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DOWNSCALING OF SOIL DRYNESS ESTIMATES

A short review

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Version	Release history	Date
1.0	Initial release of document	14/11/2017

Publisher:
Bushfire and Natural Hazards CRC

November 2017

Citation: Vinodkumar & Dharssi I (2017) Downscaling of soil dryness estimates: a short review. Bushfire and Natural Hazards CRC, Melbourne.

Cover: Rosmarie Voegtli, Flickr

Downscaling of soil dryness estimates: A short review

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Abstract

Accurate and fine-scale landscape dryness estimation is critical for the management and timely warning of disasters like landscape fires, floods, heatwaves, landslips. It has application in environmental management, agriculture and other types of farming like livestock, and silviculture as well. In a fire danger context, the estimated landscape dryness is calculated for assessing the fuel availability. Though new techniques like remote sensing and land surface modelling provide accurate soil moisture information, it is at a relatively coarser scale than that is required for the above mentioned applications. A common practice to overcome such a problem is to employ downscaling methods to increase the spatial scale of the product. The downscaling approach can be broadly subdivided into deterministic and stochastic. The present study provide a brief review on some of these downscaling methods that are used to derive finer scale information from remote sensing or land surface model outputs. We also highlight some of the studies which has used the above methods for soil moisture applications. The discussion presented here is not intended to be complete and reflect authors' interest. But we still hope that it helps to highlight some of the most commonly used downscaling approaches that are well known to the hydrological community.

1. Introduction

Accurate estimation of soil moisture is of great importance for many applications like drought monitoring (Han et al., 2014), weather and climate prediction (Dharssi et al., 2011; Seneviratne et al., 2010), irrigation water management (Bastiaanssen et al., 2000), ecological modelling (Nemani et al., 2009), vegetation productivity estimation (Reichstein et al., 2003), fire danger rating (Vinodkumar et al., 2015), flood forecasting (Camici et al., 2011) etc. However, quantifying the spatial and temporal distribution of soil moisture is still challenging due to its large variability (Njoku et al., 2003; Loew, 2008). This high variability of soil moisture in space and time is driven by a number of parameters, such as vegetation, soil type, topography, and meteorology. The importance of each of these parameters decreases or increases depending on scale (Grayson et al., 1997; Pan et al., 2001).

Typically, space resolutions are much poorer than time resolutions in hydrology (Blöschl & Sivapalan, 1995). The complex scale dependency of soil water content makes it both difficult to measure and forecast. Even in-situ measurements can hardly capture the high variability in soil moisture over short distances (Western et al., 1999). The main limitation of ground based soil moisture observations is that the effective area represented by these measurements is very small (Western et al., 2002). Since soil moisture exhibits high spatial variability, this will lead to large errors of representativity (Famiglietti et al., 2008); and in order to map extended spatial scales, a very large number of sensors are required. This however, is neither economically nor logistically practical due to the high cost involved with their procurement, installation and management.

Land surface modelling has become a great tool in continually estimating soil moisture at large scales, where mapping with the use of in-situ observations become non-feasible. However, these land surface models (LSMs) are limited by their simplification in representing land-surface processes. For instance, most of the LSMs are in a single column framework and assume no lateral flows between neighbouring columns. This limits their capability to use in fine-scale hydrological applications, where lateral flows become relevant. Further, the resolution and accuracy of these models are restricted by the availability of quality meteorological forcing data. More often than not, it means that the LSM outputs are obtained at a resolution of few kilometres.

Soil moisture retrieved from microwave sensor on board various satellites have been also used for large-scale watershed catchment and hydrological studies (Wagner et al., 2007). These sensors are either passive (i.e., use naturally emitted radiation), or active (emit and receive own signal). The soil moisture estimates from the current passive sensors have a nominal resolution of ~40km. An inverse relationship exists between wavelength and antenna size. This imposes a technological limitation in deploying large antenna in space, which is required to attain higher spatial resolution. Consequently, soil moisture estimated from the passive microwave remote sensing technique cannot meet the requirement of many applications. The active sensors can provide a higher spatial resolution observation than those obtained from a passive instrument (~1km compared to ~40 km from passive sensors). However, radar data are more strongly affected by local roughness, microscale topography, and vegetation than a radiometer, meaning that the accurate retrieval of the dataset is quite difficult (Lakshmi, 2013).

In short, the remote sensing and modelling platforms, due to their design or other limitations, are generally incapable of delivering finer scale hydrological details. For applications like the monitoring of soil moisture on an agricultural paddock scale over a region/state, or fire danger assessment over a national park, these coarser resolution products may not provide much value. A common practice to overcome such a problem is to employ methods to change the scale of a product. A common way to transfer information from one scale to another is to apply either the upscaling or downscaling methods. Upscaling describes the transition of information from a smaller scale to a higher scale whereas downscaling is defined as disaggregation of spatial information from coarser to finer scales (Becker, 1999). The focus of the present study is to provide a brief review on the downscaling methods that can be useful to provide finer scale information from remote sensing or LSM outputs. This paper is organized as follows. Section 2 outlines a brief overview of downscaling in general. Section 3 describes the downscaling in soil moisture space and section 4 contain the concluding remarks.

