Estimating profile soil moisture and groundwater variations using GRACE and Oklahoma Mesonet soil moisture data

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[1] In this study we estimate a time series of regional groundwater anomalies by combining terrestrial water storage estimates from the Gravity Recovery and Climate Experiment (GRACE) satellite mission with in situ soil moisture observations from the Oklahoma Mesonet. Using supplementary data from the Department of Energy's Atmospheric Radiation Measurement (DOE ARM) network, we develop an empirical scaling factor with which to relate the soil moisture variability in the top 75 cm sampled by the Mesonet sites to the total variability in the upper 4 m of the unsaturated zone. By subtracting this estimate of the full unsaturated zone soil moisture anomalies, we arrive at a time series of groundwater anomalies, spatially averaged over a region approximately 280,000 km^2 in area. Results are compared to observed well level data from a larger surrounding region, and show consistent phase and relative inter-annual variability.

Citation: Swenson, S., J. Famiglietti, J. Basara, and J. Wahr (2008), Estimating profile soil moisture and groundwater variations using GRACE and Oklahoma Mesonet soil moisture data, *Water Resour. Res.*, *44*, W01413, doi:10.1029/2007WR006057.

1. Introduction

[2] Water stored below the Earth's surface is fundamentally important to the well-being of most of the world's inhabitants. Nearly half the population of the U.S. use groundwater as their primary source of drinking water [*Bartolino and Cunningham*, 2003], and approximately 40% of irrigation water is extracted from the ground. Furthermore, "No comprehensive national groundwater-level network exists with uniform coverage of major aquifers, climate zones, and land uses' [*Hutson et al.*, 2004]. Globally, the situation is the same or worse, with many regions experiencing depletion, salinization, or contamination of their groundwater supply [*Shah et al.*, 2000]. Groundwater stores are experiencing increasing demands, and proper management of these resources requires better monitoring and assessment.

[3] Remotely sensed data have been used extensively to monitor surface and near-surface components of the water cycle, e.g., altimetric measurements of river and lake height [*Alsdorf and Lettenmaier*, 2003], microwave estimation of soil moisture [*Njoku et al.*, 2003] and snow water equivalent [*Kelly et al.*, 2004]. Characterizing the stores and fluxes of sub-surface water has proven less tractable to typical satellite methods. Because groundwater is stored below the land surface, nearly all methods must rely on indirect measures of various aspects of groundwater hydrology.

These include remote sensing of surface fractures and lineaments, vegetation along springs, surface displacements due to aquifer inflation and compaction, surface water bodies, and localized recharge features [*Becker*, 2006]. One exception is the use of data from the Gravity Recovery and Climate Experiment (GRACE), which is sensitive to changes in the total water column [*Wahr et al.*, 1998; *Swenson et al.*, 2006]. *Yeh et al.* [2006] demonstrated that regional average variations in groundwater could be reliably estimated by combining GRACE estimates of vertically integrated water storage with independent estimates of unsaturated zone storage using a water balance approach. (We use the term groundwater to refer to the saturated zone only, while the terms soil moisture content and unsaturated zone water content will be used somewhat interchangably.)

[4] In this paper, we apply the water balance approach used by *Yeh et al.* [2006] to estimate variations in groundwater averaged over a region centered on the state of Oklahoma in the Central U.S. As for the region studied in that paper (Illinois), the primary contributors to changes in the Oklahoma regional water balance are soil moisture and groundwater; snow and surface water are assumed negligible [*Rodell and Famiglietti*, 2001]. To estimate regional average soil moisture, we utilize observations from the Oklahoma Mesonet [*Brock et al.*, 1995]. The Oklahoma Mesonet (OM) is an automated observing network, collecting real-time hydrometeorological observations from more than a hundred stations throughout Oklahoma. As part of the suite of observations made at many of these sites, soil moisture measurements are made every 30 min at depths of 5, 25, 60, and 75 cm using Campbell Scientific 229-L heat dissipation sensors [*Basara and Crawford*, 2000]. By combining these data with total column water storage estimates from GRACE in a water balance equation, we compute a time series of spatially averaged groundwater storage variations.

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300 km Gaussian Averaging Kernel
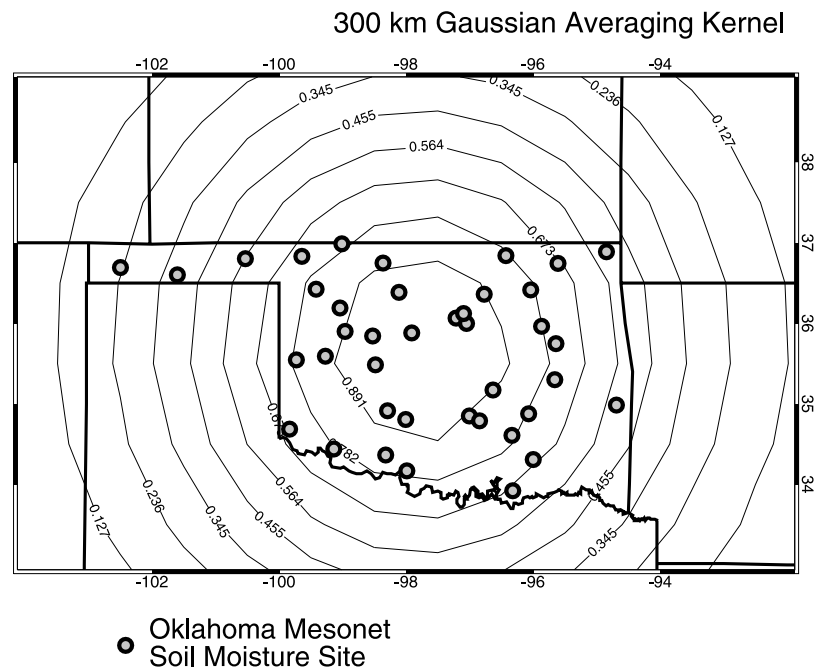
Figure 1. Map of Central U.S. showing locations of OM soil moisture sites. Contours indicate values of GRACE averaging kernel.

[5] The study of *Yeh et al.* [2006] was made possible by the existence of an extensive monitoring network of both soil moisture and groundwater well levels operated by the Illinois State Water Survey (ISWS) [*Hollinger and Isard*, 1994]. This network is perhaps unique by virtue of its combination of areal extent (~200,000 km²), a long and up-to-date period of record, and measurement of all significant water balance components. While the Oklahoma Mesonet shares the first two characteristics with the ISWS network, the third is unfortunately a point of departure.

