Advances in Water Resources 76 (2015) 81–96

Contents lists available at ScienceDirect

Advances in Water Resources

journal homepage: www.elsevier.com/locate/advwatres

A method to downscale soil moisture to fine resolutions using topographic, vegetation, and soil data

Kayla J. Ranney [a], Jeffrey D. Niemann [a,*], Brandon M. Lehman [a], Timothy R. Green [b], Andrew S. Jones [c]

[a] Department of Civil and Environmental Engineering, Colorado State University, Campus Delivery 1372, Fort Collins, CO 80523, USA
[b] USDA Agricultural Research Service, Fort Collins, CO 80526, USA
[c] Cooperative Institute for Research in the Atmosphere, Colorado State University, Fort Collins, CO 80523, USA

ARTICLE INFO

Article history:
Received 26 August 2014
Received in revised form 16 November 2014
Accepted 9 December 2014
Available online 19 December 2014

Keywords:
Catchment
Canopy
Litter
Soil texture
EMT
EOF

ABSTRACT

Soil moisture can be estimated over large regions with spatial resolutions greater than 500 m, but many applications require finer resolutions (10–100 m). Several methods use topographic data to downscale, but vegetation and soil patterns can also be important. In this paper, a downscaling model that uses fine-resolution topographic, vegetation, and soil data is presented. The method is tested at the Cache la Poudre catchment where detailed vegetation and soil data were collected. Additional testing is performed at the Tarrawarra and Nerrigundah catchments where limited soil data are available. Downscaled soil moisture patterns at Cache la Poudre improve when vegetation and soil data are used, and model performance is similar to an EOF method. Using interpolated soil data at Tarrawarra and Nerrigundah decreases model performance and results in worse performance than an EOF method, suggesting that soil data needs greater spatial detail and accuracy to be useful for downscaling.

1. Introduction

Estimated soil moisture patterns are becoming more readily available at coarse to intermediate resolutions. For example, the Advanced Microwave Scanning Radiometer (AMSR-E), Soil Moisture and Ocean Salinity (SMOS), WindSat, and Soil Moisture Active Passive (SMAP) satellites can provide soil moisture estimates at 10–60 km spatial resolutions [14,26,29,37] . Optical and thermal remote-sensing data from MODerate resolution Imaging Spectroradiometer (MODIS) can be used to downscale these estimates to an intermediate resolution (1 km) [16,34]. Optical and thermal remote-sensing can also be used to estimate intermediate-resolution soil moisture (500 m) using algorithms such as the Surface Energy Balance Algorithm for Land (SEBAL) [3,44]. Finally, intermediate-resolution (approximately 700 m) soil moisture can be obtained from the ground-based Cosmic-ray Soil Moisture Observing System (COSMOS) [59].

Many applications such as water management, agricultural production, and trafficability require finer resolutions (10–100 m), so methods are needed to downscale soil moisture estimates. To estimate fine-scale variations in soil moisture, supplemental high-resolution data are needed that are strongly associated with these variations. Topographic data are available at the appropriate resolutions and can be an important control on soil moisture. For example, Burt and Butcher [5] compared soil moisture values with several topographic indices and found that a combined index that includes plan curvature and the ratio of upslope area and slope is best correlated with soil moisture. Brocca et al. [4] observed that soil moisture is related to slope, elevation, specific contributing area, and distance from the nearest channel. Similar to Burt and Butcher [5], the strongest correlations occurred during wet conditions [4]. Grayson et al. [20] and Western et al. [53] found that the dependence of soil moisture on topography can vary through time (temporal instability). For the Tarrawarra catchment in Australia, lateral water movement controls the soil moisture patterns during wet conditions and specific contributing area is most closely associated with the soil moisture patterns. During dry periods, vertical fluxes control soil moisture and the potential solar radiation index (PSRI) becomes closely associated with the soil moisture patterns.

Several models have been developed to downscale soil moisture based on topographic data. Wilson et al. [56] developed a model to generate soil moisture patterns using empirical relationships with topographic attributes that depend on the spatial-average soil moisture. Their model can reproduce temporal instability and performs well for the locations where it was developed, but the empirical relationships are not expected to be widely applicable. Busch et al. [6] developed an empirical downscaling method based on

* Corresponding author. Tel.: +1 970 491 3517; fax: +1 970 491 7727.
E-mail address: jniemann@engr.colostate.edu (J.D. Niemann).

http://dx.doi.org/10.1016/j.advwatres.2014.12.003
0309-1708/

Empirical Orthogonal Function (EOF) analysis. This method can also reproduce temporal instability and performs well at the catchments where it was developed, but it cannot be applied to regions that are dissimilar to where it was developed [6]. Coleman and Niemann [10] proposed the Equilibrium Moisture from Topography (EMT) model, which also downscales soil moisture based on topographic indices. In this model, the relationships with the topographic indices are determined from conceptual descriptions of the vadose zone processes. This model can also reproduce temporal instability, and it outperforms the EOF method when few soil moisture observations are available for calibration [51]. Although the EMT model includes vegetation and soil parameters, it does not consider fine-resolution variations of these properties if they occur.

