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Downscaling soil moisture over regions that include multiple coarse-resolution grid cells

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ABSTRACT

Many applications require soil moisture estimates over large spatial extents (30–300 km) and at fine-resolutions (10–30 m). Remote-sensing methods can provide soil moisture estimates over very large spatial extents (continental to global) at coarse resolutions (10–40 km), but their output must be downscaled to reach fine resolutions. When large spatial extents are considered, the downscaling procedure must consider multiple coarse-resolution grid cells, yet little attention has been given to the treatment of multiple grid cells. The objective of this paper is to compare the performance of different methods for addressing multiple coarse grid cells. To accomplish this goal, the Equilibrium Moisture from Topography, Vegetation, and Soil (EMT + VS) downscaling model is generalized to accept multiple coarse grid cells, and two methods for their treatment are implemented and compared. The first method (fixed window) is a direct extension of the original EMT + VS model and downscales each coarse grid cell independently. The second method (shifting window) replaces the coarse grid cell values with values that are calculated from windows that are centered on each fine grid cell. The window values are weighted averages of the coarse grid values within the window extent, and three weighting methods are considered (box, disk, and Gaussian). The methods are applied to three small catchments with detailed soil moisture observations and one large region. The fixed window typically provides more accurate estimates of soil moisture than the shifting window, but it produces abrupt changes in soil moisture at the coarse grid boundaries, which may be problematic for some applications. The three weighting methods produce similar results.

1. Introduction

Numerous applications can benefit from knowledge of volumetric water content (soil moisture) at fine resolutions (10–30 m) over large spatial extents (30–300 km). For example, land-atmosphere models [Delworth and Manabe, 1989; Entekhabi et al., 1996; Ferranti and Viterbo, 2006], precipitation forecasting models [Koster and Suarez, 2003; Seuffert et al., 2002], regional and global climate models [Dirmeyer, 1999; Mahfouf et al., 1987; Seuffert et al., 2002], and hydrologic models at all scales [Houser et al., 1998; Lakshmi, 1998; Wood, 1997] would benefit from reliable soil moisture information. Similarly, soil moisture is important for flood forecasting [Beck et al., 2009; Dunne and Black, 1970], drought monitoring and wildfire prediction [Bartsch et al., 2009; Bolten et al., 2010], crop growth and forest regrowth after wildfires [de Wit and van Diepen, 2007; Kasischke et al., 2007], and malaria outbreak modeling [Montosi et al., 2012]. Soil moisture is an important variable in soil mechanical stability [Horn and Fleige, 2003], which is relevant in trafficability [Flores et al., 2014] and vehicle impact assessment and land rehabilitation [Shoop et al., 2005; Vero et al., 2014].

Satellite remote sensing can provide soil moisture estimates with the spatial extents necessary for such applications, but the spatial resolutions of these estimates are much too coarse. Several passive radiometers have been used to obtain global soil moisture at coarse resolutions. For example, the Advanced Microwave Scanning Radiometer (AMSR-E) uses dual polarized size frequencies in the range of 6.9–89 GHz to estimate soil moisture at resolutions of 5–60 km, where the coarser resolutions have smaller errors than the finer resolutions [Njoku et al., 2003]. Li et al. [2010] describes a physically-based land algorithm that simultaneously acquires global soil moisture, vegetation water content, and land surface temperature using WindSat dual polarized data at 10, 18.7, and 37 GHz, resulting in 10–40 km resolution soil moisture estimates. The Soil Moisture Ocean Salinity Mission (SMOS) uses an L-band (1.4 GHz) synthetic aperture radiometer to estimate soil moisture and ocean salinity at a 40 km resolution [Kerr et al., 2012; Kerr et al., 2010]. Active microwave sensing has also been used to estimate soil moisture. In particular, the Advanced Scatterometer (ASCAT) produces

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backscatter measurements from transmitted linear frequency-modulated pulses (C-band) to estimate global soil moisture at a 25 km resolution [Bartalis et al., 2007]. The Soil Moisture Active and Passive (SMAP) mission combines active and passive microwave sensing to obtain 9 km resolution global soil moisture, but currently only the passive radiometer is operational [Das et al., 2011; Entekhabi et al., 2010].

One general approach for downscaling soil moisture to appropriate resolutions is to use optical/thermal data. Such methods typically downscale to about a 1 km resolution because the most frequently collected optical/thermal data are available at this resolution. For example, Chauhan et al. [2003] downscaled soil moisture from 25 km to 1 km using an approach based on the Triangle Method. Merlin et al. [2005] downscaled 40 km SMOS data to a 1 km resolution using visible, near-infrared, and thermal infrared remote sensing data. Merlin et al. [2006] added the use of a land surface model and tested this approach. Disaggregation Based on Physical and Theoretical Scale Change (DisPATCh) was also used to downscale SMOS data to 3 km and 100 m resolutions using Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Spaceborne thermal Emission and Reflection radiometer (ASTER), and Landsat 7 data [Merlin et al., 2013]. Fang and Lakshmi [2014] disaggregated SMOS and AMSR-E data to a 1 km resolution and compared the results to in situ observations. Using similar data in an empirical algorithm, Song et al. [2014] downscaled 25 km AMSR-E data to 1 km using optical/thermal data, and it was more effective for soil moisture values <0.3 m^3/m^3.

Another group of downscaling methods focus on reproducing the statistical properties of fine scale soil moisture rather than providing accurate estimates at every location. For example, Crow et al. [2000] used a statistical approach to downscale spaceborne imaging radar (SIR-C) L-band data. They studied how patterns with 800–6400 m grid cells relate to finer (100–800 m) patterns. Kim and Barros [2002] used a modified fractal interpolation method based on contraction mapping to downscale soil moisture from 10 km to 825 m. Mascaro et al. [2011] applied a multifractal downscaling model to obtain soil moisture at the aircraft footprint scale of 800 m from a satellite footprint scale of 25.6 km.

