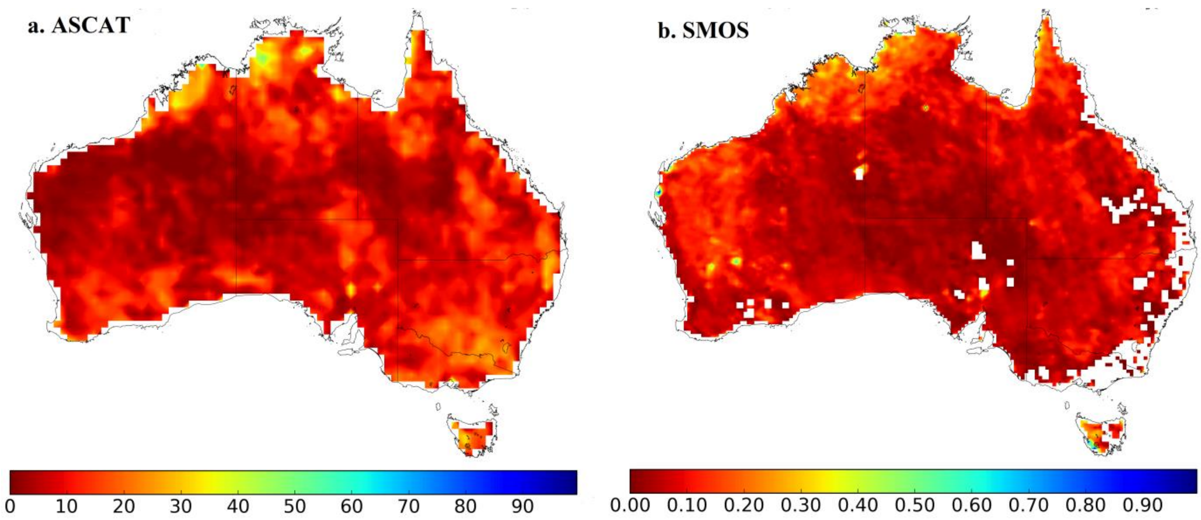

Figure 2. Five-day (1 – 5 January 2013) averaged maps of retrieved (a) soil wetness index from ASCAT and (b) volumetric soil moisture content from SMOS satellite over Australia.

2.4 SMAP

The Soil Moisture Active/Passive mission (SMAP; Entekhabi et al., 2010) was launched by NASA in January 2015. SMAP was originally designed to provide soil moisture measurements at a much higher resolution than the current systems by using an advanced L-band radiometer and a synthetic aperture radar. The original goal was to produce a 9 km resolution soil moisture product by combining the ~40 km resolution radiometer data and ~3 km radar data. However, SMAP's radar stopped transmitting on July 7 2015 due to a failure of radar's high-power amplifier. The science mission continues with data being returned only by the passive radiometer instrument. Al-Yaari et al. (2017) note that operational soil moisture retrieved using the baseline Single Channel Retrieval Algorithm has good skill when compared against observations from the OzNet network in the Murrumbidgee catchment.

3. SOIL MOISTURE DATA ASSIMILATION

3.1 WHAT IS DATA ASSIMILATION?

The basic idea of data assimilation in geophysical sciences is to combine valuable information in both observations and models to derive an optimal estimate (called analysis) of the field of interest. Both model estimates and observations are imperfect and may contain errors at the scale of interest. When combined using a data assimilation method, the resulting field may provide an accuracy level that cannot be obtained when the model or observation is used individually. The optimal combination of measurements with model information in advanced data assimilation schemes is performed by taking their respective uncertainties (error bars) into consideration. When the observational data is more accurate, analysis will be close to observations. When there are no observation for a particular time and location, the analyses may be close to the model solution. However, data assimilation can spread information in space and time and hence locations without any observations will still be subjected to the influence of observations in spatial or temporal proximity of the location of interest. Data assimilation can also spread information from observations to all model variables that are related to the observed variable.

The theory of advanced data assimilation methods rests on the mathematical framework of linear estimation theory [Cohn, 1997]. Although the data assimilation problem in earth sciences involves large scale, highly non-linear models with complicated error structures, they still rely on linear estimation theory and assume errors have a Gaussian (or normal) distribution. A fundamental reason for assuming Gaussian error distribution is to make the linear statistical estimation simplier and easier. Because Gaussian probability distribution functions are fully determined by their mean and variance, the solution of the data assimilation problem becomes computationally practical. However, the assumption of a Gaussian distribution is often not justified in gephysical data assimilation applications.