2. Downscaling: A general overview

The fundamental question that downscaling address is, what are the values, the probability distribution, or the functional relationship of variables at a smaller scale, given the same for a larger scale? Usually, it is assumed that the large scale value is an average of those at small scale (Bierkens et al., 2000). This falls under the deterministic framework. However, the average value of the property at larger scale is not always known exactly, which calls for a stochastic framework where the uncertainty about average property value at large scale is described by means of a probability distribution or probability density function. These functions can be readily developed, adding to its appeal. The downscaling problem can thus be fundamentally distinguished into three; (1) deterministic, (2) conditional stochastic and (3) unconditional stochastic (Bierkens et al., 2000).

In the deterministic approach, average value at larger scale is known exactly. A single function is sought to determine the spatial variation at smaller scale, such that the average value of this function for larger scale equates the known average. The conditional stochastic problem also assumes that an exact average value is known. But unlike the deterministic approach, a set of equally probable functions describing the variation at finer scale is chosen, such that the average of each individual function at larger scale is equal to the known average. The family of equally probable functions are called the “ensemble”, or alternatively a “stochastic function” (Bierkens et al., 2000). The advantage of choosing a family of functions is that the uncertainty about true variations in the property at finer scale is readily explained. The downscaling problem is called “conditional” stochastic because the larger scale average of each realisation must be equal to the known average. In unconditional stochastic problem, the average value at larger scale is not known exactly (Bierkens et al., 2000). Instead, only the probability distribution function (PDF) of the average is known. The problem involves finding a set of equally probable stochastic functions that describe the temporal or spatial variation at finer scale. Unlike in conditional stochastic approach, here we do not require each realisation to have the same average. It is only required for the larger scale averages of all realisations together to have same PDF.

The deterministic or stochastic functions for distribution at finer scale is described through different type of functions: empirical, mechanistic or using auxiliary information. The selection of these is based either on the availability of auxiliary information or on the availability of a mechanistic model, that will be used to explain some of the unknown temporal or spatial variation of the property at finer scale. Following Bierkens et al. (2000), Figure 1 shows a decision tree that can be constructed from these questions.

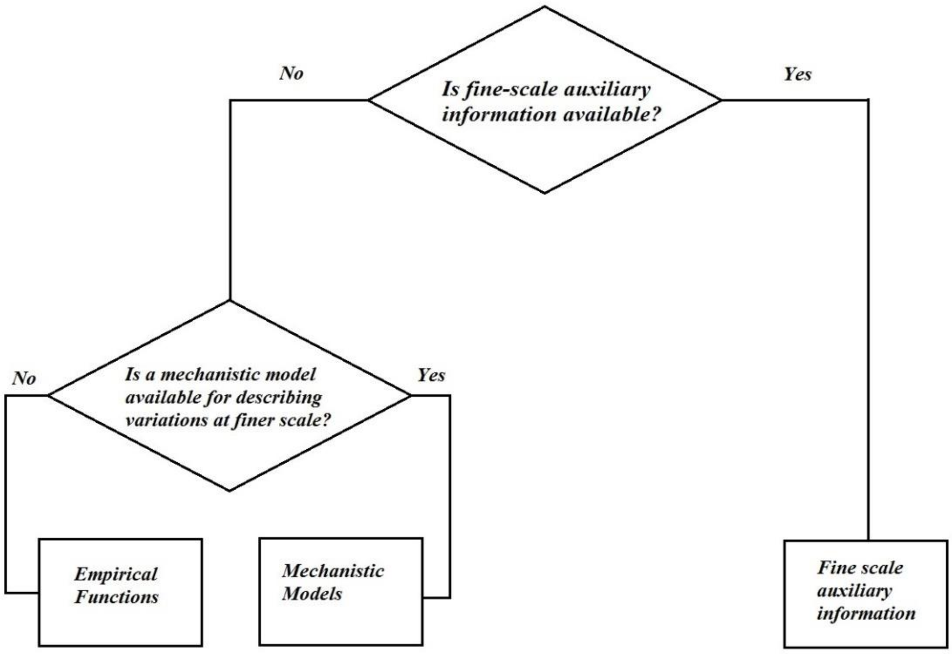

Figure 1. Decision tree for different classes of downscaling method (Bierkens et al., 2000).

3. Downscaling of soil moisture

Disaggregating state variables like soil moisture in hydrology may be required for estimating the spatial pattern of the water balance as needed for many forms of land management. Downscaling methods in soil hydrology generally adopt the two step processes of disaggregation and singling out (Figure 2; Blöschl & Sivapalan, 1995). The disaggregation procedure derives the detailed pattern within a domain, given the average value of that domain. Typically, space resolutions are much poorer than time resolutions in hydrology (Blöschl & Sivapalan, 1995) for most of the applications. Hence a lot of studies have focussed on spatial disaggregation of large scale, coarser resolution soil moisture products which usually are a large-scale 'average' values. This can be the pixel soil moisture based on satellite data, an estimate from a large-scale atmospheric or land surface model or an estimate derived from a catchment water balance. The singling out step simply finds the location of the disaggregated pattern that corresponds to the point of interest, and usually is trivial (Wu et al., 2006).