[6] Tens of thousands of wells exist in Oklahoma, but only a few are monitored more frequently than once per year. Moreover, the parameters (e.g., specific yield) necessary to convert well level to water storage are difficult to obtain and uncertain. Thus the ability to assess a remotely sensed groundwater estimate with in situ observations is limited, and this should be kept in mind when interpreting the comparison between a GRACE-derived groundwater estimate to an in situ estimate shown later in the paper.

[7] Another concern regarding the OM soil moisture data are their representativeness. Because the water table is relatively shallow in Illinois, the ISWS soil moisture measurements (which span the upper 2 m) effectively represent the entire unsaturated zone, and therefore the separation of the GRACE total column water storage is relatively straightforward in this case. In Oklahoma, however, where the mean water table depth is usually tens of meters deep, there are significant variations in unsaturated zone water storage below 75 cm depth (the deepest OM sensor depth) that are not captured by the OM soil moisture sensors. We address this issue here by utilizing an empirical method for estimating deeper soil moisture from near-surface observations, before creating a more robust residual groundwater estimate. Because the groundwater estimate is the residual term in a water balance equation, failure to sample the total

unsaturated soil moisture signal will lead to greater errors in our groundwater estimate. The method we describe to account for deeper soil moisture is applied here to the region of the Southern Great Plains of the U.S., but is applicable to other observational data sets, whether in situ or remotely sensed, that may not fully sample the variability present in the unsaturated zone.

2. Data

2.1. GRACE

[8] The GRACE satellite mission, jointly sponsored by NASA and its German counterpart DLR, has been collecting data since mid-2002. The nominal product of the mission is a series of monthly Earth gravity fields [*Tapley et al.*, 2004]. However, by exploiting the direct relationship between changes in the gravity field and changes in mass at the Earth's surface, the month-to-month gravity variations obtained from GRACE can be used to make global estimates of vertically integrated terrestrial water storage with a spatial resolution of a few hundred km and greater, with higher accuracy at larger spatial scales [*Wahr et al.*, 2004; *Swenson et al.*, 2003].

[9] GRACE data have been used in a number of studies to estimate water storage variability, e.g., to estimate terrestrial water storage variations from the scale of large river basins [*Crowley et al.*, 2006; *Seo et al.*, 2006] to the continents [*Schmidt et al.*, 2006; *Tapley et al.*, 2004], for estimating groundwater storage variations [*Rodell et al.*, 2006; *Yeh et al.*, 2006], for ice sheet and glacier mass loss studies [*Velicogna and Wahr*, 2006; *Tamisiea et al.*, 2005] and for estimating hydrologic fluxes including evapotranspiration [*Rodell et al.*, 2004], precipitation minus evapotranspiration [*Swenson and Wahr*, 2006b], and discharge [*Syed et al.*, 2005].
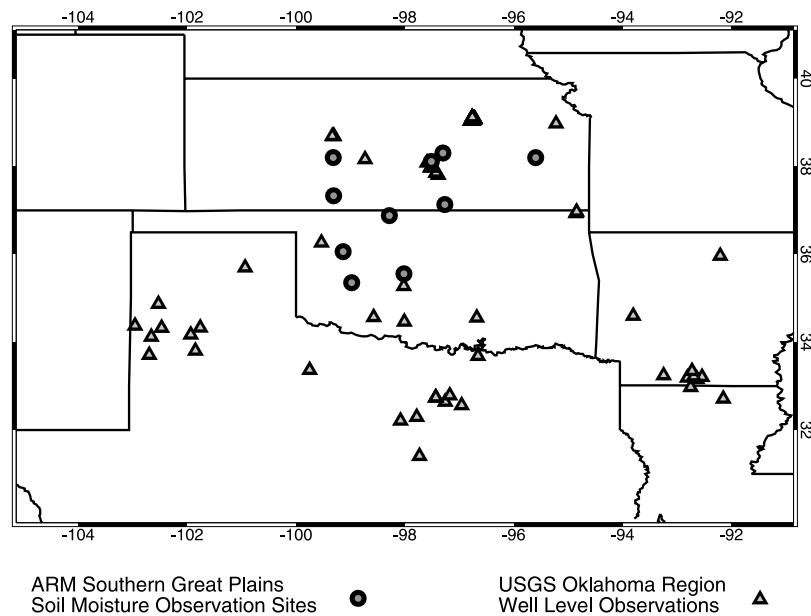
Figure 2. Map showing locations of DOE/ARM soil moisture sites and USGS observation wells.

[10] In this study, we use Release 4 (RL04) data produced by the Center for Space Research (CSR) which incorporate numerous improvements in the gravity field determination process. Additionally, we apply the post-processing technique of *Swenson and Wahr* [2006a], which has been shown to produce water storage estimates that compare well with in situ observations averaged over a region of 280,000 km² surrounding Illinois [*Swenson et al.*, 2006].

2.2. Soil Moisture Observations

2.2.1. Oklahoma Mesonet

[11] The Oklahoma Mesonetwork (Mesonet) began in 1991 as a state-wide mesoscale environmental monitoring network [*Brock et al.* 1995; *McPherson et al.*, 2007]. Soil moisture sensors were added to 60 sites and installed at four depths (5, 25, 60, and 75 cm) in 1996 and to 43 sites at two depths (5 and 25 cm) in 1999 [*Illston et al.*, 2007]. Data are collected every 30 min and processed at the Oklahoma Climatological Survey (OCS) at the University of Oklahoma. A series of automated and manual processes maintain quality control and convert the raw data into daily average values of volumetric soil water content [*Illston et al.*, 2007]. Figure 1 shows the Oklahoma Mesonet (OM) locations used in this study, as well as the contours of the averaging kernel used to compute the GRACE water storage time series.

[12] The soil moisture sensor deployed at OM sites is the Campbell Scientific 229-L heat dissipation sensor. This sensor measures its change in temperature after a heat pulse has been introduced [*Basara and Crawford*, 2000; *Illston et al.*, 2007]. During installation of the soil moisture sensors, soil cores from each site and each depth are analyzed for the soil characteristics. Using the measured temperature difference of the sensor before and after heating (i.e., heat dissipation) and the soil characteristics, hydrological variables such as soil water content and soil matric potential can be calculated.

[13] The volumetric water content is determined from a soil water retention curve. Using detailed soil characteristics and soil bulk density measurements collected at each sensor location, soil water retention curves were estimated using the *Arya and Paris* [1981] methodology. A number of automated algorithms assess the quality of the soil moisture data. In general, the algorithms ensure that the data are reporting within operational ranges, the calibration coefficients are correct, and the soil is not frozen.

