THESIS

EVALUATION OF THE PORTABILITY OF AN EOF-BASED METHOD TO DOWNSCALE SOIL MOISTURE PATTERNS BASED ON TOPOGRAPHICAL ATTRIBUTES

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ABSTRACT

EVALUATION OF THE PORTABILITY OF AN EOF-BASED METHOD TO DOWNSCALE SOIL MOISTURE PATTERNS BASED ON TOPOGRAPHICAL ATTRIBUTES

Soil moisture influences many hydrologic applications including agriculture, land management, and flood prediction. Most remote-sensing methods that estimate soil moisture produce coarse-resolution patterns, so methods are required to downscale such patterns to the resolutions required by these applications (e.g., 10-30 m grid cells). At such resolutions, topography is known to impact soil moisture patterns. Although methods have been proposed to downscale soil moisture based on topography, they usually require the availability of past high-resolution soil moisture patterns from the application region. The objective of this paper is to determine whether a single topographic-based downscaling method can be used at multiple locations without relying on detailed local observations. The evaluated downscaling method is developed based on empirical orthogonal function (EOF) analysis of space-time soil moisture data at a

reference catchment. The most important EOFs are then estimated from topographic attributes and the associated expansion coefficients (ECs) are estimated based on the spatial-average soil moisture. To test the portability of this EOF-based method, it is developed separately using four datasets (Tarrawarra, Tarrawarra2, Cache la Poudre, and Satellite Station), and the relationships that are derived from these datasets to estimate the EOFs and ECs are compared. In addition, each of these downscaling methods is applied not only for the catchment where it was developed but also to the other three catchments. The results suggest that the EOF downscaling method performs well for the location where it is developed, but its performance degrades when applied to other catchments.

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KEYWORDS:

EMPIRICAL ORTHOGONAL FUNCTION, FINE SCALE, SPATIAL VARIATION, REGRESSION, DISAGGREGATION

INTRODUCTION

Soil moisture has been shown to affect many hydrologic applications. At large scales, seasonal rainfall and other climatic variables are influenced by soil moisture patterns (Timbal et al., 2002). At smaller scales, soil moisture variations also influence hydrologic processes such as infiltration, evapotranspiration, groundwater recharge, and runoff generation (Western et al., 2001; Jacobs et al., 2003). Catchment-scale soil moisture variations can be highly associated with crop yield variations, especially in dry land farming applications (Jaynes et al., 2003; Kaspar et al., 2003; Green and Erskine, 2004), and wet antecedent soil moisture conditions have been linked to flooding and erosion (Kitanidis and Bras, 1980; Zaslavsky and Sinai, 1981; Moore et al., 1988).

Unfortunately, accurate estimation of soil moisture patterns with relatively fine spatial resolutions (e.g., grid cells with 10 to 30 m linear dimensions) is not easily achieved. The Soil Moisture and Ocean Salinity (SMOS) Mission uses a satellite equipped with a microwave radiometer to acquire information on soil moisture conditions (Wigneron et al., 2000), and Friesen et al. (2008) used the SMOS satellite to estimate patterns of soil moisture. They found that the soil moisture patterns become more homogeneous under dry and extremely wet conditions, which is also when their estimation method performs the best. However, the grid resolution ranges from 25 to 50 km, making this approach inappropriate for characterizing soil moisture within small catchments. Similarly, Njoku et al. (2003) showed that the Advanced Microwave Scanning Radiometer (AMSR-E) on the Earth Observing System Aqua satellite, which uses a low frequency microwave radiometer, provides adequate measurements of soil moisture. However, these estimates are at a 60 km resolution, which again is much too coarse to be directly used for catchment-scale hydrologic applications. Alternatively, methods have been proposed to estimate root-zone soil moisture using the visible and thermal bands of the spectrum (Scott et al., 2003). These bands are used to infer the land-surface energy balance, and then soil moisture is estimated empirically from the fraction of the available energy that is used for latent heat flux. This approach can produce soil moisture patterns at the resolution of the thermal band, which is typically between 60 m and 1 km depending on the satellite that is used. Although such resolutions are much finer, they are still coarser than the 10 to 30 m resolutions that are required for some applications.

Many methods have been proposed to downscale soil moisture patterns to finer resolutions (Pellenq et al., 2003; Kaheil et al., 2008; Mascaro et al., 2010). Crow et al. (2000) proposed a method for downscaling spaceborne radar data that resulted in patterns at resolutions ranging from 100 to 6400 m. This method was based on soil dielectric values obtained from radar imagery from which two separate volumetric soil moisture images were created, but these values can be highly affected by vegetative canopies. A soil map with a 1 km resolution provided soil texture information, and a combination of the soil moisture images and soil texture information allowed for the estimation of soil moisture patterns. Kim and Barros (2002) proposed a method which uses soil, vegetation, and terrain data to downscale soil moisture patterns from 10 km to 825 m resolutions. Merlin et al. (2006) proposed a disaggregation method using soil temperature, which is affected by soil texture, atmospheric forcing, and vegetation, to downscale the microwave pixel obtained from a satellite to a 1 km resolution. Because all of these methods begin with microwave-based estimates of soil moisture, they still produce soil moisture patterns that have relatively coarse resolutions.

Downscaling methods have also been used to estimate finer-scale (i.e. 10 to 30 m resolution) soil moisture patterns. Many of these methods use fine-scale topographic data as their supplementary information because topographic attributes are known to influence soil moisture patterns at these scales (Famiglietti et al., 1998; Western et al., 1999; Erskine et al., 2007; Korres et al., 2010). Although it was not explicitly described as a downscaling method, Wilson et al. (2005) proposed a method to generate soil moisture patterns with 10 to 40 m resolutions from a given spatial-average soil moisture. In this method, a high-resolution soil moisture dataset from other dates was used to determine relationships between soil moisture and topographic attributes as well as the patterns of residuals. The maps of the topographic attributes and residuals were then weighted based on the spatial-average soil moisture to produce high resolution soil moisture patterns on any given date. Similarly, Perry and Niemann (2007) developed a method based on empirical orthogonal function (EOF) analysis to estimate soil moisture patterns based on the average soil moisture for a catchment. EOF analysis was used to decompose the available high-resolution soil moisture dataset from multiple dates into time-invariant EOFs (which are spatial patterns of covariation), spatially-invariant expansion coefficients or ECs (which are time series that describe the importance of each EOF on each date), and the spatial-average soil moisture for each date. The most important ECs were found to be related to the spatial-average soil moisture. Thus, to downscale by this method, the spatial-average soil moisture is used to estimate the ECs. Then, the spatial average, the estimated ECs, and the EOFs (which are time-invariant) are combined to produce the downscaled soil moisture pattern. They found that this method outperforms other available methods. For the Tarrawarra catchment where it was evaluated, it reproduces on average 36% of the observed variation in soil moisture and as much as 75% on one date using a 10 by 20 m resolution. However, this method requires a high-resolution soil moisture dataset to have been collected in the past in order to determine the EOFs. Temimi et al. (2010) developed a method incorporating coarse resolution passive microwave sensors, high resolution terrain-based topographical wetness indices, and vegetation Leaf Area Index maps to produce high resolution soil moisture maps. The passive microwave sensors capture the temporal variation of soil moisture within the watershed. The topographical wetness indices provide the desired high spatial resolution, and the leaf area index maps provide information on the impact of vegetation on the spatial distribution of soil moisture. A combination of these parts through a disaggregation method allows for the development of soil moisture maps at a high spatial resolution.

The objective of this paper is to propose and test an EOF-based method to downscale soil moisture using high-resolution topographic data but without requiring previously-collected high-resolution soil moisture data from the application region. In the previously described EOF downscaling method, the high-resolution soil moisture dataset is required to determine the EOFs. However, in a paper on soil moisture interpolation, Perry and Niemann (2008) also found that the EOFs are strongly related to topographic attributes at the Tarrawarra catchment. If these relationships are not highly site-specific, one can potentially downscale soil moisture for any region by estimating the EOFs based on the topographic attributes from a digital elevation model (DEM), estimating the ECs from the spatial-average soil moisture, and combining this information to produce a high-resolution soil moisture pattern. In order to test this possibility, the EOF-based downscaling method is constructed separately at four catchments with available high-resolution soil moisture data: the Tarrawarra catchment (Western and Grayson, 1998), the Tarrawarra2 catchment (Wilson et al., 2005), the Cache la Poudre catchment (Coleman and Niemann, 2011), and the Satellite Station catchment (Wilson et al., 2003). At each catchment, the relationships between the EOFs and the topographic attributes as well as the ECs and the spatial-average soil moisture are characterized and compared. Then, the method from each catchment is applied to the other catchments in order to determine the implications of the differences in the observed relationships on the portability of the method.

The outline of the paper is as follows. The "Method" section describes the proposed downscaling method and key components in detail. The "Application Sites" section provides a brief description of the four catchments and associated datasets, and the "Results and Discussion" section evaluates the differences in the methods and their performance when applied to each of the catchments. Finally, the "Conclusions" section summarizes the main conclusions from the analysis.

METHODS

In order to develop the EOF-based downscaling method at a particular catchment, the following tasks must be completed using an available dataset for soil moisture on multiple dates and a DEM. This spatial resolution of these datasets ultimately determines the resolution to which the soil moisture pattern will be downscaled. First, an EOF decomposition is performed on the soil moisture dataset to identify the patterns of covariation (the EOFs) and their importance on each date (the ECs). Second, statistical tests are used to determine the EOF/EC pairs that are statistically significant and should be retained in the downscaling method. Third, a multiple linear regression is performed to identify empirical relationships between various topographic attributes that are calculated from the DEM and the retained EOFs. Fourth, the method of least squares is used to determine piecewise-linear relationships to estimate the retained ECs from the spatial-average soil moisture. The rest of this section describes these steps in detail.