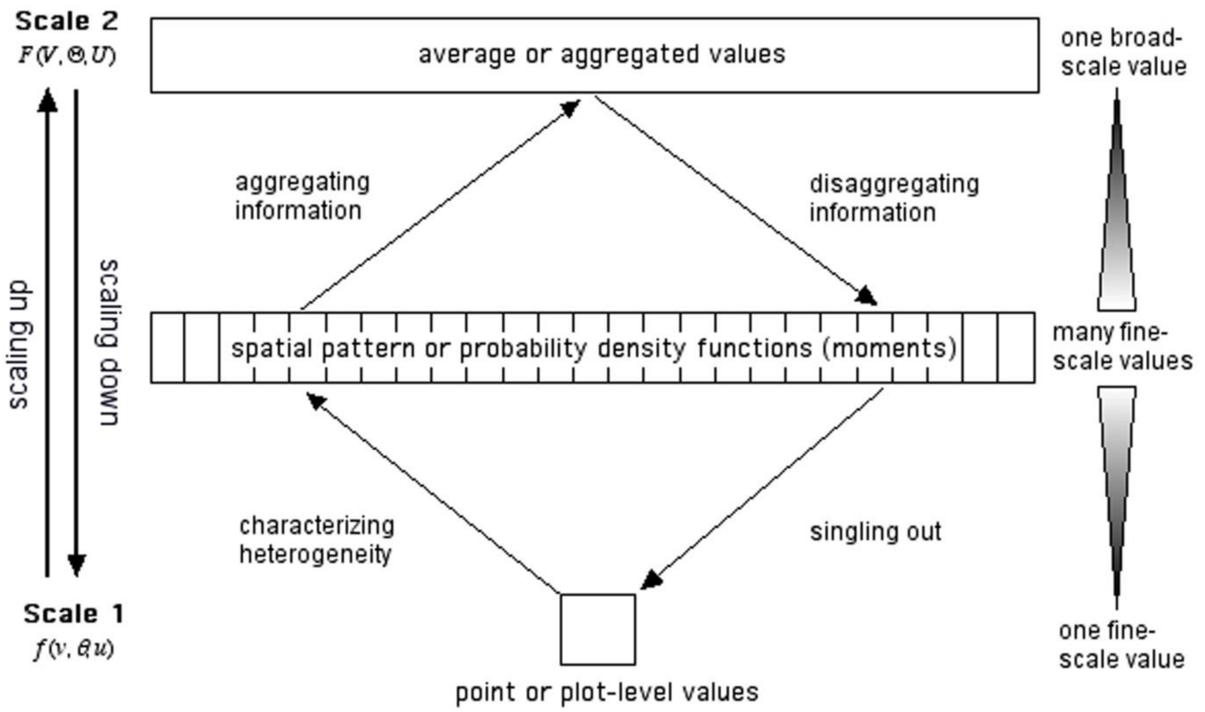

Figure 2. Two-Step Scaling Procedure (Courtesy: Blöschl & Sivapalan, 1995)

The soil moisture downscaling or disaggregation methods in the deterministic framework include techniques such as those merging remotely sensed data with terrain indices [Temimi et al. , 2010] or meteorological data [Merlin et al., 2006], and algorithms based on hydrologic models [Pellenq et al., 2003]. The statistically based approaches range from methods based on the scale invariance and multi-fractal properties [Kumar, 1999; Hu et al., 1998; Kim and Barros, 2002] or the use of empirical orthogonal function analysis [Perry and Niemann, 2007]. The disaggregation schemes in soil hydrology are often based on stochastic approaches discussed in section 2. These schemes generally correlate the quantity of interest to an auxiliary variable or covariate (e.g., topography, land-use), whose spatial distribution can more readily be measured. The spatial distribution of the quantity is then inferred from the spatial distribution of the covariate (Wu et al., 2006). In short, the downscaling of soil moisture can be performed by using simplified statistical descriptions that aim at representing the most important controls of soil moisture. These methods can either exploit the spatial statistics of soil moisture or make use of auxiliary information. The auxiliary information can be in the form of moisture index (Blöschl, 2005; Western et al., 2004) or other physical parameters that are at a finer scale (Blöschl et al, 2009).

3.1. Spatial statistics approach

Spatial statistics approaches like interpolation methods are typically much less data intensive in their application and hence were widely used in studies of upscaling and downscaling hydrological fields. In this approach, values are estimated between sparse points using spatial relationship to the neighbouring points. Studies have shown that the spatial correlations of soil moisture at small catchments are stationary and the correlation length ranges from a few metres to hundreds of meters (Mohanty et al, 2000; Western& Blöschl, 1999). In-situ soil moisture data collected over large areas in different parts of the world suggest that spatial variation could be represented as a stationary field with a correlation length of about 500 km (Entin et al., 2000). Over short scales, variation in soil moisture is more likely related to differences in soils and vegetation, while larger scale soil moisture variability is determined mainly by climate. Numerous methods of upscaling and downscaling that are based on the spatial statistics are discussed in literature (Blöschl et al, 2009). These methods involve a wide spectrum of geostatistical methods that calculates spatial patterns from point data or catchment average soil moisture (e.g. Deutsch and Journel, 1992). Some of these geostatistical methods like the conditional simulation methods are based on the assumption that soil moisture is a Gaussian random field. Various studies have suggested that the spatial distribution function of soil moisture can be approximated by a normal distribution (e.g. Mohanty et al., 2000; Nyberg, 1996). However, it is also found that the shape of the distribution does change with climate. Based on numerous studies (Western et al., 2003), variance of the soil moisture spatial distribution tends to depend on mean catchment moisture. In particular, the variance increases from near zero at wilting point to a peak at moderate moisture levels and then decreases to near zero as the mean soil moisture approaches saturation.