2.2.2. DOE ARM Network

[14] Significant soil water variability occurs below the deepest OM sensor depth of 75 cm. To accurately estimate a residual groundwater signal, the full contribution from the unsaturated zone must be removed from the total column signal as determined from GRACE data; any inaccuracies in the removed signal will contaminate the groundwater estimate. Observations of deeper soil moisture in this region can be obtained, although with less dense spatial coverage, from the Department of Energy's Southern Great Plains Atmospheric Radiation Measurement (DOE ARM) network [*Schneider et al.*, 2003].

[15] The DOE ARM network has 21 automated soil water and temperature systems, using the same heat dissipation sensor as the Oklahoma Mesonet, installed at locations in Oklahoma and Kansas. Called the Soil Water and Temperature System (SWATS), these systems provide hourly profiles of soil temperature and water at eight depths, from 0.05 to 1.75 m below the surface, in twin profiles 1 m apart. The average inter-site distance is about 75 km. Of these sites, 10 were found that both spanned the period 2002 to the present and passed our quality control criteria. Figure 2 shows the locations of the DOE ARM sites used in this study.

[16] Because this subset of the DOE ARM network lacks the density to adequately sample a region large enough to match the spatial sampling of GRACE, these data are not used to directly estimate the unsaturated zone signal. Instead, we used this data set as a testbed with which to answer certain questions regarding the variability of soil moisture with depth, such as "does the deeper DOE ARM network effectively capture all the variability of unsaturated
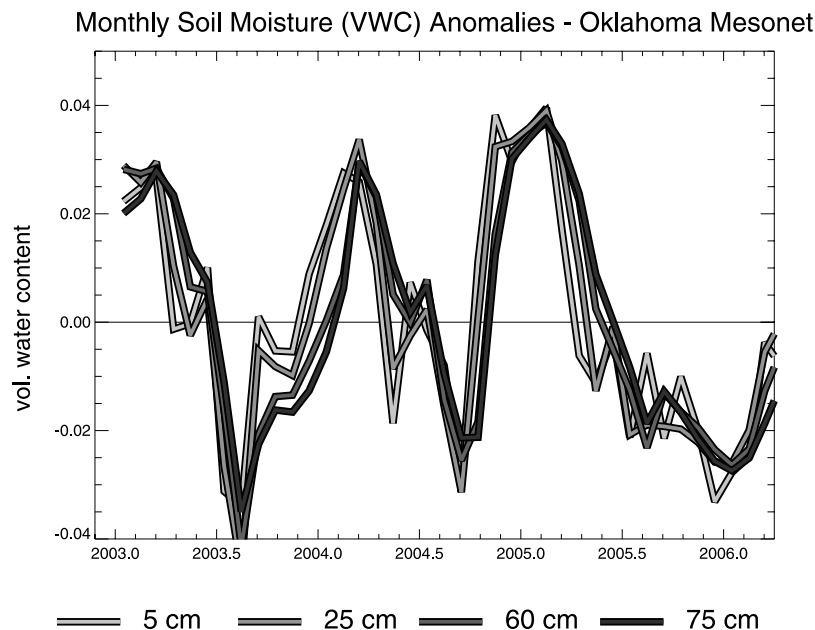
Figure 3. Regional average time series of monthly soil moisture anomalies sampled at four depths by the OM network. *X* axis is time, in years, and *y* axis is volumetric water content.

zone soil moisture?'', ''if not, can one develop a model to extrapolate these data to depth?'', and ''does such a model reveal a robust relationship between variability in near-surface soil moisture and that of the entire unsaturated zone?''. The result of this analysis, described below, is a scaling relationship between variability in the upper 75 cm to that of the entire unsaturated zone, thus allowing the estimation of a full unsaturated zone signal from the OM data.

3. Methods

3.1. GRACE

[17] Each monthly GRACE gravity field is composed of a set of spherical harmonic (Stokes) coefficients. Degree 1 terms are not part of the solution, so they are estimated from a combined land-surface/ocean model. After removal of the temporal mean and conversion of the gravity field anomalies to an equivalent water thickness, each monthly field is subjected to a two-stage filtering process by applying first the *Swenson and Wahr* [2006a] decorrelation filter, followed by a Gaussian filter with a half-width corresponding to 300 km [*Wahr et al.*, 1998]. Spatial averaging of GRACE data, via the Gaussian filter, is necessary to reduce the contribution of noisy short wavelength components of the gravity field solutions.

[18] Additionally, the effects of postglacial rebound (PGR) are also modeled and removed from the GRACE time series. PGR is the ongoing, viscoelastic response of the solid Earth to the deglaciation that occurred at the end of the last ice age. We modeled the PGR contributions to the Stokes coefficients using the ICE-5G ice deglaciation model of *Peltier* [2004], and convolving with visco-elastic Green's functions based on *Peltier*'s [1996] VM2 viscosity model.

[19] To assess the uncertainty in the filtered GRACE coefficients, the method of *Wahr et al.* [2006] is used. In brief, the temporal RMS of the high-pass filtered portion of

each coefficient is used as an estimate of the upper bound on the random component of the error. This estimate is conservative, because intraannual variations in the signal will be interpreted as error. The 1-sigma error estimates in the spatially averaged GRACE time series are then calculated from the estimates of uncertainty in the individual Stokes coefficients [*Swenson and Wahr*, 2002].

[20] To reduce the influence of errors in the monthly GRACE estimates, we construct a smoothed seasonal time series by applying a low-pass filter to the original data. The low-pass filter consists of fitting six terms (annual sine and cosine, semi-annual sine and cosine, mean, and trend) to the time series. These terms vary for different epochs due to the presence of a moving set of weights, which take the form of a Gaussian function centered on each epoch successively. The application of the low-pass filter reduces the impact of monthly errors and results in a smoothly varying time series, yet retains important interannual variability that would not be captured by examining the mean seasonal cycle for the time period spanned by the data.

3.2. Oklahoma Mesonet Data

[21] To derive a residual groundwater change estimate, a spatially averaged soil moisture estimate must be removed from the GRACE regional average time series. First, however, we need to determine whether the Oklahoma Mesonet soil moisture data capture the variability of the entire unsaturated zone.