The EOF decomposition of the reference soil moisture dataset is the foundation of the downscaling method. A detailed mathematical explanation of this process was given by Perry and Niemann (2008) and Korres et al. (2010), so only a summary of this process is provided here. A more general description of EOF analysis is given by Cooley and Lohnes (1971) and Dunteman (1989). Using the space-time soil moisture dataset, the spatial anomalies are computed by subtracting the spatial average from the individual soil moisture values on each date. Next, the covariance matrix is computed from the anomalies, and an eigenanalysis is used to produce two matrices. The first is a matrix whose columns contain the eigenvectors, and the second is a diagonal matrix whose components are the eigenvalues. The first eigenvector is a unit vector in the direction of maximum covariation, the second is perpendicular to the first and lies in the direction of the maximum residual covariation, etc. The eigenvectors are the ECs, which can be viewed as time series because they have a value associated with each date in the original dataset. The amount of covariation explained by each of the eigenvectors is represented by the associated eigenvalue. The product of the eigenvectors and the spatial anomalies produces new spatial patterns, which are the EOFs. There is an EOF associated with each EC. If the dataset contains observations on *n* dates, then *n* EOF/EC pairs will be produced. If the spatial averages, the EOFs, and the ECs are properly combined, they completely reconstruct the original soil moisture dataset.

Once the EOFs and ECs have been computed, the number of EOF/EC pairs that should be retained in the estimation method must be determined. Normally, the EOFs are sorted according to the amount of the variation in the dataset that they explain, so the first EOF explains the most variation and so forth. The higher order EOFs are less likely to represent meaningful patterns of covariation and are often associated with random variations and measurement errors (Peres-Neto et al., 2005). Such EOFs need to be removed from the estimation method because they will produce random variations in the estimated soil moisture patterns and thus increase the estimation errors. Numerous tests are available to determine whether the patterns of covariation are statistically significant, but these tests rely on different assumptions so they can produce rather different results

(Peres-Neto et al., 2005). Here, we used the same two methods implemented by Perry and Niemann (2008). The first method was proposed by Bartlett (1950). It evaluates the hypothesis that the eigenvalues of the last (n-d) EOFs are all equal (where n is the number of dates and d is ultimately the number of significant EOFs) by utilizing a χ_{crit}^2 statistic with $(1/2)(n-d-1)(n-d+2)$ degrees of freedom (Jackson, 2003). To calculate the χ_{crit}^2 values, the number of independent observations within the dataset must be known. To account for spatial correlation, a variogram analysis was performed using the soil moisture data to identify a correlation distance. The number of points in the dataset that are separated by this distance or larger is the number of independent observations. A 95% confidence level was utilized, and the statistically significant EOFs to be retained have χ_{crit}^2 values that are greater than the tabulated χ^2 variate. The second test is based on Gaussian confidence limits for the eigenvalues and was proposed by Johnson and Wichern (2002). For this test, the statistically significant EOFs have confidence limits that do not overlap with those of the next higher order eigenvalue. These Gaussian confidence limits are based on a 95% confidence level and the number of independent observations within the dataset. The Joshnson and Wichern (2002) test tends to be overly-restrictive in its estimate of the number of significant EOFs, while the Bartlett (1950) test tends to be inaccurate with larger sample sizes (Perry and Niemann, 2007). Thus, after each test is evaluated, the results are averaged to determine the final number of EOFs to be retained.

With the number of retained EOFs known, the empirical relationships between the EOFs and the topographical attributes can be determined. To accomplish this, several attributes were calculated using Terrain Analysis Using Digital Elevation Models

(TauDEM) (Tarboton et al., 2009). The attributes obtained from TauDEM are the slope, aspect, and specific contributing area (SCA). For these calculations, the d-infinity method was used to determine flow directions on the topography (Tarboton et al., 2009). With this information, other attributes were calculated including the cosine of aspect (cosAspect), the natural log of SCA (lnSCA), the wetness index which is the natural log of SCA divided by the slope (Beven and Kirkby, 1979), and potential solar radiation index (PSRI). The PSRI value represents the ratio of the potential insolation received by a point with a given slope and aspect to that of a horizontal surface at the same location (Moore et al., 1993a). Because PSRI changes with the day of year, it was calculated for the winter solstice at each catchment. Curvatures were also calculated including the profile curvature (kProfile) which is the curvature of the surface relative to a vertical plane oriented in the gradient direction, the plan curvature (kPlan) which is the curvature surface relative to a horizontal plane, the Laplace curvature (kLaplace) which is the sum of the second derivatives in the x and y directions, and the tangent curvature (kTangent) which is measured relative to a vertical plane oriented perpendicular to the gradient (Mitášová and Hofierka, 1993). Among these attributes, slope, SCA, lnSCA, wetness index, and all the measures of curvature are expected to be related to the lateral redistribution of soil moisture (Western et al., 1999). CosAspect and PSRI are expected to be related to spatial variations in evapotranspiration (Western et al., 1999). Aspect was not directly used because it has no obvious connection to a physical process. Before being used in the regression analysis, all the attributes were standardized by subtracting the average value and then dividing by the standard deviation within the catchment. The set of standardized attributes were then regressed against each retained EOF in order to allow estimation of each retained EOF from a given DEM. To accomplish this, stepwise multiple linear regression was utilized (Kabe, 1963). This method adds the most significant attribute to the equation relating the attributes to the EOFs until a local minimum of the Root Mean Square Error (RMSE) is reached. Therefore, not all attributes will be used in the final empirical equation.

The final step of the process is to estimate the retained ECs from the known spatial-average soil moisture. Perry and Niemann (2007) examined the relationship between the most important ECs and the spatial-average soil moisture at Tarrawarra and used a particular cosine function to estimate the ECs. However, they also showed that the individual EOFs at Tarrawarra are related to distinct processes such as lateral distribution and evapotranspiration. It is unlikely the importance of these processes (which is quantified by the ECs) would oscillate as implied by a cosine function as the value of the spatial average increases. To overcome this possible complication, the cosine function is replaced with a segmented-linear relationship:

$$EC = \begin{cases} \left(\dfrac{y_1}{x_1 - LB}\right)(\bar{\theta} - LB) & LB \le \bar{\theta} < x_1 \\ y_1 + \left(\dfrac{y_2 - y_1}{x_2 - x_1}\right)(\bar{\theta} - x_1) & x_1 \le \bar{\theta} < x_2 \\ y_2 + \left(\dfrac{-y_2}{UB - x_2}\right)(\bar{\theta} - x_2) & x_2 \le \bar{\theta} < UB \end{cases} \tag{1}$$

where *EC* is the value of a given EC, $\bar{\theta}$ is the spatial-average soil moisture, *LB* and *UB* are predefined lower and upper bounds for $\bar{\theta}$, and (x_1, y_1) and (x_2, y_2) are the coordinates of two breakpoints. This expression implies that first linear segment begins at zero, so that the EC is zero when the spatial-average is at a specified lower bound. The third segment also ends at zero, so that the EC is zero when the spatial-average reaches the upper bound. These lower and upper bounds have an important role because spatial variability is disallowed once the spatial-average soil moisture reaches these values. These bounds were set to 0 and 0.60 because these values are beyond the extremes that are expected for the spatial average soil moisture. Thus, some spatial variation is still allowed when the soil moisture reaches either its lowest or highest values. A sensitivity analysis was conducted, and it was found that if the lower bound increases to 0.04 and the upper bound decreases to 0.56, the results of the downscaling method change very little. The central linear segment in Equation (1) connects the two breakpoints. The coordinates of these breakpoints were estimated by an exhaustive search on a grid of potential values within specified limits. The upper and lower limits for y_1 and y_2 were set to be 1 and -1, respectively, and the limits of x_1 and x_2 were LB and UB. The resolution of the search grid was 0.01 by 0.01. For every combination of breakpoints, the sum of squared errors was calculated by comparing to the actual EC values, and the one with the minimum value was selected. This procedure was repeated for each retained EC.

Once these tasks are completed, the EOF-based downscaling method can be used for any region and date under the assumption that the identified empirical relationships hold for the application conditions. A DEM is required at the spatial resolution to which the soil moisture will be downscaled. The topographic attributes are calculated from the DEM, and the EOFs are estimated from the attributes using the regression equations. In addition, a spatial-average soil moisture is required, which is used to estimate the ECs. In most downscaling applications, a coarse grid of spatial-average soil moisture values would be used. However, the analyses presented here use only a single spatial-average soil moisture for the entire catchment because of the limited spatial extent of the available soil moisture data. Once the EOFs and ECs are known, they can be combined with the spatial average to determine the downscaled soil moisture pattern.