3.2. Auxiliary information based approach

3.2.1. Auxiliary information from various indices

The index approach is a widely used method in hydrological downscaling as it is highly efficient and less demanding numerically, and only requires a limited number of input data. This is particularly appealing in an operational context. The index approaches generally use finer scale landscape characteristics to impose spatial organisation on the given soil moisture data. The methods fundamentally rely on an index which is formulated based on the available landscape characteristics and our understanding of water movement in the landscape (Moore et al., 1991). For example, in regions where sub-surface flow dominate the lateral redistribution of soil moisture, indices reflecting upslope area, slope, or convergence could be related to the soil moisture. One of the most commonly used indices in soil moisture scaling is the topographic wetness index (TWI) of Beven and Kirkby (1979). TWI is a function of both the slope and the upstream contributing area orthogonal to the flow direction. Computation of the upstream contributing area is based on flow direction algorithms. There are generally two main types of flow direction algorithms that are used, namely, Single Flow Direction and Multiple Flow Direction algorithms. The Single Flow Direction algorithm assumes that all water from a pixel should flow into the neighbouring pixel with lowest elevation. Multiple Flow Direction assumes that flow from the current position could drain into more than one downslope neighbouring pixel.

Western et al. (1999) studied the predictability of various indices against in-situ soil moisture data collected from a small catchment in south-east Australia. A correlation analysis found that the specific upslope area is the best univariate spatial predictor of soil moisture for wet conditions and the potential radiation index is the best during dry periods. The wettest soils were collected in the gullies that have large specific contributing areas. It is also observed that the explanatory power of the indices drop rapidly as the catchment dry out. Western et al (1999) also noted that the predictive ability of these indices varies substantially with climate zones and also depends on whether their main assumptions are satisfied. All of these indices can be used as an auxiliary variable along with the geostatistical methods for the purpose of downscaling. The geostatistical methods used for downscaling include external drift kriging, co-kriging and geo-regression (e.g. Blöschl and Grayson, 2000). For example, Green and Erskine (2004) compared a geostatistical analysis with linear geo-regression using terrain indices to derive fine scale soil water content maps.

3.2.2. Auxiliary information from remotes sensing

3.2.2.1. Auxiliary information from Optical or thermal infrared sensors

Remote sensing can provide complementary or direct information of soil moisture patterns at spatial resolutions in the order of few meters to several kilometres (Lakshmi, 2013). Optical or thermal infrared (TIR) and microwave sensors are often used for soil moisture downscaling studies. Active research is being undertaken by different groups to develop techniques that use both microwave and optical/TIR remote sensing data to estimate soil moisture at different spatial resolutions. A wide range of approaches, from regression methods to physics based models, are adopted to estimate soil moisture (Kim and Hogue, 2012; Sahoo et al., 2013; Fang and Lakshmi, 2014).

The soil moisture estimation from the optical sensors is done using an empirical relationship between vegetation index and observed surface reflectance (Gao et al., 2013). The common method used by thermal infrared remote sensing to estimate soil moisture is to construct a functional relationship between soil moisture and thermal inertia (Qin et al., 2013; Verstraeten et al., 2006). Some studies have explored the relationship between land surface temperature (T_S) and vegetation index to estimate soil moisture. It is observed that T_S exhibits different sensitivity to soil moisture variations over bare soil and vegetated areas (Peng et al, 2016). This results in the scatter plots resembles a triangular or trapezoidal feature space (Figure 3), which is more physically meaningful (Peng et al., 2016). Based on this feature space, several indices such as the vegetation temperature condition index (Wan et al., 2004) and temperature vegetation dryness index (Sandholt et al., 2002) have been developed to assess the soil moisture conditions (Karnieli et al., 2010; Peng et al., 2013). Recently, Peng et al. (2016) demonstrated that the spatial resolution of microwave soil moisture can be improved by using vegetation temperature condition index as the exclusive downscaling factor.