[22] Figure 3 shows the time series of soil moisture, expressed as monthly anomalies (relative to the mean value during the period 2003–2006) of volumetric water content at each of the four depths at which OM sensors are located, averaged over all sites. A phase lag with depth can be seen, consistent with the findings of other studies [e.g., *Hirabayashi et al.*, 2003; *Wu et al.*, 2002; *Entin et al.*, 2000]. The amplitudes of the four layers, however, are quite similar, showing little dampening at 75 cm depth, implying signifi-
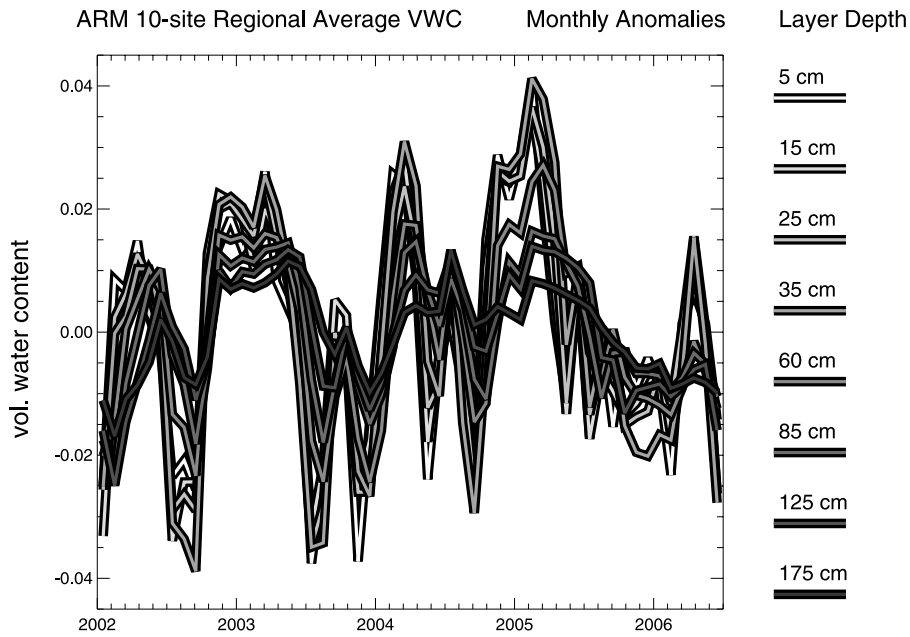
Figure 4. Regional average time series of monthly soil moisture anomalies sampled at eight depths by the DOE/ARM network. *X* axis is time, in years, and *y* axis is volumetric water content.

cant variability in deeper layers. This finding motivates our analysis of the DOE ARM data, which extends another meter to 1.75 m depth. In the following section, we examine the DOE ARM data to determine the nature of the relationship between soil moisture variability and depth in this region.

3.3. DOE ARM Data

[23] The availability of the DOE ARM data allows us to explore the depth dependence of soil moisture below the 75 cm lower limit of the OM network. As with the OM data, the hourly DOE ARM soil moisture observations at each of
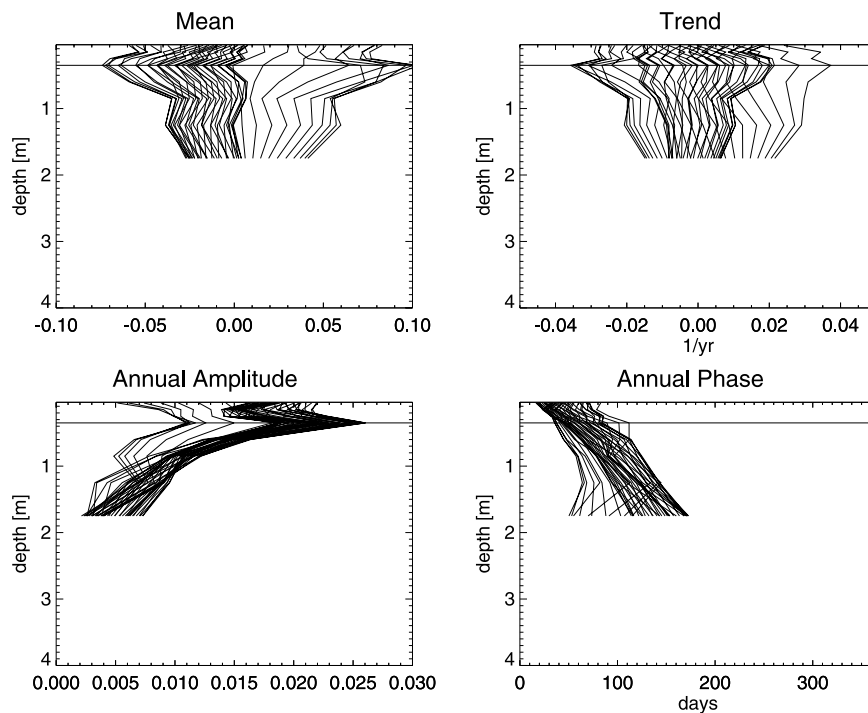
Figure 5. Spectral coefficients describing DOE/ARM soil moisture observations, plotted as a function of depth. Each line represents the coefficients of an individual monthly epoch. Upper left: temporal mean; upper right: trend; lower left: annual amplitude; lower right: annual phase. *Y*-axes are depth below surface, in meters.
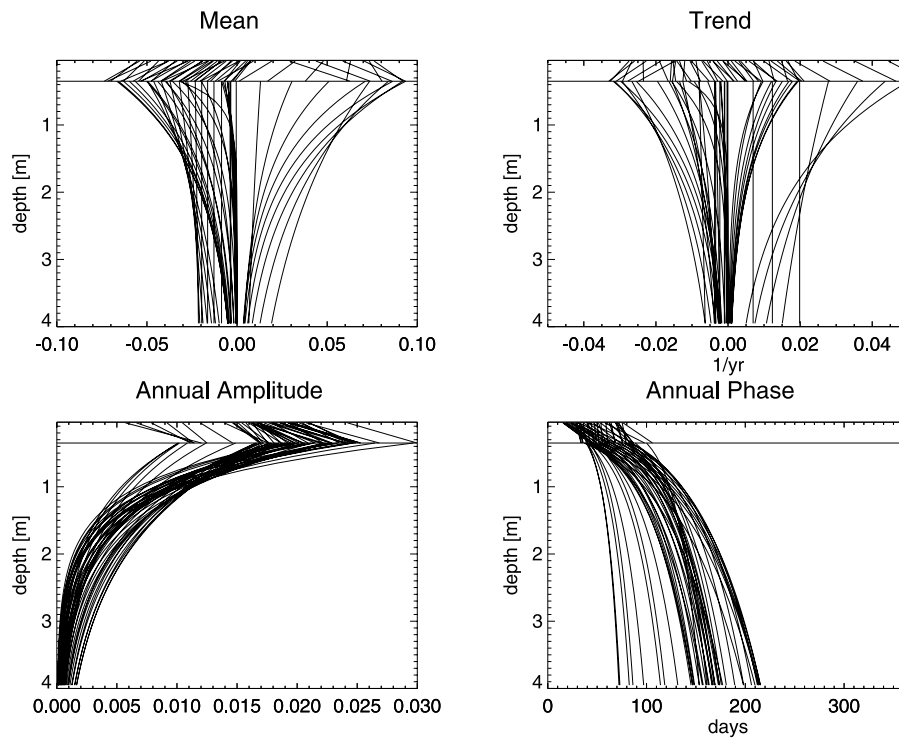
Figure 6. Empirically modeled spectral coefficients, plotted as a function of depth. Upper left: temporal mean; upper right: trend; lower left: annual amplitude; lower right: annual phase. *Y*-axes are depth below surface, in meters.

