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Estimating soil water content in tallgrass prairie using remote sensing

PATRICK J. STARKS AND THOMAS J. JACKSON

Authors are Soil Scientist, USDA-ARS, Grazinglands Research Laboratory, El Reno, Okla. 73036, and Hydrologist, USDA-ARS, Hydrology Laboratory, Beltsville, Md. 20705.

Abstract

Increased demand for available water supplies necessitates that tools and techniques be developed to quantify soil water reserves over large land areas as an aid in management of water resources and watersheds. Microwave remote sensing can provide measurements of volumetric water content of the soil surface (θ_{vSL}) up to about 10 cm deep. The objective of this study was to examine the feasibility of inferring the volumetric water content of the soil profile (θ_{vBL}) by combining remotely sensed estimates of θ_{vSL}, in situ measurements, and modeling techniques. A simple soil water budget model was modified to estimate θ_{vBL} from assimilated values of θ_{vSL}. Four modeling scenarios were evaluated at 4 tallgrass prairie sites located in central and south central Oklahoma: 1) unmodified model, 2) assimilation of field-measured θ_{vSL} at 2-day intervals, 3) assimilation of field-measured θ_{vSL} matching dates of remote sensing data acquisitions during the study period, and 4) assimilation of remotely sensed θ_{vSL}. The unmodified model (scenario 1) underestimated measurements with root mean square errors (RMSE) between 0.03 and 0.06 m^3m^{-3} and mean errors (ME) between 0.02 and 0.04 m^3m^{-3}. Model output from scenario 2 agreed well with measurements at all study sites ($|ME| \leq 0.01$ m^3m^{-3}, RMSE ≤ 0.03 m^3m^{-3}). The RMSE and ME values from scenario 3 were comparable to those of scenario 2. Simulations from scenario 4 agreed well with measured data at 2 study sites (0.00 $m^3m^{-3} \geq$ ME ≤ 0.02 m^3m^{-3}, RMSE ≤ 0.03 m^3m^{-3}) but underestimated measurements at the remaining sites, in one case by as much as 0.15 m^3m^{-3}. The underestimation was due largely to inaccurate remotely sensed θ_{vSL} values. These preliminary results suggest that it is feasible to infer θ_{vSL} in tallgrass prairies by combining remotely sensed estimates of θ_{vSL}, in situ field measurements, and modeling, provided that the remotely sensed data correctly estimates surface conditions.

Resumen

La creciente demanda del suministro de agua disponible necesita que se desarrollen herramientas y técnicas para cuantificar las reservas de agua en el suelo en grandes extensiones como una ayuda en el manejo de los recursos de agua y las cuencas hidrológicas. Los sensores remotos de microondas pueden proveer de medidas del contenido volumétrico de la superficie (θ_{vSL}) hasta cerca de 10 cm de profundidad. El objetivo de este estudio fue examinar la factibilidad de inferir el contenido volumétrico de agua del perfil del suelo (θ_{vBL}) al combinar las estimaciones de sensores remotos de θ_{vSL}, mediciones in situ y técnicas de modelaje. Un modelo simple de las reservas de agua se modifico para estimar θ_{vBL} a partir de valores asimilados del θ_{vSL}. Se evaluaron cuatro escenarios de modelaje en cuatro sitios de pradera de zacates altos localizados en las regiones central y sur-central de Oklahoma: 1) El modelo sin modificaciones, 2) la asimilación de mediciones de campo del θ_{vSL} a intervalos de 2 días, 3) la asimilación de mediciones de campo del θ_{vSL} concordantes con las fechas de adquisición de datos de sensores remotos durante el periodo de estudio y 4) la asimilación del θ_{vSL} a partir de sensores remotos. El modelo sin modificar (escenario 1) subestimo las mediciones con la raíz de los cuadrados medios de los errores (RCME) entre 0.03 y 0.06 m^3m^{-3} y los errores medios (EM) entre 0.02 y 0.04 m^3m^{-3}. El modelo resultante del escenario 2 concordó bien con las mediciones en todos los sitos de estudio ($|EM| \leq 0.01$ m^3m^{-3}, RCME ≤ 0.03 m^3m^{-3}). Los valores de RCME y EM del escenario 3 fueron comparables con los del escenario 2. Las simulaciones del escenario 4 concordaron bien con los datos obtenidos en dos sitios de estudio (0.00 $m^3m^{-3} \geq$ ME ≤ 0.02 m^3m^{-3}, RCME ≤ 0.03 m^3m^{-3}) pero subestimaron las mediciones en el resto de los sitios, en un caso por tanto como 0.15 m^3m^{-3}. La subestimación se debió en gran parte a que los valores del θ_{vSL} de los sensores remotos eran inexactos. Estos resultados preliminares sugieren que es posible inferir el θ_{vSL} en las praderas de pastos altos mediante la combinación de estimaciones del θ_{vSL} obtenidas a partir de sensores remotos, mediciones de campo en el sitio y modelaje y que los datos de sensores remotos estimaron correctamente las condiciones de la superficie.