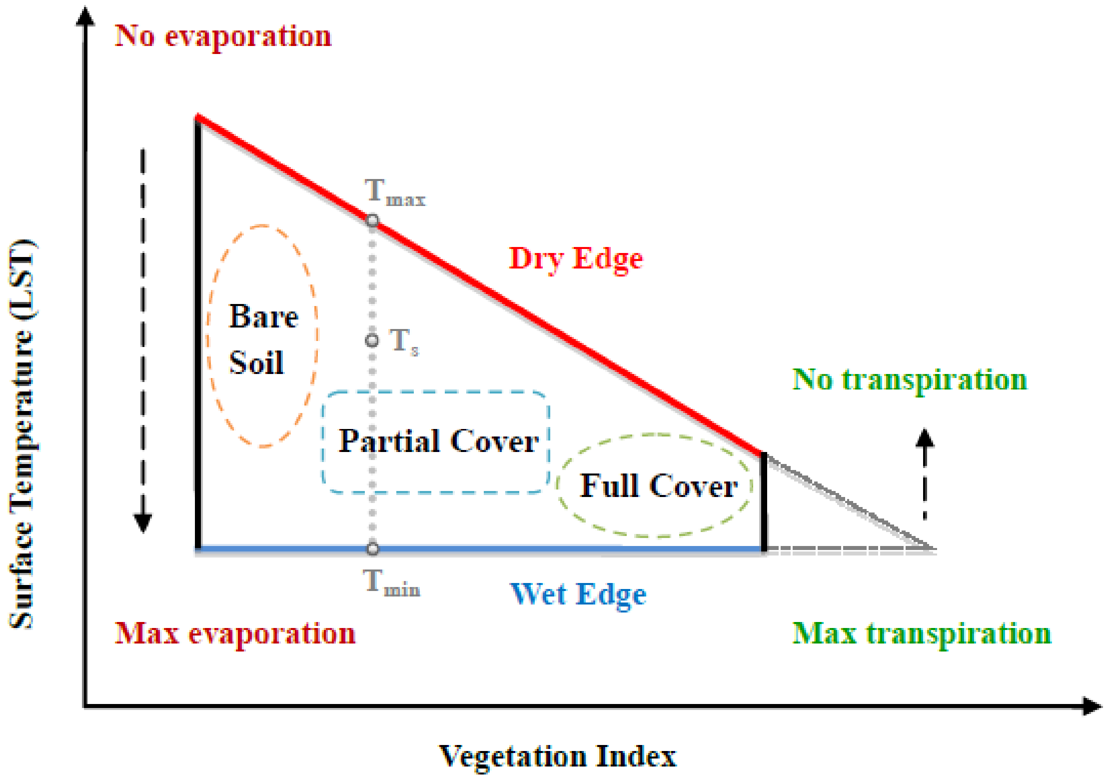

Figure 3. Conceptual diagram of the triangular/trapezoidal feature space that is constructed by land surface temperature and vegetation index (Courtesy: Pen et al., 2016).

Chauhan et al. (2003) evaluated an approach for the estimation of soil moisture at high resolution using satellite microwave and optical/infrared (IR) data. The approach links the microwave-derived low-resolution soil moisture to the scene optical/IR parameters, such as Normalized Difference Vegetation Index (NDVI), surface albedo, and T_S. The linking is based on the 'universal triangle' approach of relating land surface parameters to soil moisture through a regression model. The linkage model in conjunction with the above mentioned land surface parameters are then used to disaggregate microwave soil moisture into high-resolution soil moisture. Following the work of Chauhan et al. (2003), a number of studies have tried to improve the regression models by including other inputs such as brightness temperature and surface emissivity (Piles et al., 2011; Piles et al., 2014; Sobrino et al., 2012).

The work done by Piles et al. (2011) also used a method based on "universal triangle" concept to retrieve high resolution soil moisture from Soil Moisture and Ocean Salinity (SMOS) mission using NDVI and T_S data from Moderate Resolution Imaging Spectro-radiometer (MODIS) over south-eastern Australia. In this method, the SMOS brightness temperature (T_B) is added to the regression model that describes the relationship between soil moisture, MODIS NDVI, and MODIS T_S. The authors argued that the use of T_B in the linking model is necessary to capture soil moisture (*sm*) variability at high resolution. This relationship is expressed as:

$$sm = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=0}^{n} a_{ij}\, NDVI^{i} {T_S}^{j} {T_B}^{k} \qquad (1)$$

where n should be chosen so as to give a reasonable representation of the data.

The linking model between SMOS observations, MODIS derived NDVI & T_S is given by:

$$sm = a_{000} + a_{001}T_{BN} + a_{010}T_N + a_{100}F_r + a_{002}T_{BN}^2 + a_{020}T_N^2 + a_{200}F_r^2 + a_{011}T_NT_{BN} + a_{101}F_rT_{BN} + a_{110}F_rT_N \qquad (2),$$

where T_N is the normalized MODIS surface radiant temperature and F_r is the fractional vegetation cover based on MODIS NDVI and T_{BN} is the normalized SMOS brightness temperatures.