the two profiles at the ten sites are first combined to form monthly averaged time series for each of the eight layers.

[24] Figure 4 shows the monthly averaged soil moisture anomalies, expressed as volumetric water content, for each layer as a function of time. The increasing phase lag with depth seen in Figure 3 is also apparent in Figure 4. Additionally, for depths below about 20 cm, the amplitude of the signal decreases with depth, although it is still a large fraction of the amplitude in the upper layers. This implies that even below 1.75 m depth, soil moisture variability is significant. However, because the variation with depth is more apparent in the deeper DOE ARM data set, it may be possible to create a simple model with which to extrapolate these observations to depth, and so better represent the full unsaturated zone signal.

[25] To provide a clearer picture of the depth dependence of the soil moisture observations, we use a weighted spectral filter to estimate a four-term annual cycle (amplitude, phase, mean, and linear trend) at each monthly epoch. Two key aspects of the observed soil moisture variability as a function of depth are the amplitude damping and the phase lag. The spectral decomposition allows the effects of decreasing amplitude and increasing phase lag with depth to be considered independently [*Wu et al.*, 2002]. The weights take the form of a Gaussian taper with a halfwidth of three months. When the taper is centered on a particular month, the spectral filter is most sensitive to the nearest monthly epochs. The coefficients describing the annual cycle thus vary with time, and retain the inter-annual variability that would be lost by examining only the mean annual cycle.

[26] Figure 5 shows the spectral coefficients computed from the monthly averaged soil moisture values, plotted as a

function of depth. Each line represents the coefficients of each layer for a particular month. The *y* axis spans 4 m depth because it appears that the annual amplitude decays to a negligible value at about this depth (see Figure 6). From the surface to roughly 35 cm depth (denoted by a horizontal line), the mean, trend, and amplitude coefficients generally increase toward a maximum absolute value, and then decrease with increasing depth. The amplitude damping seen in the lower layers of Figure 4 is clearly expressed by the rapidly decreasing values of the annual amplitude coefficients (lower left panel of Figure 5). The phase of the annual cycle generally increases monotonically with increasing depth, corresponding to the phase lag seen in Figure 4.

[27] The relatively smooth variation with depth of these spectral coefficients indicates that it may be possible to extend the observed depth dependence with a simple parameterization. On the basis of the apparent change in behavior occurring around 35 cm depth, which may correspond to the depth at which root density takes its maximum value, we chose to model the upper layers separately from the lower layers. By isolating the well-correlated lower layers, a model of their depth dependence can be created with a minimum of parameters.

[28] For depths shallower than 35 cm, each coefficient is approximated by a linear function ($A(z) = az + b$, where A is any spectral coefficient and a and b are model parameters, z is depth). For the deeper layers, we chose two models. Mean, trend, and amplitude coefficients are modeled as exponential functions of depth ($A(z) = ae^{-z/b}$). Implicit in this choice of model is an assumption that the values of the spectral coefficients decrease with depth. This assumption is
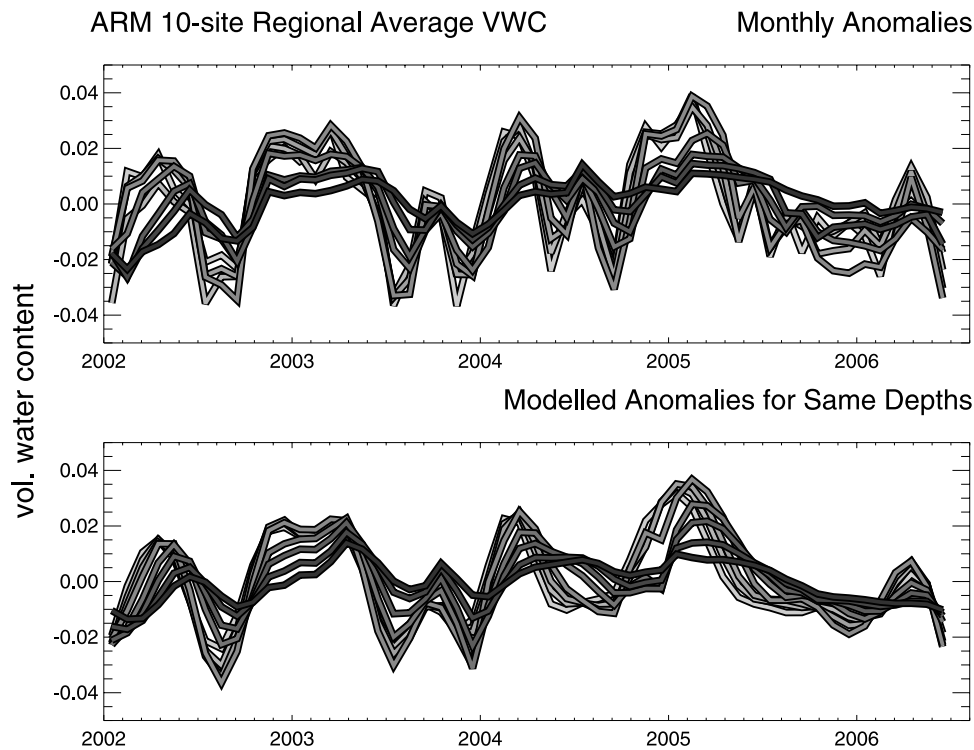
Figure 7. Top panel: same as Figure 4; bottom panel: modeled monthly soil moisture anomalies, constructed using spectral coefficients shown in 6.

not applied to the phase, whose logarithm is modeled as a linear function of depth ($ln(A) = az + b$).