APPLICATION SITES

The first catchment considered is Tarrawarra, which is located near Melbourne in southern Victoria, Australia (Western and Grayson, 1998). Tarrawarra is in a temperate climate with an annual precipitation of about 820 mm and an annual potential evapotranspiration (PET) of about 830 mm. The catchment area is 10.5 ha and has topographical relief of 27 m. The soils are fairly uniform across the site and consist of a silty loam A horizon, ranging in depth from 15 to 40 cm, over a clay B horizon. The vegetation is also relatively uniform and consists of grassy pasture used for grazing. A wet season occurs between April and September when precipitation exceeds PET, and a dry season occurs between October and March when PET exceeds precipitation. Soil moisture data were collected at Tarrawarra on 13 dates over a period of 14 months from September 1995 to November 1996. The measurements were collected using a time domain reflectometry (TDR) device measuring soil moisture from a 0 to 30 cm depth. The measurements were taken on a 10 m by 20 m grid (Figure 1a). The available soil moisture observations were filtered to include only those locations that were observed on all dates (454 locations). The DEM for Tarrawarra is available at a 5 m by 5 m resolution, which was created by interpolating elevations that were collected using a total station on a paced (approximate) 10 m grid. Among the catchments considered here, Tarrawarra is the only one where EOF analysis has been performed previously.

The second catchment is Tarrawarra2, which surrounds the original Tarrawarra catchment (Figure 1b) and is described by Wilson et al. (2005). The catchment area is approximately 115 ha with topographical relief of 41 m. The climate, precipitation, PET, soils, and vegetation are similar to those found in the Tarrawarra catchment. Thus, among the four catchments considered, the soil moisture patterns at Tarrawarra and Tarrawarra2 are most likely to exhibit similar behavior. Soil moisture data were collected on 8 dates over a period of 17 months from June 1998 to October 1999 (so these observations were collected a few years after those for Tarrawarra). The measurements were also taken using a TDR from 0 to 30 cm depth in the soil. After filtering the soil moisture data to include only the locations measured on all sampling dates, the dataset includes 374 points. The measurements were taken on a 40 m by 40 m grid, and the available DEM has a 10 m by 10 m resolution.

The third catchment is called Cache la Poudre (Figure 1c) and is located in the foothills of the Front Range approximately 40 km west of Fort Collins, Colorado, USA (Lehman and Niemann, 2008; Coleman and Niemann, 2011). It is located in a semiarid climate where annual precipitation is about 40 cm and annual PET is about 93 cm. Thus, this catchment is substantially drier than Tarrawarra and Tarrawarra2. The catchment area is about 8 ha with total relief of 115m. It contains steep slopes with scattered granitic outcrops and shallow, gravelly, sandy soils. The north-facing hillslope is primarily covered with pine trees while the south-facing hillslope is primarily covered with shrubs and grasses. Soil moisture data were collected on 9 dates over a period of 3 months from April to June 2008. A TDR was also used to collect data at this catchment, but due to the shallowness of the soils, the soil moisture was only measured from 0 to 5 cm depth. The soil moisture data were collected on a 15 m by 15 m grid, and includes 347 locations that were measured on all sampling dates. This grid was also used to survey a matching 15 m by 15 m DEM.

The fourth site is Satellite Station (Figure 1d), which is located about 70 km north of Auckland, New Zealand and is described by Wilson et al. (2003). The catchment is in a warm, humid climate where annual precipitation around 160 cm and annual pan evaporation around 130 cm. Consequently, Satellite station is the wettest catchment consider here. It has an area of about 60 ha and a total relief of about 50 m. The soils have a clear distinction between the hillslopes and lowland valleys. The hillslopes are comprised of a silty clay loam up to a 30 cm depth, and the valleys contain high clay content to a 30 cm depth. The catchment is used as a pasture. Soil moisture data were collected on 6 dates over a period of 20 months from March 1998 to October 1999. These measurements were made with a TDR from 0 to 30 cm depth and were collected on a 40 m by 40 m grid. The grid includes 322 locations that were measured on every sampling date. The available DEM has a 10 m by 10 m resolution.

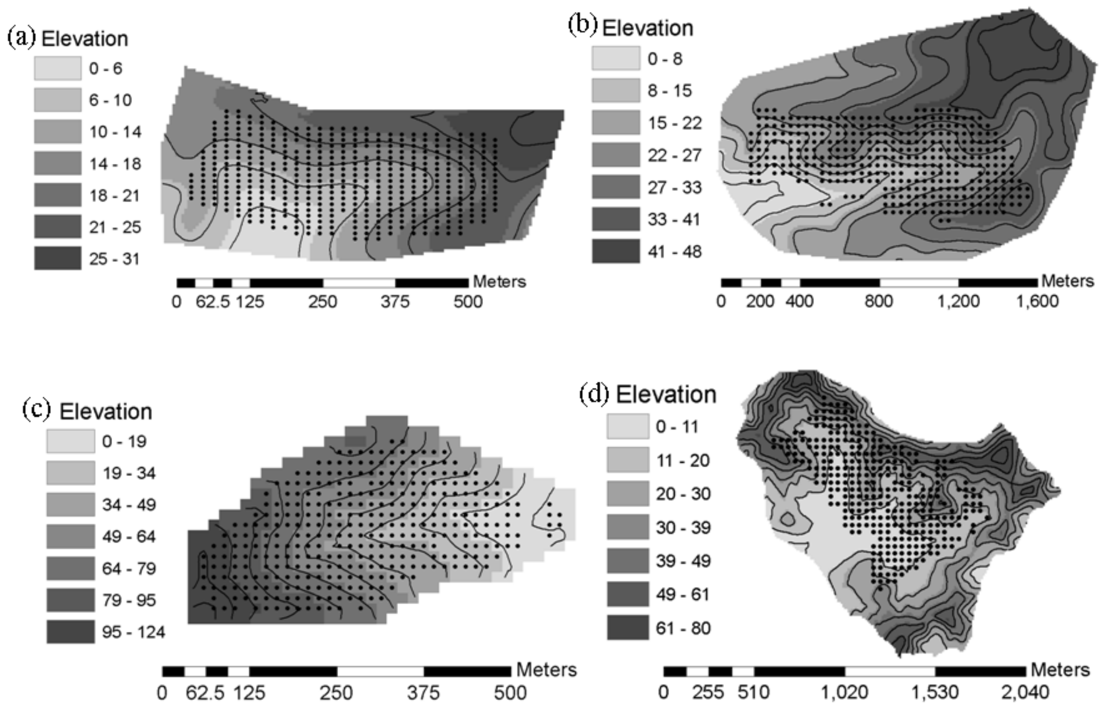

Figure 1. Topography and soil moisture sampling grid at (a) Tarrawarra, (b) Tarrawarra2, (c) Cache la Poudre, and (d) Satellite Station. Elevations are in meters and are relative to the lowest elevation in each case.

RESULTS AND DISCUSSION

Figure 2 displays the significant EOFs for the four analyzed catchments. For Tarrawarra, the Bartlett (1950) test indicates that five EOFs are significant, while the Johnson and Wichern (2002) test identifies only one as significant. Thus, three EOFs were retained in the downscaling method. These three EOFs explain 54.9%, 9.4%, and 5.9% of the variation in the soil moisture dataset, respectively, for a total of 70.2%. At Tarrawarra2, the Bartlett (1950) test identifies three EOFs as significant, while the Johnson and Wichern (2002) test identifies one as significant. Thus, the first and second EOFs were retained, which explain 25.3% and 15.9% of the variation, respectively, for a total of 41.2%. At Cache la Poudre, the Bartlett (1950) test indicates three EOFs are significant, and the Johnson and Wichern (2002) test indicates one is significant. Therefore, the first two EOFs were retained, which explain 50.2% and 13.9% of the variation, respectively, for a total of 64.2%. For Satellite Station, both the Bartlett (1950) and Johnson and Wichern (2002) tests indicate only one EOF is significant, so one is retained. This EOF explains 29.8% of the variation in the dataset. In each EOF analysis, the total number of EOFs that are generated is equal to the number of dates in the dataset. The percentage of total EOFs that were retained is fairly consistent between the four datasets with approximately 23% for Tarrawarra, 25% for Tarrawarra2, 22% for Cache la

Poudre, and 17% for Satellite Station. These results suggest that larger datasets allow identification of more subtle yet meaningful patterns of covariation.