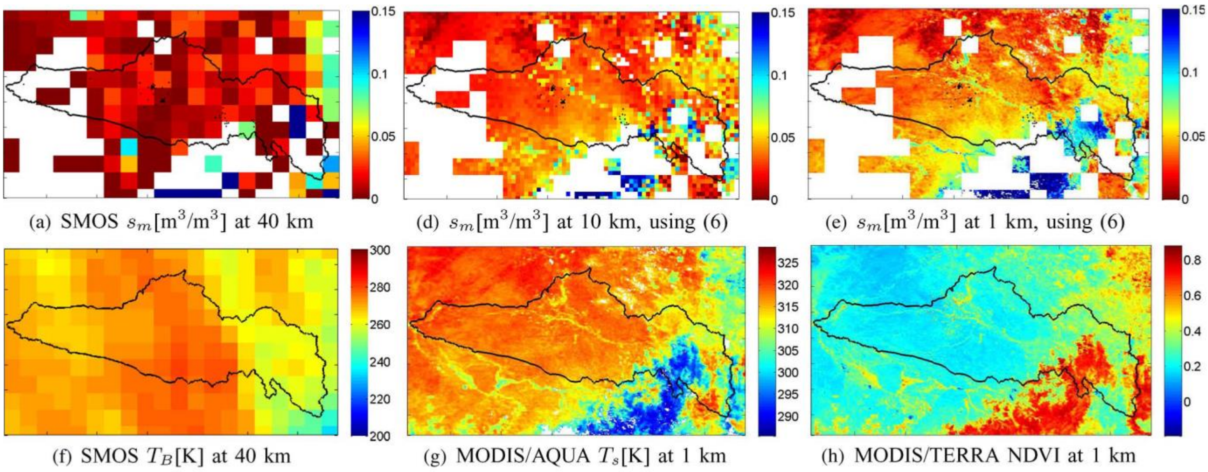

Figure 4. Downscaling results obtained by Piles et al. (2011) by applying the "universe triangle" based algorithm to a SMOS image over the Murrumbidgee catchment in south eastern Australia. (a) SMOS soil moisture [m³/m³] at 40 km resolution grid. Downscaled SMOS soil moisture maps at (d) 10 km, and (e) 1 km. (f) SMOS T_B image [K] at 40 km resolution, (g) 1 km MODIS/AQUA Ts [K] 1 km MODIS/TERRA NDVI. White areas indicate missing values post retrievals. Courtesy: Piles et al. (2011).

The linking model in (2) thus calculates the regression coefficients a_{ijk} at each grid point which are specific of the day and scene being analysed. Piles et al (2011) compared the downscaled soil moisture products with in-situ soil moisture measurements and found that the root mean squared errors remained somewhat similar to the coarser resolution product. Further, the soil moisture sensitivity was preserved for the 10 km downscaled product and moderately decreased for the product at 1 km resolution. Figure 4 shows the results obtained by Piles et al. (2011) on the application of the algorithm to an SMOS image over the Murrumbidgee catchment, gathered on January 19, 2010.

Gillies and Carlson (1995) also used the "universal triangle" concept to estimate regional patterns of surface soil moisture availability from a Soil Vegetation Atmosphere Transfer (SVAT) model using NDVI and T_S. Merlin et al. (2010) explored the relationship between fractional vegetation cover and soil evaporative efficiency over a catchment in South-eastern Australia using MODIS data. Prior to this study, Merlin et al. (2008) had developed a simple method to downscale soil moisture by using two soil moisture indices: evaporative fraction (EF) and the actual EF. A method based on sequential model which used MODIS as well as Advanced Scanning Thermal Emission and Reflection Radiometer (ASTER) data was also proposed for downscaling soil moisture [Merlin et al., 2012a, Merlin et al., 2012b] .

Though the downscaling algorithms that use auxiliary information from optical sensors provide a good high resolution soil moisture estimates, there are several limitations that still exist. The optical sensors are often influenced by cloud cover, limiting the methods using them from being an all-weather algorithm for downscaling. Also, the representative depth of the auxiliary information and the targeted product may differ. For example, Piles et al. (2011) noted that the thermal regime of SMOS (measurement depth ~0–5 cm) soil moisture product and MODIS VIS/IR skin temperature (measurement depth ~0–1 mm) are likely to be quite different. The skin temperature is subject to more rapid fluctuations compared to temperature from a deeper soil profile that most of the remotes sensing and model represent. Thus the use of IR skin temperature in the downscaling algorithm may lead to misrepresentation of spatial and temporal variability of underlying soil temperature with a specific depth. Another limitation of this method is that the acquisition time of the optical and IR auxiliary information doesn't necessarily match to that of targeted soil moisture product, and soil moisture status may change within these two acquisition times depending upon soil type, terrain, vegetation and meteorological conditions. The triangle method also imposes some constraints that could limit the accuracy of the estimated soil moisture. The identification of triangular shape requires a flat surface and a large number of pixels over an area with a wide range of soil wetness and fractional vegetation cover. This means that a perfect triangle can only be achieved by collecting a timely record of data over the region under study, or by selecting a particular scene with a wide range of T_s

and NDVI. Also, the determination of warm edge and the vegetation limits of bare soil and full cover requires some subjectivity (Carlson, 2007).

3.2.2.2. Auxiliary information from microwave only

Wagner et al. (2008), using ENVISAT Advanced Synthetic Aperture Radar (ASAR) backscatter data, found that time-invariant relationships can be used for connecting soil moisture and radar backscatter measurements across different spatial scales. The authors, demonstrated that the backscatter scaling parameter can be expressed as a function of soil moisture properties, vegetation and topography. An important application of the method is that it can be used for downscaling coarse resolution soil moisture data retrieved from active (ASCAT) and passive (SMOS, AMSR-E) instruments. Several studies have also discussed methods that use higher resolution active sensors to downscale coarse resolution passive microwave soil moisture retrievals (Narayan et al., 2006, Narayan et al., 2008, Das et al., 2011). Piles et al. (2009), in preparation for the Soil Moisture Active Passive (SMAP; Entekhabi et al., 2010) mission, conducted an observation system simulation experiment (OSSE) where they mimicked the SMAP radiometer and radar. The OSSE experiment was driven by high-resolution parameters generated from a distributed land surface model. They applied a change detection algorithm to combine the relatively noisy 3 km resolution radar backscatter coefficients and the more accurate 40 km radiometer brightness temperature into an optimal 10-km product (figure 5). They found that the change detection algorithm perform better than the direct inversion of the radiometer brightness temperatures and improve the root mean square error by 2% of volumetric soil moisture content. It is worth noting that the malfunctioning of the radar in SMAP post launch has limited its capability to achieve the goal to retrieve soil moisture information at planned 9 km resolution.