3.2 WHY DATA ASSIMILATION?

In addition to obtaining a more accurate geo-physical state, there are additional potential benefits that can result from combining measurements and model through data assimilation. They include:

3.2.1 Coverage

With the advances made in microwave remote sensing of soil moisture, a number of satellites were launched specifically for monitoring. Their spatial and temporal coverage, however, is still not sufficient for many applications. Such coverage is not possible with future satellite sensors either. Data assimilation methods can propagate information contained in measurements in both horizontal space and time using the physical relationships embodied in the model, providing a continuous state estimate.

Also, the satellite observations are limited to parts of the Earth surface that can be penetrated by electromagnetic radiation. Thus, remote sensing can only provide soil moisture information of a surface (~ 5 cm) layer, not of the deeper layer including the root zone. Hence, these data may not directly satisfy the need of many users. Land surface models can estimate soil moisture at deper layers. Data assimilation systems can spread the surface information from these remote sensing observations to deep model layers.

3.2.2 Resolution

The spatial resolution of remote sensing data is often too coarse or too fine for a given application. For example, soil moisture retrievals from the ASCAT are available at a resolution of around 25 km, much coarser than the resolution needed for fire prediction. However, land surface models used in regional numerical weather prediction (NWP) systems run at sub-10 km resolution. By merging the satellite data with models that resolve the scale of interest, data assimilation methods are capable of aggregating or downscaling the remote sensing data.

3.2.3 Data organization

Depending on the instrument, there may be an overwhelming amount of data available from remote sensing observations, which can be beyond the processing capabilities with in a periodic time interval of an operational prediction. A high data density leads to high computational costs and need for large disk space. Data assimilation methods employ sophisticated thinning algorithms to retrieve the essential information content of the observation data for optimal use. Further, there may be a great deal of overlapping information from different remote sensing platforms. For instance, polar orbiting satellites measuring land surface temperatures may cross over locations that are simultaneously observed by geostationary platforms carrying similar sensors. These two pieces of information are useful, but may not necessarily agree due to measurement errors and errors in the retrieval algorithms. Data assimilation systems can organize and merge potentially redundant or conflicting satellite data and conventional observations into a single best estimate.

3.2.4 Provide supplementary information

Geophysical models are built on the basic conservation principles of mass, momentum, and energy. However, remote sensing data are not constrained by any of these basic principles. In an assimilation system, the physical constraints imposed by models offer additional valuable information. Data assimilation uses the parsimonious observations and model's physical equations to estimate unobserved quantities. This allows a more complete understanding of the true state of a hydrologic (or other geophysical) system, which would be impossible without assimilation. Further, models are often forced with an analysis based on other independent observations (for example, precipitation inputs for land surface models). Such additional independent observational information about the remotely sensed fields (for example, soil moisture) can be captured through data assimilation.

3.2.5 Quality control and validation

The data assimilation system imposes some quality controls on observations by comparing them against model estimates. This allows identification and elimination of spurious data in observations. By using the statistics of this model versus observation comparison, it is possible to calibrate observing systems and identify biases or changes in observation system performance. The data assimilation system also validates and improves the models by continuous confrontation with quality data. This helps to identify systematic errors in the model and correct them.

3.3 INTRODUCTION TO SOIL MOISTURE DATA ASSIMILATION

Soil moisture data assimilation aims to utilise both our knowledge of factors governing soil moisture dynamics, as embodied in a land surface model, and information that can be gained from observations. Both model predictions and observations are imperfect. For example, a land surface model prediction is affected by errors resulting from inadequate model physics, parameters and forcing data. Thus when measured soil moisture data are available, their use to constrain the simulated data should improve the overall estimation of the soil moisture profile. Figure 3 provides an example of how data assimilation supplements a model simulation by using complementary observations. The general outcome of the studies which ingested surface soil moisture products from various satellites also is that the assimilation of these products yields a better estimate of the soil moisture. Draper *et al.* (2012) found that, even though correlation between *in situ* measurements and an open-loop (no assimilation) Land Surface Model (LSM) run (R_{im}) was better than that between the *in situ* and satellite data (R_{ir}), assimilation of this satellite data still yielded positive impact on the analysed soil moisture. Their study showed that assimilation of satellite observation with R_{ir} no more than 0.2

below R_{im}, generally increased the soil moisture skill up to 40% as R_{ir} increased relative to R_{im} (Figure 4).