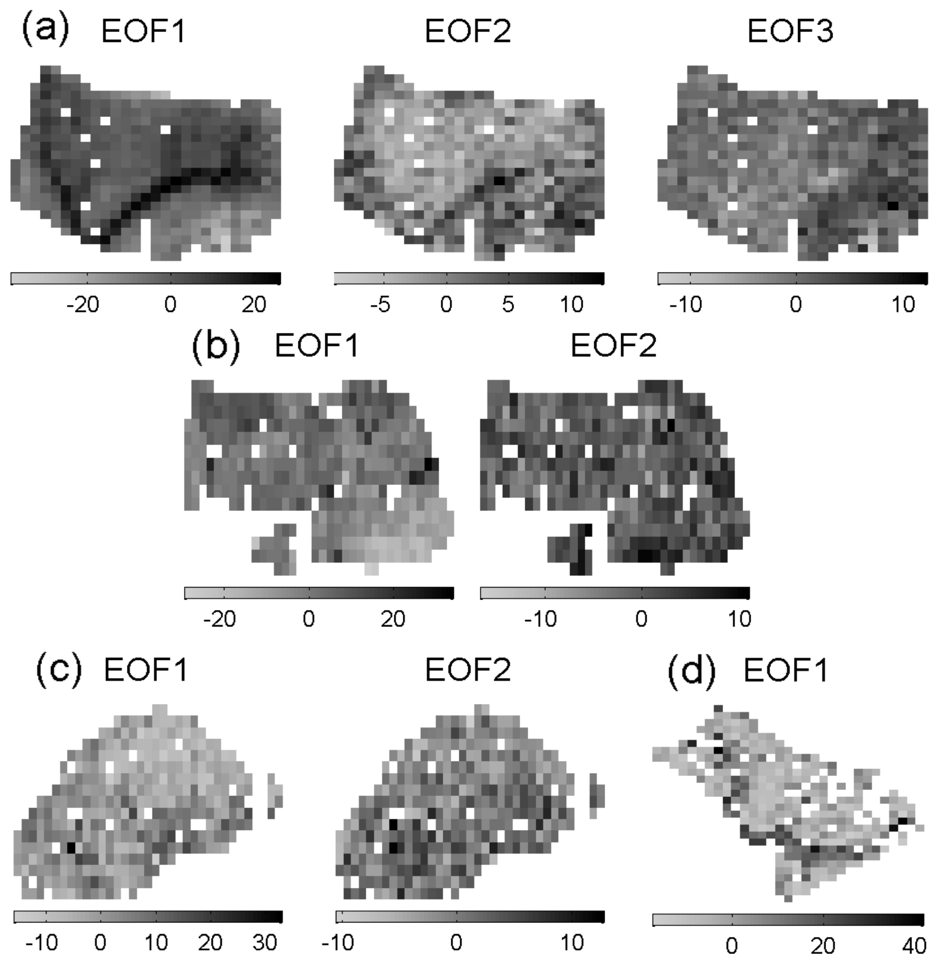

Figure 2. Retained EOFs for (a) Tarrawarra, (b) Tarrawarra2, (c) Cache la Poudre, and (d) Satellite Station. White cells indicate locations that were excluded from the EOF analysis because soil moisture observations were missing in the original dataset.

The EOFs generated from the datasets at the different catchments have some visual similarities. EOF1 at Tarrawarra (Figure 2a) clearly resembles the valley pattern of this catchment (Figure 1a) with large positive numbers occurring in the valley bottoms. EOF1 at Tarrawarra2 might exhibit a similar tendency, but it is more difficult to discern because the spacing of the observations is much wider for this dataset. EOF1 at Satellite Station (Figure 2d) also exhibits a clear similarity to the valley pattern at this catchment (Figure 1d) with large positive values occurring in the valley bottoms. In contrast, the drier catchment, Cache la Poudre, exhibits no such behavior in any of its EOFs. Instead, its first EOF (Figure 2c) seems to distinguish the two opposing hillslopes more than the valley locations (Figure 1c).

Stepwise multiple linear regression was utilized to quantify the relationships between the topographic attributes and these EOFs. Table 1 shows the coefficients used to estimate each of the retained EOFs from the standardized topographic attributes. Blank entries identify attributes that are not used in the regression model. Because the attributes are standardized, the intercepts of the regression equations are always zero. No consistent set of attributes is identified for all the catchments, but several qualitative similarities are observed. For EOF1 at Tarrawarra, a large coefficient is observed for the wetness index and further dependence is inferred for the variables that are contained in the wetness index (slope and lnSCA). All of these attributes are associated with the process of lateral redistribution, which influences soil moisture both as a hydrologic flux and through its role in soil formation (Moore et al., 1993b). The dependence on both the wetness index and the variables within the wetness index suggests that the wetness index (although used in the regression analysis) is not the ideal way to combine these underlying topographic attributes. EOF1 for Tarrawarra2, which surrounds Tarrawarra, exhibits no dependence on wetness index or its component variables. However, it depends on the tangent curvature, which exhibits a very similar spatial pattern to wetness index (not shown). EOF1 at Satellite Station exhibits very similar dependencies to those seen for EOF1 at Tarrawarra. Specifically, wetness index has a large positive coefficient, lnSCA has a moderate negative coefficient, and slope has a moderate positive coefficient in both cases. Another similarity observed in Table 1 is a consistent dependence on attributes related to evapotranspiration. EOF1 at Tarrawarra, EOF1 at Tarrawarra2, and EOF2 at Cache la Poudre all exhibit a negative dependence on PSRI. EOF2 at Tarrawarra and EOF2 at Tarrrawarra2 both exhibit a positive dependence (when examining the ECs below, it is observed that these two EOFs act to reduce the role of PSRI in determining the soil moisture patterns that is implied by EOF1 under certain conditions). Satellite Station, the wettest catchment, exhibits a positive dependence on PSRI, which counter-balances some of the dependence on cosAspect.

Table 1. Coefficients calculated by stepwise multiple linear regressions performed between the retained EOFs and the topographic attributes at each catchment. Dashes indicate attributes that are not selected in the regression equations.

Coefficients from Stepwise Multiple Linear Regression								
	Tarrawarra			Tarrawarra2		Cache la Poudre		Satellite Station
Variable	EOF 1	EOF 2	EOF 3	EOF 1	EOF 2	EOF 1	EOF 2	EOF 1
Slope	3.83	-0.52	0.85	-	-	-1.11	-	5.19
cosAspect	-	-	0.99	-	-1.37	3.05	-	-4.03
SCA	-0.72	0.49	-	-	-	-	-	-
lnSCA	-7.60	-	-0.59	-	-1.07	-	-	-17.06
Wetness	15.62	-	-	-	-	-	-	24.55
kLaplace	-	60.13	-	-	-	-	-	-
kProfile	-	-40.95	-	-	-	-2.04	-	-
kPlan	-	-	-0.69	-	-	0.71	0.61	-1.43
kTangent	2.08	-30.92	1.46	2.79	0.93	-	-	-
PSRI	-2.64	1.77	-	-4.58	2.26	-	-1.19	3.06

Figure 3 displays the EOF patterns that are estimated using these regression equations. The estimated EOFs are denoted as REOFs to distinguish them from the actual EOFs. When comparing the REOFs to the actual EOFs shown in Figure 2, it can be seen the REOFs are usually reasonable representations of the EOFs. However, the REOFs appear to be smoother than the EOFs. The speckled texture in the original EOFs might be associated with soil structure, soil composition, vegetation, and other unresolved variability—none of which are directly accounted for in this method. Wilson et al. (2005) observed the same smooth appearance in plots produced by an alternative method relating topographic attributes to soil moisture patterns. For Tarrawarra, the portion of the variation in the original EOFs that is explained by the REOFs is 0.72 for EOF1, 0.39 for EOF2, and 0.22 for EOF3. For Tarrawarra2, the amount of variation explained is 0.41 for EOF1 and 0.09 for EOF2. For Cache la Poudre, the amount of variation explained is 0.26 for EOF1 and 0.13 for EOF2, and for Satellite Station, the amount of variation explained within EOF1 by the empirical relationships is 0.38. Thus, overall, the topographic attributes are more successful at explaining the most important EOFs at each catchment. Among the four catchments, Tarrawarra's EOFs are generally most strongly related to the topographic attributes, while Cache la Poudre's EOFs are most weakly related.

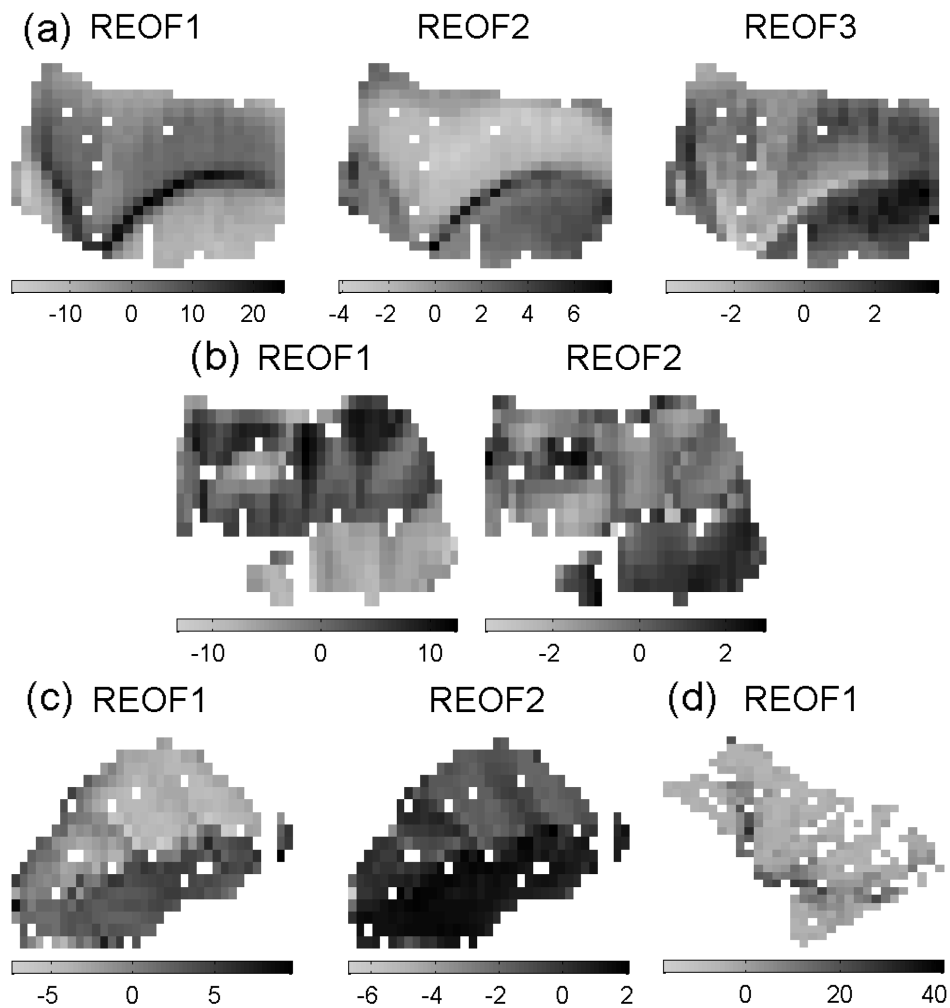

Figure 3. EOFs estimated based on the regressions against topographic attributes for (a) Tarrawarra, (b) Tarrawarra2, (c) Cache la Poudre, and (d) Satellite Station. White cells indicate locations with no values in the original soil moisture dataset.