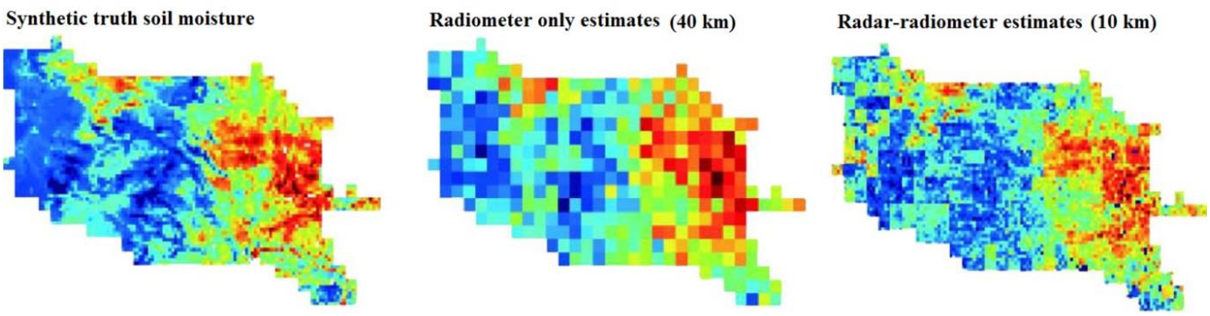

Figure 5. The comparison of synthetic ground-truth soil moisture with lower resolution (40 km) radiometer and the higher resolution (10 km) soil moisture estimates obtained from the active-passive method. The active and passive soil moisture retrievals are synthetically produced from an OSSE. Courtesy: Piles et al. (2009).

One of the most exciting developments in current soil moisture monitoring capability is the European Space Agency's Sentinel satellite mission which is a constellation of two polar-orbiting C-band radar satellites for operational Synthetic Aperture Radar (SAR) applications. The goal is to map the global land mass once every twelve days in Interferometric Wide Swath (IWS) mode. Near Real Time products from Sentinel satellites are available within 3 hours of acquisition. One of the features of Sentinel mission is that the soil moisture can be retrieved at a spatial resolution of about 5 x 20 m^2. This can be of great implication when it comes to soil moisture downscaling, as this high resolution dataset can be used to deduce finer resolution products from coarser remote sensing or land surface modelling products. Such resolution enables local and regional studies, and an improved understanding on soil moisture heterogeneity at these scales. A multiple sensor approach where Sentinel data are combined with the radiometers will allow us to capture the soil moisture spatial variability across the scales (Figure 6; de Jeu, 2015), where the micro-scale variability is captured by the Sentinel satellites and the macro-scale variability by the current breed of radiometers and/or land surface models.