Data assimilation techniques were pioneered by meteorologists [Daley, 1991] and have been used very successfully to improve operational weather forecasts. Since land parameters such as soil moisture, soil temperature and snow cover exhibit a strong influence on weather forecasts, assimilation schemes for the land surface component of NWP models to constrain these fields were also developed. One of the earlier approaches in land surface assimilation in NWP is to use an indirect Newtonian nudging method, where the evolving screen-level temperature and humidity — through their assimilation — are used to correct model soil temperature and moisture [Vinodkumar et al., 2009; Dharssi et al., 2011]. This method makes use of the denser screen level observations available, and surrogates the sparseness of hydrological observations to some extent. The Newtonian nudging scheme relaxes the model field towards observations by adding a term to the prognostic equation which is proportional to the difference between model and observed states.

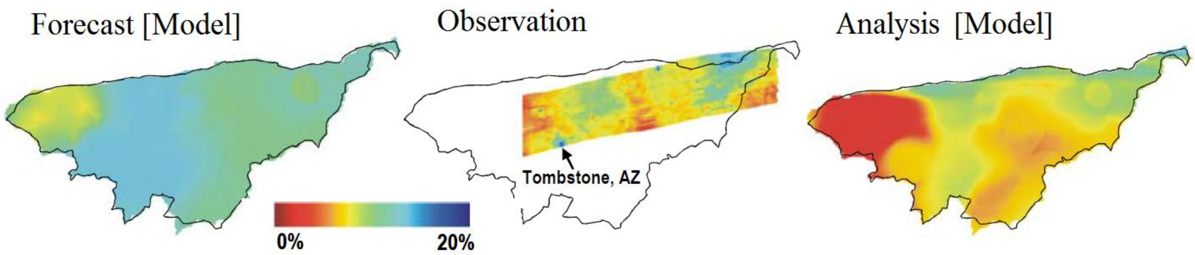

Figure 3. An example of assimilation procedure. Push Broom Microwave Radiometer (middle column) images gathered over the Walnut Gulch Experimental Watershed in southeast Arizona were used to update soil moisture from Topmodel based Land Atmosphere Transfer Scheme model (first column). The observations were found to contain horizontal correlations with length scales of several tens of kilometres, thus allowing soil moisture information to be advected beyond the area of the observations (last column). Adapted from Houser et al., [1998].

However, the availability of progressively more observations, especially satellite observations, spurred significant advances to be made in land surface data assimilation in a short period of time. This was also helped by the knowledge gained from the experience of data assimilation in the field of meteorology and oceanography. Today, advanced approaches in data assimilation are widely used by land surface modelling community to get the best estimate on fields of primary interest, such as soil moisture content. More recently, operational NWP centres, such as the European Centre for Medium Range Weather Forecasting (ECMWF) and the UK Met Office, have developed specific land assimilation schemes based on the Kalman Filter methodology [e.g. de Rosnay et al., 2012]. These advanced data assimilation methods are based on some measure of model and observation error characteristics. The nudging, optimum interpolation or other simple approaches attempted in earlier studies do not account for observation uncertainty or utilise system dynamics in estimating model background state uncertainty. Variational methods (used widely in atmospheric data assimilation) are also not generally used in land surface data assimilation due to the fact that the development of robust adjoints are difficult due to the non-linear and on-off processes involved in land surface models. The adjoint is simply a mathematical operator that allows one to determine the sensitivity of the objective cost function to changes in the solution of the model state equations.

The advantage of Kalman filter based data assimilation techniques is that they allow flexibility in handling all sources of uncertainty along with the possibility of ingesting the data sequentially as it becomes available. These algorithms can also make use of both screen level and remote sensing observations and are found to be superior to earlier techniques such as optimal interpolation (de Rosnay et al., 2012). In addition to this, there is also the potential for using other remote sensing observations which contain indirect information about the surface moisture, such as skin temperature (e.g. Ghent et al., 2010).