Figure 4 shows values for each retained EC along with the segmented-linear equations that are used to estimate these values from the spatial-average soil moisture. Overall, the qualitative behavior of the ECs is rather similar among the catchments. In all four catchments, the first EC is largest for intermediate values of the spatial-average soil moisture, which indicates that the associated EOF is most important for these intermediate values. However, the exact value of the spatial-average soil moisture where the EC reaches its maximum varies considerably between the catchments. Another qualitative similarity is seen for the second EC. In all cases where EOF2 was retained, its EC changes sign at some point. As mentioned earlier, when the sign of EC2 is positive at Tarrawarra and Tarrawarra2, it acts to dampen out the dependence on PSRI that occurs in EOF1. When the sign is negative, it enhances the definition of the PSRI related patterns. In most cases, the EC values exhibit clear dependence on the spatial-average soil moisture and are well characterized by the segmented linear equations. For Tarrawarra, the EC1 equation explains 0.93 of the variation, the EC2 equation explains 0.82 of the variation, and the EC3 equation explains 0.73 of the variation in the associated EC data. For Tarrawarra2, the EC1 equation explains 0.85 of the variation, and the EC2 equation explains 0.67 of the variation in the associated observed EC values. For Cache la Poudre, the EC1 equation explains 0.96 of the variation, and the EC2 equation explains 0.85 of the variation in the associated EC data. For Satellite Station, the EC1 equation explains 0.97 of the variation in the EC1 data. At all catchments, the relationships become less successful at explaining the EC variation as the order of the EC increases.

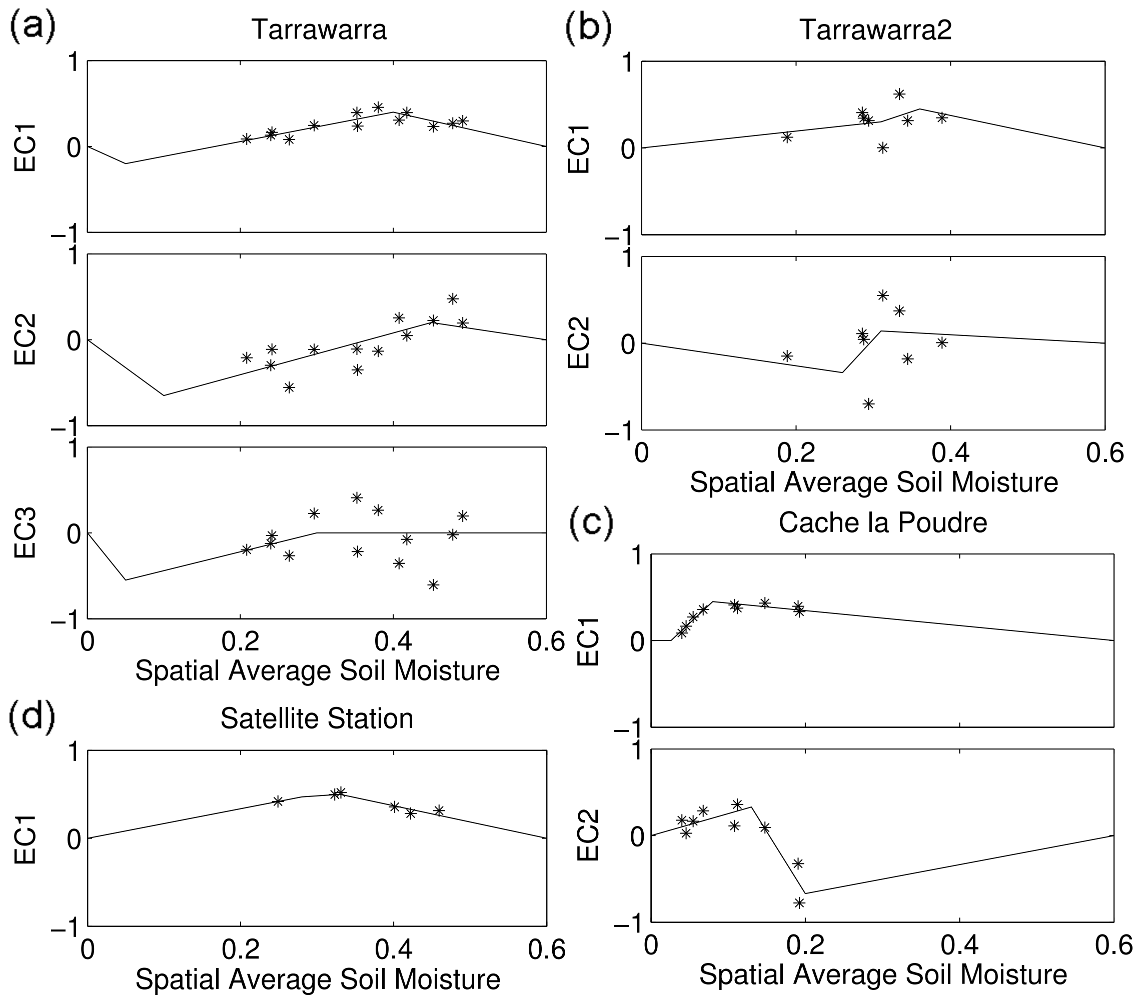

Figure 4. EC values (asterisks) and the segmented-linear relationships (lines) used to estimate the EC values (Eq. 1) for (a) Tarrawarra, (b) Tarrawarra2, (c) Cache la Poudre, and (d) Satellite Station.

Now that all of the elements of the downscaling method have been developed at the four catchments, downscaling results can be produced. We begin by using the relationships that were developed at each catchment to downscale the spatial-average soil moisture at that same catchment. To understand the origins of the errors in the downscaled patterns, the downscaling method is applied to each catchment in four ways. First, each downscaling method is applied when the actual EOFs and ECs are used.

Second, the downscaling method is applied using the actual EOFs and the estimated ECs. Third, the method uses the estimated EOFs and the actual ECs, and fourth, it uses the estimated EOFs and the estimated ECs. For this analysis, the complete soil moisture dataset is used in the EOF analysis for each catchment. Thus, none of these results represent a real scenario where only the spatial-average soil moisture is known for the date that is being downscaled. However, Perry and Niemann (2007) observed that the performance of their method was similar when the soil moisture observations from all of the dates were included and when the observations from all but the estimation date were included. The Nash Sutcliffe Coefficient of Efficiency (NSCE) (Nash and Sutcliffe, 1970) was used to measure the difference between the observed and downscaled soil moisture patterns. The maximum value of NSCE is one, which implies the estimated pattern matches the observed pattern exactly. Values above zero indicate that the downscaled pattern explains more of the observed variability than using the supplied spatial average does.

Figure 5 shows the results of this analysis. When the actual EOFs and ECs are used to downscale soil moisture patterns for all dates in each dataset, the average NSCE values are 0.65 for Tarrawarra, 0.63 for Tarrawarra2, 0.58 for Cache la Poudre, and 0.68 for Satellite Station. In this application of the method, the only source of disagreement between the observed and downscaled soil moisture patterns is the discarded EOF/EC pairs. Because these pairs do not represent statistically significant patterns of covariation according to the statistical tests described earlier, the resulting NSCE values are estimates of the maximum variation that can be explained at each catchment. The remaining variation is considered unpredictable noise. These NSCE values are relatively consistent between the four catchments, suggesting that roughly 0.60 of the variation is explained by significant patterns of covariation. When the analysis is repeated using the estimated ECs instead of the actual ECs, the average NSCE values are 0.50 for Tarrawarra, 0.35 for Tarrawarrra2, 0.49 for Cache la Poudre, and 0.67 for Satellite Station. When applying the method in this way, we are essentially using the approach described by Perry and Niemann (2007) but replacing the cosine functions with the segmented linear relationships when estimating the ECs. To obtain these results in a downscaling application, one would require a space-time dataset of soil moisture to determine the actual patterns of covariation and those patterns are used directly in the downscaling method. However, their importance is being estimated on the basis of the spatial-average soil moisture. Thus, these numbers are roughly the best possible performance that could be achieved by an EOF-based downscaling method. They are not strictly the best because the relationship used to estimate the ECs could be improved using other parametric or nonparametric methods. Here, the performance between the four catchments is more varied. The performance at Satellite Station is almost identical to the previous case, while only 0.35 of the variation is explained at Tarrawarra2. One possible reason for reduced performance is hysteresis, which could produce a non-unique relationship between the patterns of covariation and the spatial average soil moisture. Ivanov et al. (2010) showed that patterns of soil moisture variability are strongly dependent on the initial conditions of the catchment in a model, which suggests that such hysteresis might be present. When combining the estimated EOFs (i.e. the REOFs) with the actual ECs, the average NSCE values are 0.40, 0.22, 0.14, and 0.25, respectively. By comparing these numbers to the original scenario, one can see the error that is introduced by estimating the patterns of covariation from the topographic attributes. Based on the results, Tarrawarra's soil moisture patterns contain the strongest relationship to the topographical attributes because the NSCE drops from 0.63 to only 0.40, while Cache la Poudre exhibits the weakest relationship because its NSCE drops from 0.58 to 0.14. Satellite Station is an interesting case because its lone EC is estimated very well from the spatial-average soil moisture (NSCE drops from 0.68 to 0.67), but its EOF is poorly estimated from the topography (NSCE drops from 0.68 to 0.25). Overall, estimating the EOFs from topographic data is the largest source of error in the proposed downscaling method. Thus, the use of additional data such as vegetation patterns and soil texture variations might represent a viable path for improving the downscaling method. Finally, when the downscaling method uses both the REOFs and the estimated ECs, and the average NSCE values are 0.35, 0.15, 0.14, and 0.25, respectively. As expected, the NSCE decreases because both the EOFs and ECs are being estimated. However, the advantage of this final method is that it might be portable for use in similar catchments where no space-time soil moisture observations have been collected.