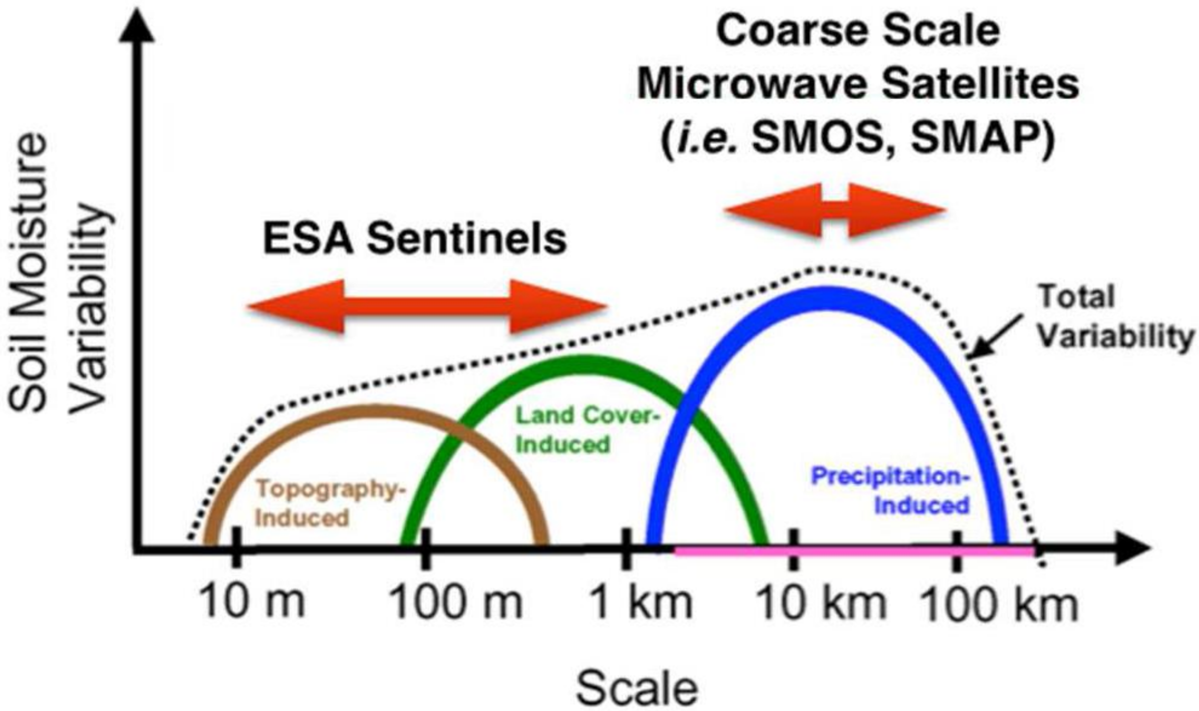

Figure 6. Diagram depicting the scales measured by different sensors and soil moisture spatial variability captured. Courtesy: de Jeu (2015).

The downscaling algorithms based on the synergy between passive (radiometer) and active (radar) microwave observations is arguably the most promising approach currently available. Microwave observations are less attenuated by the atmosphere and can penetrate through clouds, making them all weather capable. Also, microwave observation are becoming increasingly available from satellites at global scale. Another important aspect of the microwave observations are that they are less reliant on ancillary information such as meteorological observations (Wu, 2014). However, regions of densely vegetated areas and high topography can reduce the capability of active microwave signal to sense accurate soil water content. This could result in a lack of estimates in such regions. Further the penetration depth of the microwave products are confined to the upper few centimetres. For some application, this may not be adequate.

Summary & Conclusion

The present review deals with the spatial disaggregation of coarse resolution soil moisture datasets. A lot of applications, like fire danger rating, require soil moisture estimates at high resolution (<= 1km) over large regions. Remote sensing and water balance modelling are the two widely used techniques for estimating soil moisture at such broad spatial scales. However, spatial resolution of the product they offer are not finer enough for several applications. Hence studies explored the use of downscaling techniques to derive soil moisture at finer resolution. The downscaling approach can be broadly subdivided into (i) deterministic and (ii) stochastic. Majority of the soil moisture downscaling work use the stochastic framework, where a statistical method is combined with an auxiliary information to estimate soil moisture at finer scale. This auxiliary information is supposed to have a functional relationship with soil moisture dynamics.

One of the most common and early framework used in this regard is the use of landscape indices, especially terrain indices, to downscale the coarser resolution soil moisture data. Recent advancements in optical remote sensing has allowed researchers to use different remote sensing products, that deem to have an effect on soil moisture variability, as ancillary information. A method based on "universal triangle" concept is used by a number of studies where a relationship between soil moisture and different land surface parameters like NDVI, T_S or surface albedo derived from optical remote sensing sensors are established. Out of the different land surface parameters, NDVI and T_S are the most widely used ones. Theoretical and experimental studies have demonstrated the relationship between soil moisture, NDVI and T_s for a given region under specific climatic conditions and land surface types. Though this method is by large used to downscale microwave remote sensing retrievals of soil moisture, studies have used it effectively to disaggregate model soil moisture as well.

Rapid progress is made in microwave remote sensing to deliver high resolution soil moisture estimates using a combination of active (radar) and passive (radiometer) soil moisture retrievals. The high resolution radar data is used to disaggregate coarse resolution radiometer observations to produce a soil moisture product at resolutions of finer resolution. One of the advantage of the microwave observations are that they are less affected by the clouds. Given the limitations of optical techniques with respect to cloud cover, atmospheric attenuation and vegetation cover, the combined use of microwave sensors has the best potential to produce reliable high resolution global soil moisture products. However, this approach is still in its early developmental phase and the fact that they are theoretically proven to be a very effective approach opens up a wide range of exciting possibilities for development.

Most of the downscaling techniques that use statistical approaches combined with ancillary information are applied to soil moisture estimates from remote sensing. There is a lack of literature on the applicability of such techniques to model soil moisture, especially that from land surface models. Since model soil profiles are much deeper than that from satellites, it raise an interesting question on whether these techniques can be applied to downscale deep model soil moisture estimates. Despite the considerable progress made in soil moisture downscaling over the years, it is hence reasonable to assume that a clear guidance to which methods are most promising for a given application doesn't exist still. Grayson and Western (1998) suggested that concepts of time stability can be used to identify certain parts of the landscape which consistently exhibit mean behaviour irrespective of the overall wetness. Blöschl et al. (2009) proposed that a combination of the index approach and the time stability assumption based on the spatial statistics seems to be a useful strategy for soil moisture downscaling. However, a detailed evaluation on the validity of these techniques on either model or remote sensing soil moisture is absent in the literature. Even a detailed evaluation and comparison of different downscaling approaches applied to satellite based soil moisture products are lacking. One of the reason for this could be that, many of these works in optical, IR and microwave remote sensing are fairly recent. Future studies should evaluate the potential of some of these algorithms to downscale soil moisture from land surface models and remote sensing platforms.

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