[29] Figure 6 shows the results of fitting these models to the DOE ARM data. As can be seen from the lower left panel of Figure 6, the extrapolated amplitude coefficients generally decrease to near zero by about 4 m depth. The models can now be used to estimate the soil moisture variability at arbitrary depths, in particular, those depths below the deepest observations. As a test of the model's ability to reproduce the observations, we first compare the observations to the model values computed at the observation depths. The upper panel of Figure 7 shows the regional average time series for each of the eight ARM DOE depths. The model results for the same depths are shown in the lower panel. The model results in general look quite similar to the observations. The most notable differences occur in the summer of 2004 and the extended dry period seen in the second half of 2005. It is important to note that we are interested mainly in the model's description of the depth dependence of soil moisture, not its ability to render every feature of the observed time series, which includes errors of its own. The amplitude damping and phase lag with depth seen in the observed time series are both well represented by the model.

[30] The goal of this two-step modeling procedure is to determine whether a relationship exists between the variability of the soil moisture in the upper soil and the variability integrated over the entire unsaturated zone. Using the model, we now create two time series of vertically integrated soil moisture anomalies. These time series are obtained by summing the product of volumetric water content and layer depth, and therefore have units of water

thickness. One time series is computed by summing modeled soil moisture values in the upper 75 cm; this time series simulates the OM data set. The second time series includes soil moisture variations from the surface to 4 m depth, the approximate depth at which variability becomes negligible in the model. This time series represents the full unsaturated zone (UZ) signal. The upper panel of Figure 8 shows both time series. The importance of estimating deeper soil moisture is apparent in the relative amplitudes of the two time series; the full unsaturated zone signal is nearly twice that of the upper 75 cm time series.

[31] The lower panel shows the same 75 cm time series, but now overplotted with an estimate of the UZ signal that is obtained by scaling the 75 cm time series. To scale the 75 cm time series, we find the factor which minimizes, in a least squares sense, the difference between the UZ and 75 cm time series shown in the upper panel. Applying the best fit value of 1.75 for the scale factor results in a scaled time series that explains 77% of the variance of the full UZ time series. The root-mean square difference between the UZ and scaled time series is 10.3 mm, and we use this as an estimate of the errors in the scaled time series. In the next section, we will apply this scale factor to the original OM data, resulting in an estimate of the full unsaturated zone signal for the region spanned by the Oklahoma Mesonet data set.

3.4. Scaled Oklahoma Mesonet Data

[32] Because the GRACE time series represents a weighted spatial average, it is necessary to implement the same weighting when averaging the OM data into a regional average time series. In this case, a Gaussian function with a
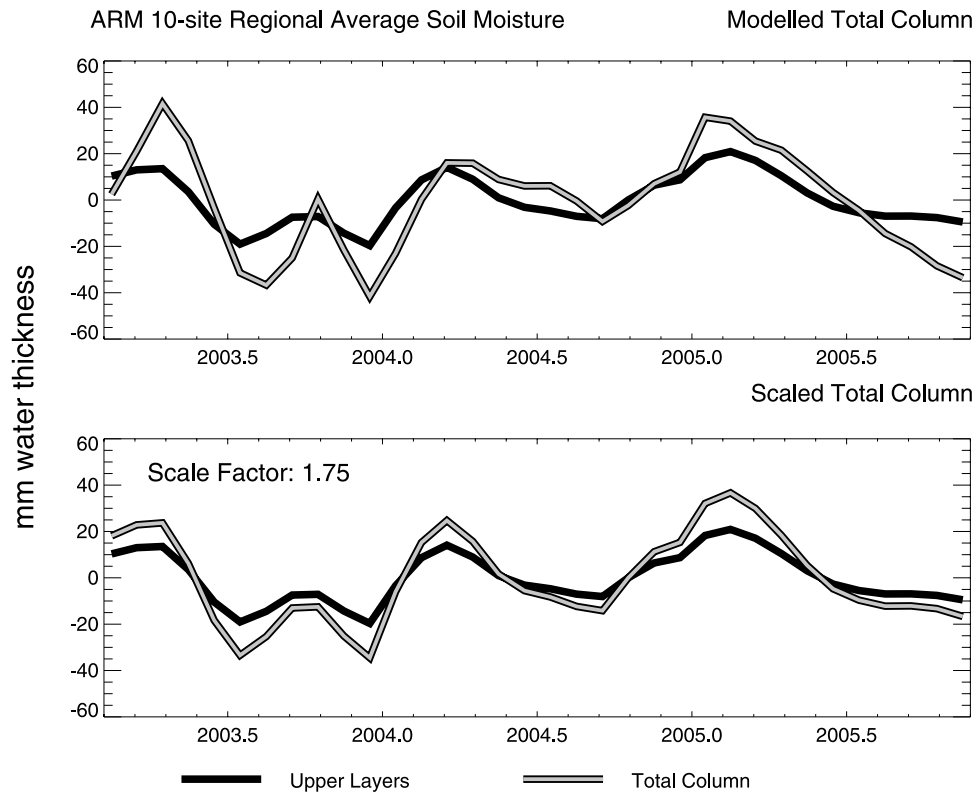
Figure 8. Top panel: modeled regional average time series of monthly total soil moisture anomalies. Black line computed from only depths of 75 cm and shallower, gray line computed from depth from 0 to 4 m. Bottom panel: Black line is the same as above, gray line computed by scaling 0−75 cm result (black line) to fit 0−4 m result (top panel gray line) via least squares. *X* axis is time, in years, and *y* axis is volumetric water content, in per cent.

halfwidth of 300 km, centered on the mean coordinates of the Mesonet stations is used. Figure 1 shows the contours of the averaging kernel amplitude. This halfwidth was chosen to keep the averaging kernel localized about the OM network, while still suppressing the higher degree errors in the filtered GRACE coefficients. After averaging the soil moisture data into monthly anomalies, the time series is low-pass filtered in the same way as the GRACE time series, and scaled using the factor derived in the preceding section. This scaled time series is then removed from the GRACE total water storage time series to obtain a residual regional average groundwater estimate.