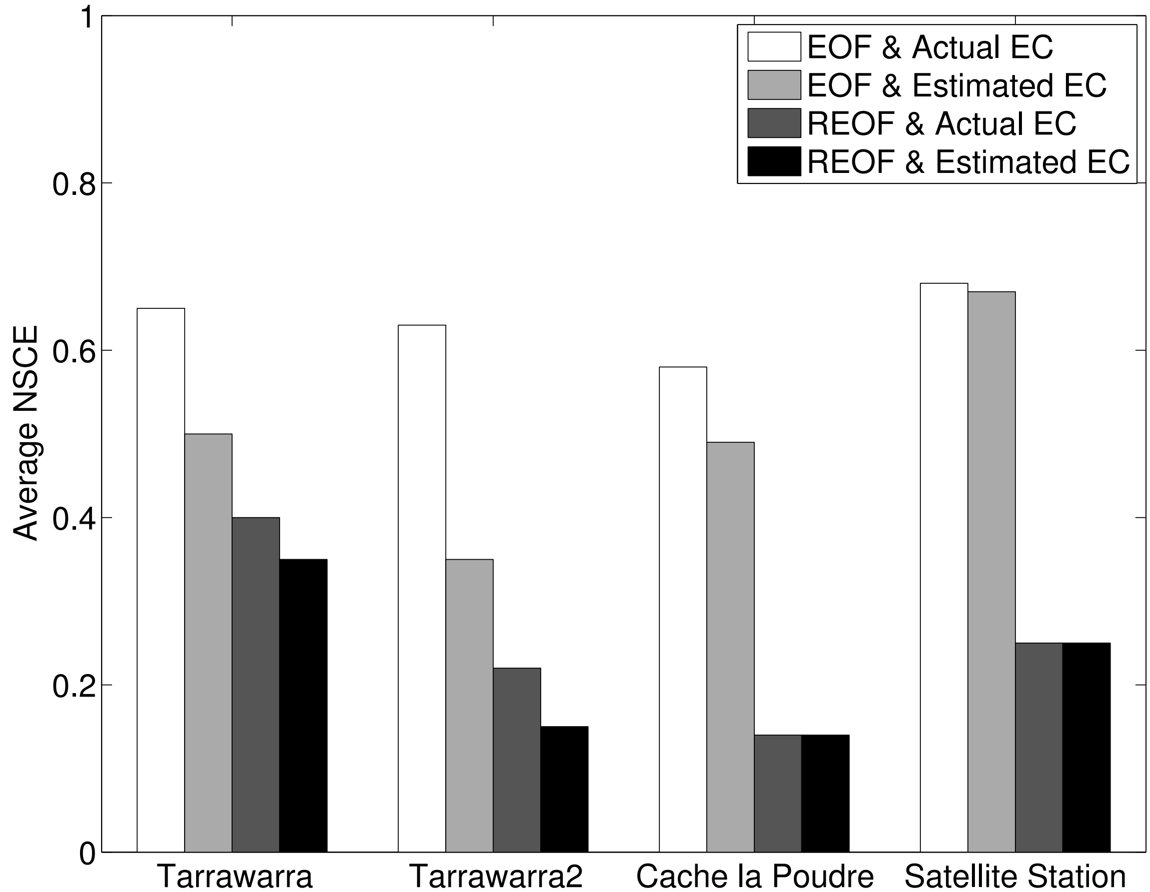

Figure 5. Performance of the downscaling method at each catchment as the estimated ECs and EOFs replace the actual ECs and EOFs in the method. In the legend, "EOF" indicates that the downscaling method uses that actual EOF, and "REOF" indicates that the method uses the estimates obtained from the topography. Similarly, "actual EC" means that the method uses the EC values obtained from the EOF analysis, while "estimated EC" means that the method uses the estimates obtained from the spatial-average soil moisture.

Figure 6 shows the observed soil moisture pattern, the downscaled soil moisture pattern (when both the EOFs and ECs are estimated), and the resulting estimation errors for a selected date at each catchment. These dates were selected because they have NSCE values closest to the averages given earlier (the NSCE values for the displayed patterns are 0.33 for Tarrawarra, 0.16 for Tarrawarra2, 0.15 for Cache la Poudre, and 0.19 for Satellite Station). At Tarrawarra, the downscaled pattern successfully identifies the valley bottom as wet, which is the most visible attribute of the observed pattern. At Tarrawarra2, some of the wetter and drier regions are reproduced, but neither pattern exhibits a visually clear structure. At Cache la Poudre, the downscaled pattern produces slightly wetter locations on the north-facing slope, which is consistent with the observed pattern. At Satellite Station, both the observed and downscaled soil moisture patterns have wetter locations in the valley bottoms. All of the predicted patterns are much smoother in appearance than the observed patterns because the REOFs are much

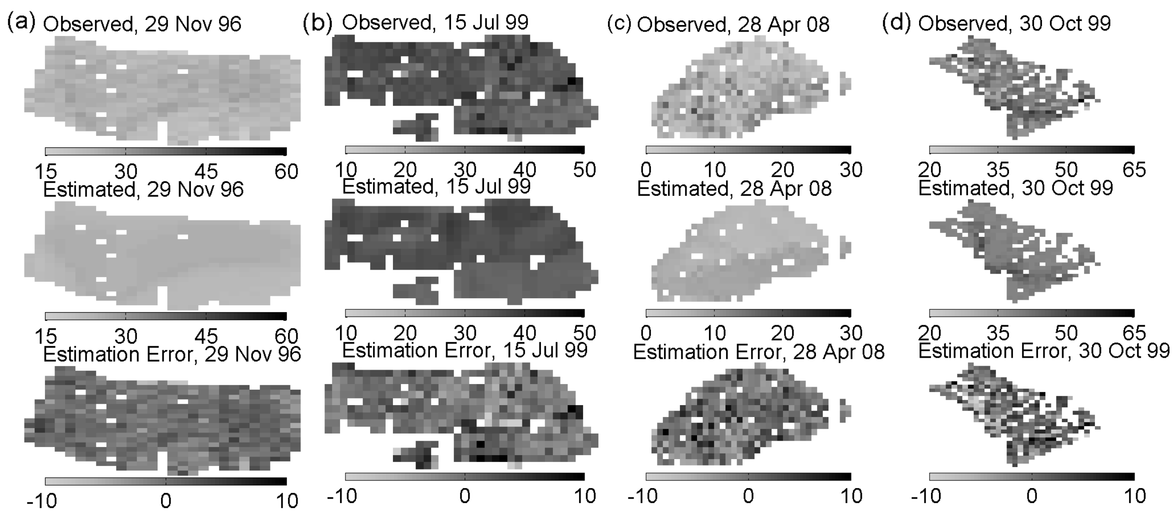

Figure 6. Comparisons of observed soil moisture patterns and those estimated by the EOF-based downscaling method (when both the EOFs and the ECs are estimated) at (a) Tarrawarra, (b) Tarrawarra2, (c) Cache la Poudre, and (d) Satellite Station. These dates were selected because their NSCE values are the closest to the average among all dates at the given catchment. Estimation errors are calculated as the observed soil moisture minus the downscaled soil moisture. Soil moisture values refer to volumetric soil moisture (volume of water per bulk volume) expressed as a percentage. White cells indicate locations with no values.

Figure 7 plots the observed patterns, downscaled patterns, and estimation errors on the date where the downscaling method performs the best at each catchment. The NSCE values for these patterns are 0.67 for Tarrawarra, 0.35 for Tarrawarra2, 0.33 for

Cache la Poudre, and 0.34 for Satellite Station. Once again, the downscaled patterns capture most of the major features in the observed patterns at all four catchments. In some cases, the downscaled patterns in Figure 7 exhibit some different tendencies than the patterns in Figure 6. Notice in particular, that the downscaled pattern at Tarrawarra has relatively drier soil moisture values on the north-facing slope in Figure 7a compared to Figure 6a. Such differences arise because the spatial-average soil moisture changes between the two dates. A change in the spatial average produces different EC values and thus different weighting of the underlying EOFs. In contrast, the structure of the soil moisture pattern at Satellite Station exhibits time stability because only one EOF is used in that case (Lin, 2006; Guber et al., 2008).