Other statistical methods have been used to estimate soil moisture at fine resolutions. Perry and Niemann [2007] applied an Empirical Orthogonal Function (EOF) approach to the Tarrawarra catchment (downscaling from a catchment-wide average to a 20 m by 10 m resolution). However, this method requires local soil moisture measurements to derive the EOFs. In a similar manner, Kaheil et al. [2008] downscaled soil moisture based on local measurements. The Southern Great Plains (SGP 97) dataset (from airborne imagery) was downscaled from a coarse resolution of 800 m to a fine resolution of 50 m.

Other downscaling methods use topographic data, which is known to affect soil moisture variations at particularly fine resolutions [Famiglietti et al., 1998; Gomez-Plaza et al., 2001; Western et al., 1999]. Wilson et al. [2005] downscaled soil moisture in five catchments to 10–40 m resolutions using empirical relationships with topographic attributes. Busch et al. [2012] extended the EOF method of Perry and Niemann [2007] by estimating the soil moisture EOFs from topographic data, and Coleman and Niemann [2013] used a conceptual water balance called the Equilibrium Moisture from Topography (EMT) model to downscale a catchment-wide average soil moisture to 10–40 m patterns at three catchments. In some cases, topographic downscaling methods also use other types of data. Pellenq et al. [2003] presented a model to downscale soil moisture to a 100 m resolution at the Nerrigundah catchment using both topographic and soil depth information. Temimi et al. [2010] used an index that combines topographic attributes and the leaf area index (LAI) to estimate soil moisture at a 90 m resolution. Ranney et al. [2015] generalized the Coleman and Niemann [2013] model to accept fine scale soil and vegetation data and called it the Equilibrium Moisture from Topography, Vegetation, and Soil (EMT + VS) model. Using this approach, vegetation data were found to provide more value for downscaling than soil data, particularly if the soil data are sparse or uncertain.

When any of these downscaling methods are used over large spatial extents, they must inevitably accept and downscale multiple coarse-resolution grid cells (i.e. a coarse grid of soil moisture values rather than a single average soil moisture value). Some studies have not encountered this issue because they have focused on downscaling within an area that falls within a single coarse grid cell [Busch et al., 2012; Coleman and Niemann, 2013; Pellenq et al., 2003; Perry and Niemann, 2007; Ranney et al., 2015; Wilson et al., 2005]. Other studies have downscaled multiple coarse grid values but have not considered this issue in depth. Some of these algorithms downscale each coarse grid cell independently from the adjacent coarse grids [Fang and Lakshmi, 2014; Merlin et al., 2013; Merlin et al., 2012], but the resulting soil moisture maps show unnatural discontinuities in the soil moisture values at the coarse grid boundaries. Such discontinuities might be problematic for applications like routing vehicles across the landscape [Flores et al., 2014]. Song et al. [2014] downscaled in a way that uses information from neighboring coarse grid values and avoids such discontinuities. Only a few studies have directly discussed the treatment of multiple coarse grid cells [Kaheil et al., 2008; Kim and Barros, 2002; Sahoo et al., 2013]. Kim and Barros [2002] used a sliding window to statistically downscale soil moisture and avoid the discontinuities at the boundaries. Kaheil et al. [2008] applied a spatial pattern search where pixels are sorted and interpolated to overcome the issue. Sahoo et al. [2013] used a localization radius (distance from fine grid cell being downscaled), which is a function of the spatial correlation of the errors, to determine which coarse grids affect each particular fine grid pixel. Malbeteau et al. [2016] and Merlin et al. [2012, 2013] took advantage of the overlapping grid cells of SMOS data by downscaling each grid cell indepedently and then averaging the fine resolution results. However, no studies have examined the treatment of multiple grid cells for topographically-based downscaling methods or considered how their treatment affects the downscaling performance.

The objective of this paper is to develop and test approaches for accepting multiple coarse grid cells when downscaling soil moisture. In particular, the EMT + VS model is generalized to accept multiple coarse grid cells, and approaches for treating the coarse grids are implemented and compared. The EMT + VS model is selected because it is a flexible topographically-based downscaling method. This flexibility allows it to reproduce both valley-dependent and hillslope-dependent soil moisture patterns, and it can reproduce temporally unstable soil moisture patterns [Coleman and Niemann, 2013]. It has also been shown to outperform a statistical downscaling method when calibration data are limited [Werbylo and Niemann, 2014]. The methods for accepting multiple coarse grid cells are evaluated by application to three small catchments (Tarrawarra, Cache la Poudre, and Nerrigundah) and one large region (Eastern Victoria).

2. Methodology

2.1. EMT + VS model overview

This sub-section briefly summarizes the pre-existing EMT + VS model. More details can be found in Coleman and Niemann [2013] and Ranney et al. [2015]. The EMT + VS model downscales soil moisture using a water balance of the hydrologically active soil layer. That layer begins at the ground surface and ends at the depth where the hydraulic conductivity begins to decrease significantly due to a lower permeability soil layer or bedrock. The hydrologically active layer has ranged from 5 cm and 30 cm depth in past model applications [Ranney et al., 2015]. Over this range of depths, soil moisture is assumed to be uniform.

Four processes are represented in the water balance: infiltration, deep drainage (or groundwater recharge), lateral flow, and evapotranspiration (ET). Each process is written as a function of topographic, vegetation, and soil characteristics. Infiltration uses the fractional vegetation cover to account for interception losses. Deep drainage is described using Darcy's Law with a percolation assumption. Lateral flow is