4. Results

[33] The upper panel of Figure 9 shows the time series of monthly GRACE total water storage anomalies (circles), as well as the seasonal time series (line). The mean standard error in the monthly estimates, which includes measurement error, errors induced by the decorrelation filter, and errors in the fields used to model and remove the atmospheric gravity signal, is 11.4 mm. Plotted in the middle panel of Figure 9 are the original (0−75 cm) and scaled (0−4 m) OM soil moisture anomalies and seasonal time series. The bottom panel of this figure compares the GRACE and scaled OM time series. The phase of the GRACE and OM time series agree quite well, both peaking around February/March and

reaching a minimum near August/September. The amplitude of the GRACE time series ranges from about 100−150 mm peak-to-peak, or 1.2 to 1.7 times the scaled OM time series amplitude.

[34] By removing the scaled OM soil moisture time series from the GRACE total water storage time series, we obtain a residual time series describing regional groundwater variations. The upper panel of Figure 10 shows the monthly and seasonal GRACE-OM groundwater time series. We assume that the errors in the GRACE and scaled OM time series are uncorrelated, resulting in a total error of 15.3 mm in the monthly values. The peak amplitude generally occurs later than either the GRACE or OM time series by 4−6 weeks. The peak-to-peak amplitude is comparable to that of soil moisture, ranging from 40 to 80 mm. This partitioning of the total water storage nearly equally between soil moisture and groundwater is consistent with water balance studies of Illinois [*Rodell and Famiglietti*, 2001; *Swenson et al.*, 2006].

[35] The middle panel of Figure 10 represents our best effort at confirming the results shown in the upper panel. Because neither the USGS nor the Oklahoma Water Resources Board (OWRB) actively monitor more than a few wells on timescales shorter than a year, it is difficult to obtain well level data within the region spanned by the Oklahoma Mesonet. However, by including wells from neighboring states, it is possible to make a rough estimate of the
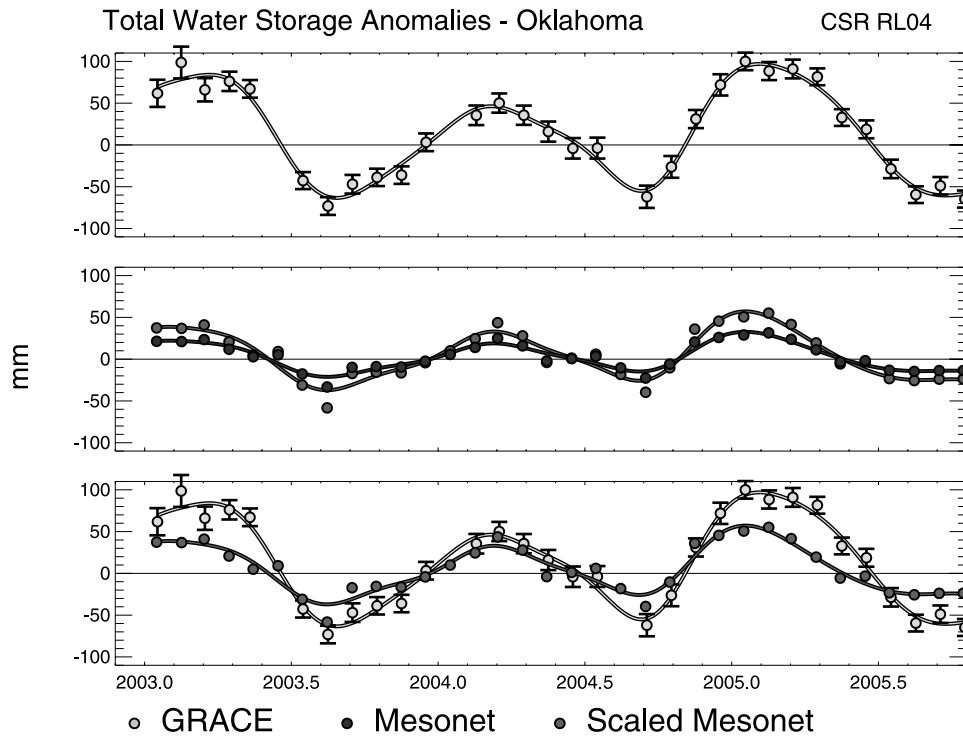
Figure 9. Top panel: GRACE regional average time series of total water storage anomalies. Circles represent monthly values, line represents seasonally varying values. Middle panel: monthly OM unsaturated zone soil moisture anomalies. Black circles represent 0–75 cm values, gray circles represent scaled 0–4 m values. Bottom panel: comparison of GRACE and scaled OM time series. X axis is time, in years; y axis is water equivalent thickness, in mm.

groundwater variations averaged over a larger region. From the USGS database, well level data were found for Oklahoma (5 wells), Northern Texas (19 wells), Southern Kansas (5 wells), and Western Arkansas (10 wells). Figure 2 shows the locations of these sites. One reason for the relatively small number of sites having usable well level data is the need for an estimate of the material composition or geologic formation where the well is located; this information can then be used to assign a value of specific yield, which is necessary to convert well level to water storage, to each well. Another constraint is the requirement that the data span some part of the period 2002 to the present. The varying time periods of these time series further necessitated the removal of temporal trends that would otherwise cause spurious offsets in the regional average.

[36] The thin lines shown in the middle panel of Figure 10 show groundwater storage estimated from the ~40 USGS well levels in the region around Oklahoma, scaled by the weight of the GRACE averaging kernel shown in Figure 1 used to create the regional average. The circles show the monthly anomalies of the regional average; the thick line shows the seasonal time series. The bottom panel of Figure 10 compares the two groundwater estimates. The well level groundwater time series (dark gray line) appears to confirm the general characteristics of the regional groundwater signal estimated as a residual from GRACE (light gray line). Both time series show a mainly seasonal cycle, and the phases of the time series agree well, giving a

correlation coefficient is 0.89 and an RMS difference is 9.1 mm.

5. Discussion and Summary

[37] Although there are significant discrepencies in both spatial and temporal sampling between the data used to create the two groundwater estimates, the overall agreement is good. Both time series show similar interannual variability: a relatively dry 2004, followed by a much wetter 2005, and the 2003 signal lying between the other years. While the smaller amplitude of the well level derived time series is not surprising based on its larger sampling area, where signals separated by larger distances are likely to be less well correlated, the degree of similarity perhaps is surprising given the dearth of well sites within the region most strongly sampled by both GRACE and the OM network. This may indicate that variations in both soil moisture and groundwater are well correlated at scales even larger than that examined here. The correlation between month-to-month changes in the two time series may also indicate that the method for estimating GRACE uncertainty is overly pessimistic, and that some of the monthly (non-seasonal) variability should be in fact interpreted as real signal, thus decreasing the GRACE error estimate.