The next step is to evaluate the portability of downscaling method that was developed at each catchment. In this analysis, the downscaling method that was developed at each catchment is applied to the other three catchments. The only change that is made when applying the downscaling methods to the other catchments is to account for whether the catchment is in the northern or southern hemisphere. In particular, the sign of the CosAspect coefficient in Table 1 is changed if the development and application catchments are in opposite hemispheres (i.e. north or south). Table 2 shows the average NSCE values that are calculated when each downscaling methods is applied to each catchment. As discussed earlier, the methods perform relatively well when the empirical relations are applied to the catchments where they were originally

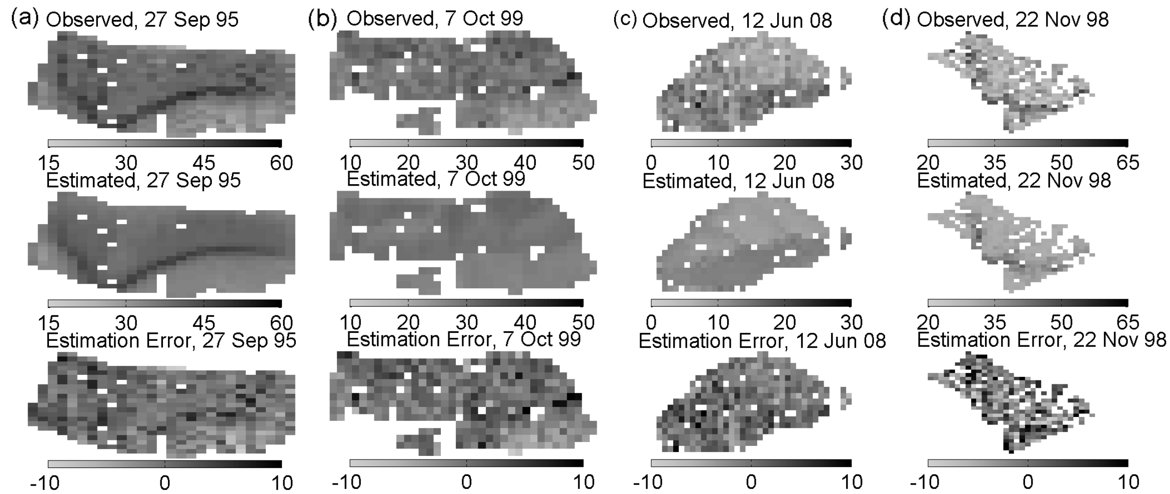

Figure 7. Comparisons of observed soil moisture patterns and those estimated by the EOF-based downscaling method at (a) Tarrawarra, (b) Tarrawarra2, (c) Cache la Poudre, and (d) Satellite Station. These dates were selected because their NSCE values are the highest among all dates at the given catchment. Soil moisture values are volumetric soil moisture expressed as a percentage. White cells indicate locations with no values.

developed. When applied to the other catchments, however, the performance of the methods is almost always worse. One would expect that the downscaling method that was developed at Tarrawarra would be relatively successful at Tarrawarra2 (and vice-versa) because Tarrawarra2 surrounds and includes the Tarrawarra catchment. Applying the downscaling method that was developed at Tarrwarra2 to Tarrawarra produces a nearly identical average NSCE value, but applying the downscaling method from Tarrawarra to Tarrwarra2 produces a negative average NSCE. It should be noted that the spatial resolution of the DEMs for these two catchments also differs (5 m for Tarrwarra and 10 m for Tarrawarrra2), so some of this observed error might be due to changing the resolution at which the topographic attributes are calculated. The role of the DEM resolution will be examined in more detail later. When applying the Tarrawarra downscaling method to Cache la Poudre and Satellite Station, the NSCE values are still negative. However, when applying Tarrawarra2 to these catchments, the NSCE value at Cache la Poudre is positive (but not far from zero) while the NSCE value at Satellite Station is negative. This result suggests a certain degree of portability is possible for the method developed at Tarrawarra2. In this case, the first REOF is produced using only two attributes, and the second REOF is produced using four attributes. This result suggests the use of fewer attributes might be advantageous when applying the method to other catchments because subtle dependencies on attributes might be more site specific. When reviewing the ECs from Tarrawarra2, it appears they are rough approximations of the ECs from the other three catchments. A combination of fewer attributes used in producing REOFs and a reasonable estimate of the EC equations could be the reason Tarrawarra2 performs the best overall.

Table 2. Average NSCE values calculated when the EOF-based downscaling method is applied to all dates in the soil moisture dataset for each catchment. "Development Catchment" refers to the catchment where the downscaling method was developed, and "Application Catchment" refers to the catchment where the NSCE values were calculated. In each case, the downscaling method uses the original-resolution DEM to calculate the topographic attributes.

Development Catchment	Application Catchment			
	Tarrawarra	Tarrawarra2	Cache la Poudre	Satellite Station
Tarrawarra	0.35	-0.30	-0.25	-0.05
Tarrawarra2	0.17	0.15	0.05	-0.11
Cache la Poudre	-0.09	-0.06	0.14	0.04
Satellite Station	-0.01	-0.27	-0.03	0.25

Figures 8 and 9 show the results that are obtained when the Tarrawarra2 method is applied to the three other catchments. Figure 8 shows the results for the date with performance that is closest to the average for each catchment. For the dates shown, the NSCE is 0.17 at Tarrawarra, 0.06 at Cache la Poudre, and -0.10 at Satellite Station. For

Tarrawarra and Cache la Poudre, little variation is observed in the estimated soil moisture patterns, but the observed patterns also display little variation on these particular dates. At Satellite Station, the NSCE value is negative, so the spatial-average soil moisture is a better estimate of the pattern than the downscaled pattern. Figure 9 shows the results on the date with the best performance at each catchment. For these dates, the NSCE is 0.41 at Tarrawarra, 0.15 at Cache la Poudre, and -0.04 at Satellite Station. At Tarrawarra (Figure 9a), the observed soil moisture is wetter in the valley bottom and on the south-facing hillslope. The downscaled pattern reproduces the differences in soil moisture between the two hillslopes, but it underestimates the wetness in the valley bottom. At Cache la Poudre (Figure 9b), the two opposing hillslopes have very different soil moisture values. Although the downscaled soil moisture pattern exhibits a similar qualitative pattern, it underestimates the difference in moisture between the two hillslopes. At Satellite Station (Figure 9c), the observed soil moisture pattern mainly exhibits wetter conditions in the valley bottoms. The downscaled soil moisture pattern does not capture this behavior, which results in a negative NSCE.

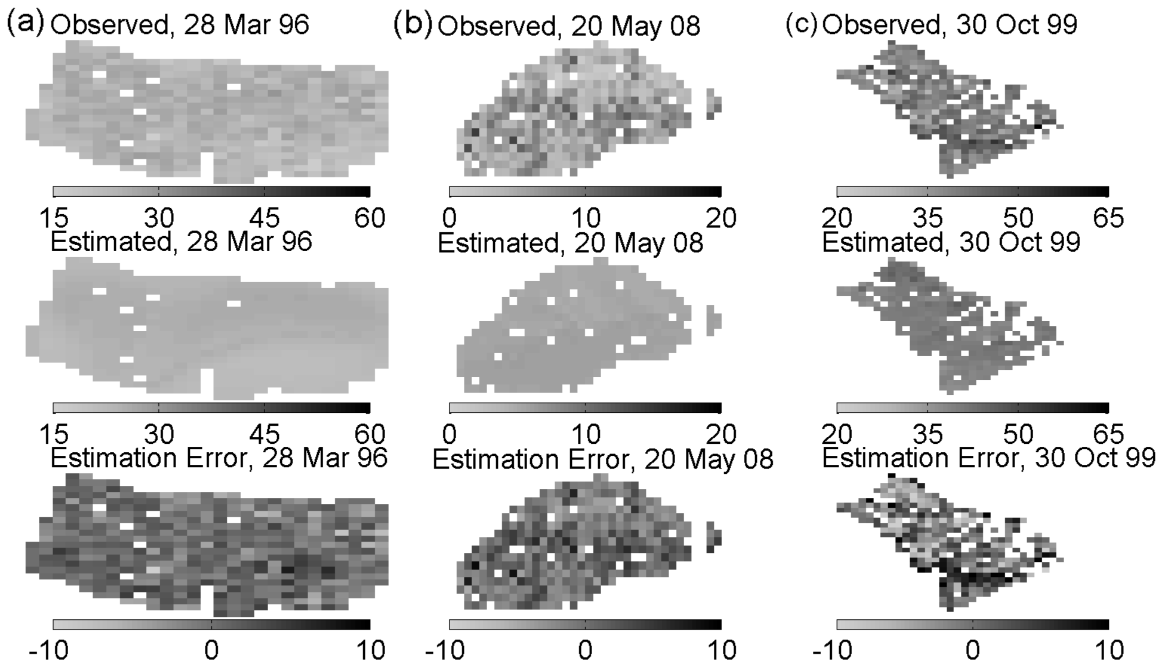

Figure 8. Comparison of the observed soil moisture patterns and those estimated using the empirical relationships derived at Tarrawarra2 for (a) Tarrawarra, (b) Cache la Poudre, and (c) Satellite Station. These dates were selected because their NSCE values are the closest to the average among all dates at the given catchment. Soil moisture values are volumetric soil moisture expressed as a percentage. White cells indicate locations with no values.