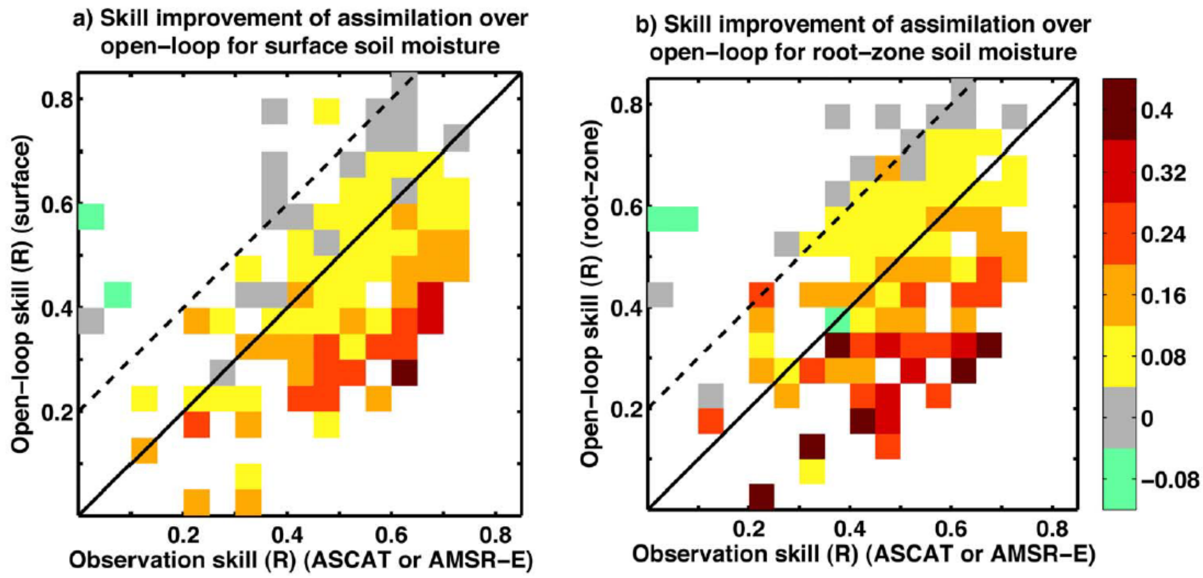

Figure 4. Skill improvement from assimilating either ASCAT or AMSR-E soil moisture measurements as a function of the open-loop skill and observation skill. The results show that assimilation can improve skill provided the observation skill minus open-loop skill > -0.2. Skill is defined as the temporal correlation against ground based observations. The open-loop is a LSM run without data assimilation. Courtesy: Draper et al. (2012).

The standard Kalman filter (KF) is used as a data assimilation method for linear systems and measurement processes with Gaussian error statistics (Gelb, 1974). For non-linear systems like land surface models, an extended Kalman filter (EKF) has been used (Entekhabi et al. 1994). EKF is found to be a computationally feasible data assimilation method for single column land surface models and hence is widely used. In EKF, the estimation of model error at the time of observation is achieved by propagating the covariance matrix of model errors with a dynamic equation. EKF is the operational assimilation scheme for soil moisture in the UK Met Office's operational NWP model [Candy, 2014]. It will be the soil moisture data assimilation scheme used in the Bureau of Meteorology's next operational NWP update. The EKF is capable of handling some non-linearity in model operators used to propogate errors as well as departure from Gaussian model errors distributions. However, if the model becomes too non-linear or the errors become highly non-Gaussian, the trajectories computed by the EKF will become inaccurate [Evensen, 1994; Reichle et al., 2002].

To overcome the above limitations in EKF, a Monte Carlo (ensemble) based approach has been introduced [Evensen, 1994]. In this method, the necessary error covariances at the time of an update are estimated using an ensemble of non-linear model runs. Each ensemble member is subject to a different realization of model and forcing errors. Each ensemble member could also employ different sets of model parameters or even entirely different land surface models. Thus, unlike EKF, the estimation of priori model covariance is not needed. The technique has since become known as the ensemble Kalman filter (EnKF). Numerous research studies have used EnKF to assimilate soil moisture or soil temperature measurements from in-situ observation or remote sensing data [e.g., Crow & Wood, 2003, Reichle & Koster, 2005; Sabater et al, 2007]. The EnKF is also used by Environment Canada in their operational NWP system [Candy, 2014].