[38] The model used to extrapolate the DOE ARM soil moisture observations to greater depths is simple and empirical. Physically based models for flow through porous media, such as the USGS VS2DI model [*Hsieh et al.*, 2000]
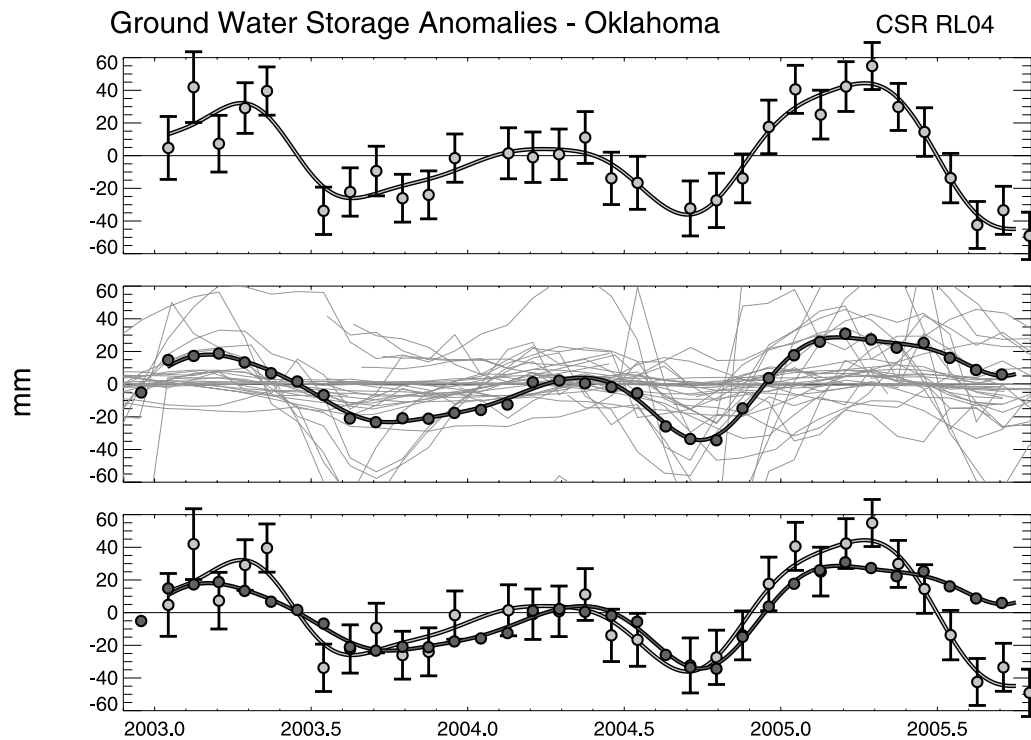
Figure 10. Top panel: regional average time series of residual groundwater storage anomalies, computed by subtracting scaled OM time series from GRACE time series. Circles represent monthly values, line represents seasonally varying values. Middle panel: monthly groundwater anomalies, computed from USGS well level observations. Thin gray lines represent individual wells, thick gray line represents regional average. Bottom panel: comparison of GRACE-OM and USGS groundwater time series. *X* axis is time, in years; *y* axis is water equivalent thickness, in mm.

could also be used for this purpose. However, such models require forcing data (e.g., infiltration, evaporation, plant-transpiration), site-specific information regarding hydraulic properties of the media, and functional relationships between moisture content, saturated hydraulic conductivity, and pressure head. Because we are ultimately interested in a simple scaling relationship between the available observations and the total unsaturated zone signal at those sites, the benefit of using sophisticated models may be small.

[39] The value of the scaling factor derived here (1.75) depends on both the vertical sampling and the climate, soil, and vegetation characteristics of the Oklahoma Mesonet and DOE/ARM soil moisture networks, and therefore may not apply elsewhere. The method we have described, however, is general, and can be used to extend data sets or synthesize data sets having insufficient vertical resolution, such as the OM, with those having insufficient lateral resolution, such as the DOE/ARM network. Furthermore, the result that over 40% of the variability in unsaturated zone water storage occurs below the deepest OM sensors should provide a note of caution to those who wish to use these and other soil moisture observations in water balance studies and/or in conjunction with GRACE data; failing to account for the entire unsaturated soil moisture signal will degrade a residual groundwater estimate much more than the errors in the data.

[40] When extensive in situ observations capable of resolving the upper soil depths are not available, physically based models may be the best means to estimate soil moisture variability in the unsaturated zone. For example, remotely sensed soil moisture in the upper few cm of soil from microwave instruments such as The Advanced Microwave Scanning Radiometer - Earth Observing System (AMSR-E) sensor aboard NASA's Aqua satellite (launched 2002) [*Njoku et al.*, 2003] or ESA's Soil Moisture and Ocean Salinity (SMOS) mission (planned for 2008 launch) [*Kerr et al.*, 2000] may help constrain unsaturated zone porous media flow models. The combination of these model simulations of the unsaturated zone could then be combined with GRACE to provide regional estimates of groundwater variability all over the globe.

[41] Given the rising demands on the Earth's freshwater resources by an ever increasing human population, questions exist on our ability to meet these demands in the future [*Dennehy*, 2005]. To better assess and manage groundwater supplies, there is a strong need to improve monitoring of these resources, especially at the regional scale [*NRC*, 2000]. Aquifer depletion occurs not just in arid regions, but in any location where they are overstressed. Although well-level measurements are the principal source of information on the hydrologic stresses felt by aquifers, water-level monitoring in the United States is fragmented and stable networks of monitoring wells exist only in some locations. Monitoring often occurs in individual states, but aquifers that cross boundaries are not subject to coordinated study [*Bartolino and Cunningham*, 2003]. Furthermore, similar to the state of surface discharge observations, [*Alsdorf and Lettenmaier*, 2003] there has been an ongoing

decrease in the number of observing wells, both nationally and globally [*Taylor and Alley*, 2001].

[42] Many of the obstacles to monitoring water resources at a variety of spatial and temporal scales may be potentially overcome through the application of remotely sensed measurements. In this study, we have combined regional total water storage anomalies estimated from GRACE with in situ soil moisture observations from the Oklahoma Mesonet and DOE ARM network to derive a monthly time series of groundwater variations spatially averaged over an area of about 280,000 km^2. This large-scale estimate complements the point estimates obtained from individual observation wells, which are subject to considerable spatial heterogeneity.

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