One factor that might be affecting the portability of the method between catchments is the spatial resolution of the DEM. Recall that the resolutions of the DEMs from which the EOFs are being estimated are 5 m at Tarrawarra, 10 m at Tarrawarra2, 15 m at Cache la Poudre, and 10 m at Satellite Station. It is possible that error is introduced in the downscaling estimates because the topographic attributes like slopes and curvatures are being calculated at different spatial scales at different catchments. To evaluate the potential impact of the DEM resolution, the Tarrawarra DEM was coarsened to 10 m, which makes it more similar to the other catchments. The elevations on the coarser grid were calculated by averaging the elevations of all points on the finer grid that

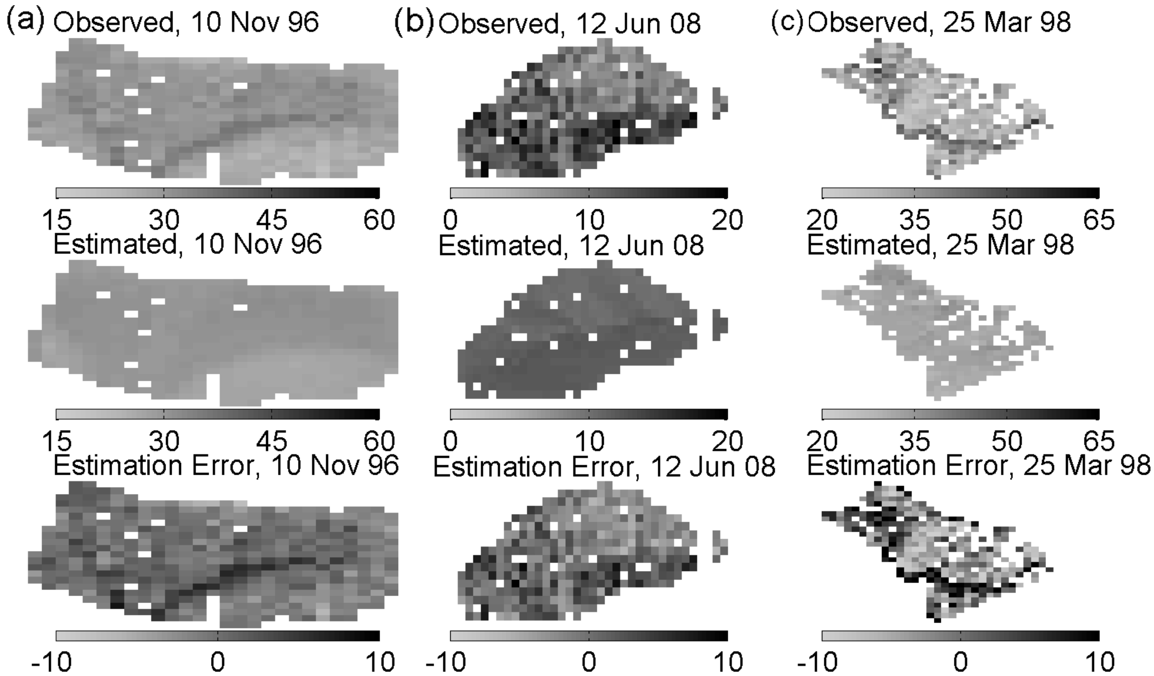

Figure 9. Comparison of the observed soil moisture patterns and those estimated using the empirical relationships derived at Tarrawarra2 for (a) Tarrawarra, (b) Cache la Poudre, and (c) Satellite Station. These dates were selected because their NSCE values are the highest among all dates at the given catchment. Soil moisture values are volumetric soil moisture expressed as a percentage. White cells indicate locations with no values.

are contained in each cell of the coarser grid. All the topographic attributes were recalculated using this coarsened DEM and the downscaling methods were regenerated and reapplied to this catchment. Table 3 shows the average NSCE values that were calculated using this new DEM. Comparing the results in Table 3 and Table 2 suggests that the performance typically improves although by a smaller amount when the DEM resolution is more consistent between the catchments. This analysis was also repeated when the coarsened DEM at Tarrawarra was calculated by sampling rather than averaging the finer DEM. Similar results were observed, but a smaller improvement was observed in the performance. More improvement is expected when the averages are used because averaging reduces measurement errors that are associated with point elevations. Erskine et al. (2007) have shown that calculation of topographic attributes, particularly curvatures, is sensitive to such errors in the elevations.

Table 3. Average NSCE values calculated when the EOF-based downscaling method is applied to all dates in the soil moisture dataset for each catchment. In this analysis, the Tarrawarra DEM was coarsened to a 10 m linear resolution to be more consistent with the DEM resolutions at the other catchments (the Tarrawarra related results in Table 2 use a 5 m DEM).

Development Catchment	Application Catchment			
	Tarrawarra	Tarrawarra2	Cache la Poudre	Satellite Station
Tarrawarra	0.35	-0.19	-0.18	-0.08
Tarrawarra2	0.18			
Cache la Poudre	-0.09			
Satellite Station	0.06			

In addition to using a consistent DEM resolution when applying the downscaling methods to different catchments, it is possible that use of a particular DEM resolution (e.g., 10 m or 40 m) at a given catchment produces better results. To examine this possibility, the EOF downscaling method was developed and applied at the Tarrawarra2 and Satellite Station catchments using a 40 m DEM. These two catchments were selected for analysis because the soil moisture observations are available at a 40 m spacing, so coarsening the DEM does not change the soil moisture dataset considered. Table 4 shows the average NSCE values obtained for this experiment. Comparing the results in Table 4 and Table 2 indicates that using 40 m DEMs improves the performance in 3 out of 4 cases (although this improvement is generally small). These results are consistent with Erskine et al. (2007) who used linear regression analysis to show that the relationship between crop yield, which is related to soil moisture, and topography is strongest at a 30 m resolution.

Table 4. Average NSCE values calculated when the EOF-based downscaling method is applied to all dates in the soil moisture dataset for each catchment. In this analysis, the Tarrawarra and Satellite Station DEMs were coarsened to 40 m (the results in Table 2 were based on 10 m DEMs in both cases).

Development Catchment	Application Catchment			
	Tarrawarra	Tarrawarra2	Cache la Poudre	Satellite Station
Tarrawarra				
Tarrawarra2		0.17		0.04
Cache la Poudre				
Satellite Station		-0.40		0.28

CONCLUSIONS

In this paper, a method was proposed to downscale a spatial-average soil moisture value using topographic data. The method is based on an EOF decomposition of a soil moisture dataset from a reference catchment. After the EOF decomposition is performed, the retained EOFs are estimated from topographic attributes and the associated ECs are estimates from empirical relationships to the spatial-average soil moisture. Once the method has been developed at a catchment with available soil moisture observations, it can potentially be applied to any catchment if the underlying empirical relationships continue to hold. The proposed downscaling method was developed separately at four catchments: Tarrawarra, Tarrawarra2, Cache la Poudre, and Satellite Station. At each catchment, empirical relationships were determined to estimate the EOFs and the ECs and these relationships were compared between catchments. Then, each method was applied to the other three catchments, and the performance of the method was evaluated. Based on these analyses, the following conclusions can be made.

1. The relationships used to estimate the EOFs from topographic attributes are quantitatively different all four catchments, but several qualitative similarities are observed. For example, the most important EOF at Tarrawarra and Satellite Station depends on many of the same topographic attributes (wetness index, slope, and the log of specific contributing area), which are associated with the lateral redistribution of soil

moisture. Although, the most important EOF at Tarrawarra2 depends on a curvature measure, it is also associated with lateral redistribution.

2. Similarly, the segmented-linear relationships that were used to estimate the ECs are quantitatively different but exhibit some qualitative similarities between catchments. In all four catchments, the first EC reaches its peak at an intermediate value of the spatial-average soil moisture, and it decreases to zero as the spatial-average reaches its extremes. In addition, the second EOF (when retained) consistently changes sign at some intermediate value of soil moisture.

3. When the EOF-based downscaling method is applied to the catchment where it was developed, its performance is relatively good. In all four catchments, the average NSCE value is greater than zero, which suggests that the downscaled patterns provide better estimates of the observed soil moisture pattern than the spatial-average soil moisture. An analysis of the origin of the errors in these patterns suggests that most of the error is introduced by estimating the EOFs based only on topographic attributes. Thus, a plausible avenue to improve the downscaling method would be to include additional site attributes, such as vegetation and soil characteristics, into the stepwise linear regression for estimating the EOFs. Additional attributes could allow the method to explain variation in the EOFs (and thus the soil moisture patterns) that is unrelated to topography.

4. When the EOF-based downscaling method is applied to the three catchments where it was not developed, the performance deteriorates because of the quantitative differences in the EOFs and ECs that apply to each catchment. The exception to this statement is the method developed at Tarrawarra2, which performs nearly the same when applied to the Tarrawarra catchment (the Tarrawarra catchment is contained within Tarrawarra2).

Overall, the Tarrawarra2 method performs the best when applied to other catchments, but the results suggest that none of the EOF-based downscaling methods can achieve good performance universally.

5. The performance of the method was found to improve if the DEM resolution remains relatively consistent between the catchment where it is developed and the catchment where it is applied. In particular, the downscaling methods that were developed at Tarrawarra2, Cache la Poudre, and Satellite Station using 10 to 15 m DEMs all perform better when applied to Tarrawarra using a 10 m DEM instead of a 5 m DEM. In addition, the downscaling method typically performs better when it uses a 40 m resolution DEM instead of a 10 m DEM.

Overall the results in this paper suggest that the application of a single EOF-based downscaling method to a wide range of catchments produces reasonable results in the sense that the downscaled patterns reproduce some qualitative characteristics of the observed patterns. However, the quantitative estimates of soil moisture are not consistently superior to the spatial average. This difficulty likely occurs because site specific characteristics such as soil texture, soil depth, and vegetation patterns mediate the relationships between topographic attributes and soil moisture variations. Further investigation should consider how such site characteristics could be included in topographic-based downscaling methods.

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