Key Words: hydrology, microwave, water budget

Rangelands comprise over 60% of the land area of the 48 contiguous states, and agricultural, industrial, recreational, and municipal water supplies in many areas of the U.S. are linked directly to rangeland watershed management (Spaeth et al. 1996). An important part of the water budget of any watershed is the amount of water stored in the soil. Although soil water accounts for only about 0.0001% of the total water on earth, it is a key component in describing the transfer and distribution of mass and energy between the land surface and the atmosphere, it exerts major influences on forage and crop productivity, and it partitions rainfall into runoff and infiltration (Islam 1996). Increased

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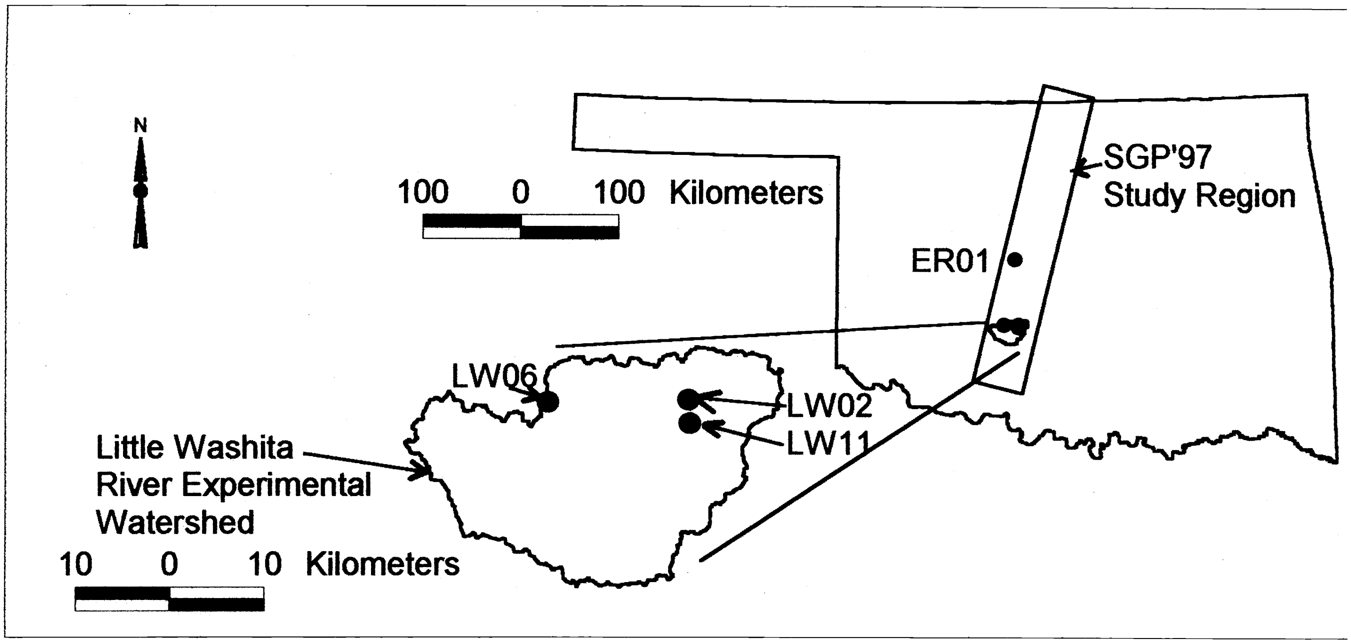