3.4.1 A few examples of application studies

Most studies try to address the important conceptual problems in soil moisture assimilation such as: i) the propagation of information from the surface to the entire model soil profile; ii) the optimization of assimilation techniques and update frequencies; and iii) estimation of uncertainty in observations. A number of studies have demonstrated that root-zone soil moisture in land surface models can be constrained accurately through the assimilation of near-surface soil moisture [e.g.: Walker and Houser, 2001; Crow and Wood, 2003; Reichle et al., 2007]. Assimilation of in-situ surface soil moisture observations have shown to improve the root-zone soil moisture in the model initial conditions [Calvet and Noilhan, 2000]. Crow and Wood [2003] improved the root-zone soil moisture forecasts from the Land Surface-Atmosphere Transfer Scheme, by assimilating L-band brightness temperature observations from the SGP97 field experiment using an EnKF scheme. Reichle and Koster [2005] assimilated C-band Scanning Multichannel Microwave Radiometer (SMMR) data into the NASA Catchment Land Model with an EnKF to obtain marginal improvements to root-zone soil moisture.

Walker et al. [2001] showed that soil moisture assimilation can solve issues with errors in forcings or initial conditions. Georgakakos and Baumer [1996] documented the impact of observation noise on Kalman filter results. The effect of assimilation frequency was studied by Li and Islam [1999] where they used gravimetric measurements as surrogates for remote sensing data. De Lannoy et al. [2007] studied the vertical information propagation, and the effect of assimilation depth and frequency for an extensive set of soil profiles using an EnKF method. Sabater et al. [2007] used different types of filtering and ground data from the Surface Monitoring of the Soil Reservoir EXperiment (SMOSREX) to study the propagation of surface observations to deeper model layers. Han et al. [2012] used an EnKF scheme and surface observations to further identify and address conceptual problems with soil profile estimation.