Studies have demonstrated that fine-scale vegetation patterns can also affect soil moisture patterns. For example, Pariente [38] studied soil moisture under and between shrubs and found downslope and radial soil moisture gradients around the shrubs. During precipitation events, the soil was wetter between shrubs than under shrubs due to interception. During drying periods, the soil was wetter under shrubs than between shrubs in part because the canopy shaded the surface and decreased soil evapotranspiration (ET) [38]. Lin [31] also found greater soil moisture and less soil evaporation for medium and highly shaded areas than for weakly shaded areas. Root-water uptake can also affect soil moisture patterns, as soil with more roots tends to dry faster [50]. Root compensation (higher root water uptake from wetter soil regions) and hydraulic redistribution (root water flux from wetter to drier soil regions) can reduce spatial variations in soil moisture at the plant scale [21]. Temporal instability in soil moisture patterns can be introduced by vegetation cover [25] and seasonal variations in the demand for soil water by plants [19]. Naithani et al. [35] found that soil moisture and vegetation patterns are similar from leaf-onset to maturity but different from leaf maturity to senescence. Overall, soil moisture patterns have been found to be inversely related to patterns of leaf area index (LAI) [22], and vegetation has been shown to be important particularly under dry conditions [2,33].

Spatial patterns of soil moisture also depend upon variations in soil properties including porosity [15], hydraulic conductivity [15,32], soil texture [45,57], and soil depth [15,45,47]. The influence of soil properties may be greater during wet conditions [2] and more important relative to topography when the topography is flatter [58]. Famiglietti et al. [15] examined the influence of both soil properties and topographic attributes on soil moisture through correlation analyses. For wet conditions, porosity and hydraulic conductivity controlled soil moisture patterns, but for dry conditions, topography was more important and relative elevation, cosine of aspect, and clay content influenced soil moisture patterns. In a regression analysis, Takagi and Lin [45] also showed that soil moisture variability was explained best by slope, curvature, wetness index, depth to bedrock, percentage clay, and percentage of rock fragments. Finally, Tromp-van Meerveld and McDonnell [47] observed that differences in soil depth caused variations in soil moisture content.

The objective of this paper is to generalize the EMT model to accept fine-resolution vegetation and soil information if available. It is hypothesized that including spatial variations in vegetation and soil characteristics will improve the model's ability to downscale soil moisture patterns. The generalization is called the Equilibrium Moisture from Topography, Vegetation, and Soil (EMT + VS) model. The model's representation of vegetation is improved by introducing its primary roles in interception, transpiration, and soil evaporation. In addition, the structure of the model is revised to allow both vegetation and soil properties to vary at the fine resolution. To test the model, vegetation and soil data were collected at the Cache la Poudre catchment in Colorado where detailed soil moisture and topographic data were already available. This catchment has substantial variations in vegetation cover including forested, shrubland, and bare soil areas. The model is also tested at two catchments in Australia (Tarrawarra and Nerrigundah) where detailed soil moisture and topographic data are available along with limited soil data. These catchments have soil property data that are not available at Cache la Poudre, and while they do not have vegetation data, the vegetation at both catchments is relatively homogeneous. In addition, the feasibility of using interpolated soil data can be evaluated.

2. Methodology

2.1. EMT + VS model development

The EMT + VS model (like the EMT model) focuses on simulating the hydrologically active layer, which is defined as the depth of soil through which most lateral flow occurs. This layer is considered as beginning at the ground surface and ending at a depth where the hydraulic conductivity decreases substantially due to the occurrence of bedrock or a lower permeability soil layer. Specifically, the model is based on the water balance for the active layer in the land area that is upslope from an edge of a grid cell in a digital elevation model (DEM). Soil moisture is assumed to be uniform with depth in the layer, and infiltration is assumed to be balanced by deep drainage (groundwater recharge), lateral flow, and ET. This equilibrium assumption disallows hysteresis in the estimated soil moisture patterns [10]. The water balance can be written as:

$$\int_A F dA = \int_A G dA + L + \int_A E dA \tag{1}$$

where A is the area that is upslope from the edge of the DEM cell, F is the infiltration rate, G is the deep drainage, and E is the ET for the fine-resolution grid cells included in the upslope area. L is the lateral outflow through the edge of the DEM cell, which is the only location where lateral flow exits the control volume.

Infiltration F is assumed to be spatially constant in the EMT model. However, interception is known to decrease infiltration [28], so infiltration in the EMT + VS model is represented as:

$$F = F_{\max}(1 - \lambda V) \tag{2}$$

where $F_{\max}$ is the maximum infiltration rate, V is the fractional vegetation cover at the location, and λ $(0 \leqslant \lambda \leqslant 1)$ is a temporally-constant interception efficiency, a parameter that aims to account for factors that influence interception, such as the foliage holding capacity, which depends on vegetation type. Similar interception models have been used previously. For example, the Gridded Surface Subsurface Hydrologic Analysis (GSSHA) model diverts a constant fraction of the rainfall to interception after an initial loss is met [12,13]. The Variable Infiltration Capacity (VIC) model determines interception using a constant multiplied by the LAI [30], which is similar to Eq. (2).

Deep drainage G in the EMT + VS model is the same as the EMT model. Specifically, it is assumed to occur by gravity drainage with no capillary gradient, so G is equal to the unsaturated vertical hydraulic conductivity, which is determined from the Campbell [7] equation. Thus,

$$G = K_{s,v}\left(\frac{\theta}{\phi}\right)^{\gamma_v} \tag{3}$$

where $K_{s,v}$ is the saturated vertical hydraulic conductivity, θ is the volumetric soil moisture in the hydrologically active layer, ϕ is the porosity, and γ_v is the vertical pore disconnectedness index [7].