3.4.2 Example Land Data Assimilation System

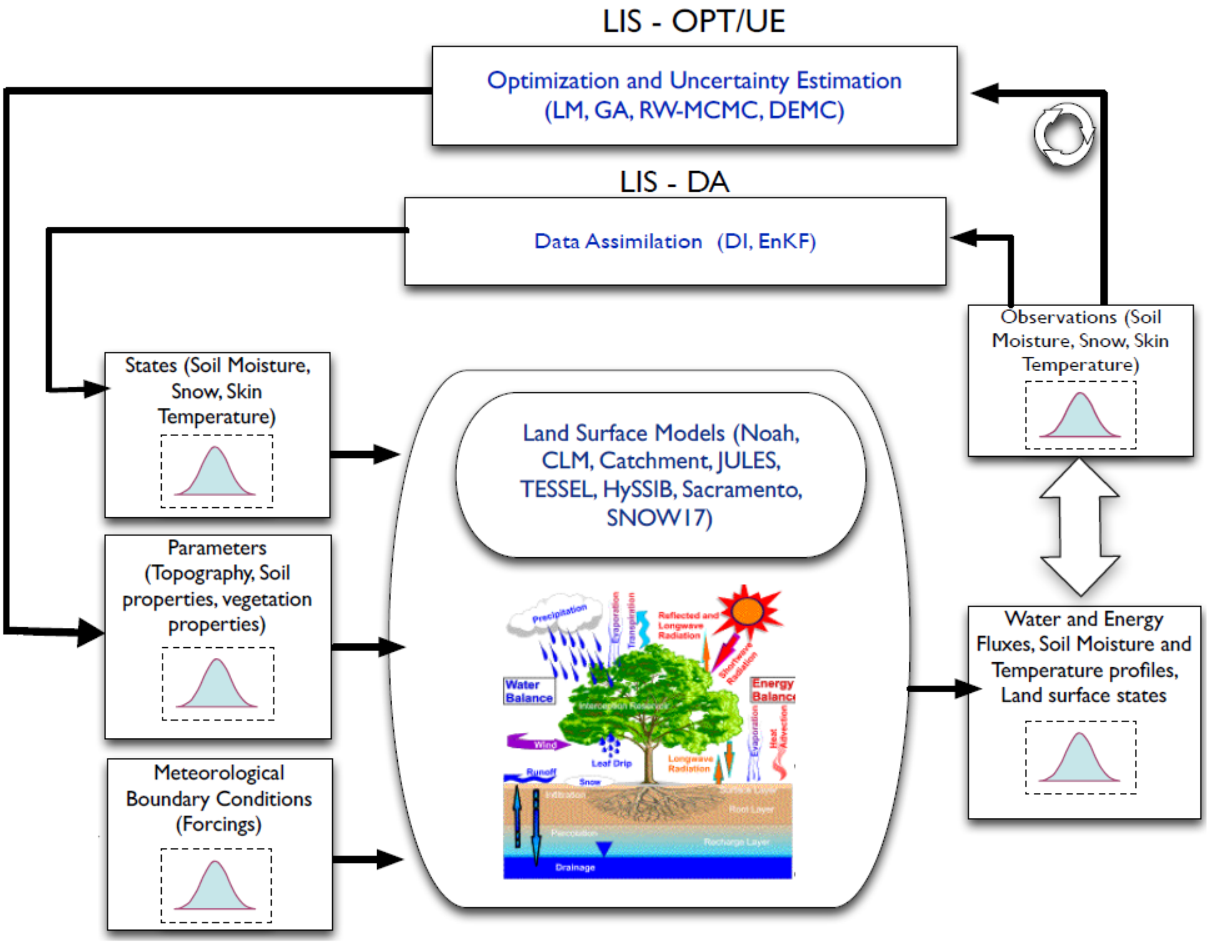

Figure 4. A schematic of NASA's LIS. Courtesy: Kumar & Arsenault [2014].

For illustrative purposes, we briefly describe the National Aeronautics and Space Administration's (NASA's) Land Information System (LIS; Kumar et al., 2008). LIS is a flexible land surface modeling and data assimilation framework developed to integrate satellite and ground-based observations with land surface models. LIS operates several community land surface models including JULES and CABLE which are widely used in Australia. LIS allow one to incorporate diverse data sets as input to the LSMs. LIS has a highly sophisticated high performance computing capability that enables the running of LSMs at global scales with spatial resolutions as high as 1 km. All functional modules in LIS are implemented as extensible components, including LSMs, data assimilation schemes, sources of meteorological inputs and land surface parameters, modeling domains and running modes. This design enables the inclusion of user defined extensions for each of these functional abstractions.

The LIS data assimilation component includes Direct Insertion (DI), and the Ensemble Kalman filter (EnKF) approaches. The data assimilation extension in LIS is designed to be a sequential operator, where variables are updated at every observation time. Various sources of observational data including surface soil moisture [Kumar et al., 2014], terrestrial water storage [Kumar et al., 2016], land surface temperature [Reichle et al., 2010] and snow water equivalent [De Lannoy, 2012] retrievals can be assimilated through LIS. The outputs from LIS has been used for a wide range of appilcations including drought estimation [Kumar et la, 2014], food and water security applications [McNally et al., 2017], and streamflow prediction [Liu et al., 2015].

4. SUMMARY

Landscape dryness measurement and forecasting is critical for the management and warning of fires, as well as numerous other phenomena of concern to emergency managers. Emerging approaches to evaluate landscape dryness through the use of satellite remote sensing data, land surface modelling and data assimilation techniques are available, measuring dryness more systematically than existing empirical methods. This report describes the available sources of soil moisture data and shows that existing satellite systems such as ASCAT and SMOS together with future systems such as SMAP are a valuable source of land dryness measurements.

The above satellite measurements can be assimilated with land surface model simulations to provide more accurate, detailed and confident estimates and forecasts of land dryness, and hence more accurate operational predictions of fire danger and fire behaviour, flood prediction, landslip warning, and heatwave events. Because of its success in highly non-linear land surface modelling [Reichle, 2008], the assimilation using EnKF has gained a lot of attention. NASA's LIS framework provides a great oppurtunity to effectively assimilate the different remote sensing observations with land surface models for national scale estimation of soil dryness. Our future work intends to head in exactly this direction. It is well established that high skill in short- and medium-range forecasts of temperature and humidity over land requires proper initialization of soil moisture [Beljaars et al., 1996; Mahfouf et al., 2000; Drusch and Viterbo,2007]. Hence, improved soil moisture estimates from the proposed system can be used to initialize soil moisture in the Bureau of Meteorology's operational regional NWP models. This has implications for fire danger ratings and other natural hazard predictions.

While this report focuses on soil moisture state estimation, land surface parameter estimation and forcing data correction using data assimilation have also been successfully attempted [Moradkhani et al., 2005; De Lannoy et al., 2007; Vrugt et al., 2012]. Also, assimilation of other state variables like evapotranspiration, surface or skin temperature, LAI (leaf area index), discharge and water storage are also possible. Future studies will investigate the assimilation of these additional observed variables.

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