Fig. 1. Study site locations within the SGP '97 study area.

demand for available water supplies necessitates that tools and techniques be developed to quantify soil water resources over large land areas, such as rangelands, as an aid in management of water resources and watersheds. Equipping watersheds with soil water content measurement sites for routine monitoring is impractical and expensive, especially if the watershed is large or spatially variable in its topography, soil types, and vegetation cover. Remote sensing is a technique that offers potential for providing frequent measurements over large land areas in a timely and cost-effective manner.

Microwave remote sensing can provide measurements of volumetric water content (θ_v) up to about 10 cm deep, depending upon sensor type and wavelength used (Engman and Chauhan 1995). The Southern Great Plains 1997 Hydrology Experiment (Jackson et al. 1999), referred to herein as SGP '97, provides a recent example of attempts to use new microwave technologies to quantify surface soil water content (θ_{vSL}) over large, spatially diverse regions at satellite spatial resolutions. One specific objective of SGP '97, and the objective of this paper, was to examine the feasibility of inferring soil profile water content (θ_{vBL}) by combining remotely sensed estimates of θ_{vSL}, in situ measurements, and modeling techniques (SGP 1997).

Ragab (1995) introduced a simple soil water budget model designed to incorporate θ_{vSL} measurements (in situ or remotely sensed) to provide estimates of water content within the soil profile. The model requires basic meteorological data and easily obtained soil parameters, which makes it attractive for use in areas where little may be known about the underlying soils. The model was evaluated at 2 short grass pasture sites in England, and found to produce satisfactory results for those conditions (Ragab 1995), but the model was not used with remotely sensed data as input.

In this paper, remotely sensed θ_{vSL} and in situ measurements are combined in Ragab's model to estimate θ_{vBL} to a depth of 60 cm. First, the original model's ability to reproduce measured time series of θ_{vBL} is evaluated using measured meteorological, soil, and vegetation conditions at 4 experimental sites within the study area and period (18 June—16 July 1997) of the SGP '97 experiment.

Model simulations tend to drift because numerical algorithms are simplifications of complex physical processes. Because of this drift, data assimilation techniques may be employed whereby measured data are incorporated into the model to initialize or constrain the model to produce more realistic simulations. Applications of data assimilation arose within the meteorological community (Daley 1991), but the application of these techniques to remote sensing and soil water modeling is relatively new (e.g., Calvet et al. 1998, Houser et al. 1998, Wigneron et al. 1999a, 1999b; Hoeben and Troch 2000, Walker et al. 2001). A number of data assimilation techniques exist and they vary in complexity (Walker et al. 2001). The direct insertion technique is used herein to determine if assimilation of frequent, regularly-spaced field measurements of θ_{vSL} improves model estimations of θ_{vBL} compared to that provided by the original model. Next, the effect of assimilating field-measured θ_{vSL} at irregular intervals is assessed. Lastly, remotely sensed estimates of θ_{vSL} are assimilated into the model to detect the effects of remotely sensed observations of θ_{vSL} on model estimates of θ_{vBL}.

Materials and Methods

Site Descriptions

Four study sites within the SGP '97 experimental area were chosen for model evaluation. Three of the sites (LW02, LW06, LW11) were located on ARS' Little Washita River Experimental Watershed (LWREW), near Chickasha, Okla. (Lat. 34° 53' Long. 98° 07'), and one (ER01) was located at ARS's Grazinglands Research Laboratory near El Reno, Okla. (Fig. 1). All of these sites were classified as native grassland (SGP 1997) and were dominated by big bluestem (*Andropogon gerardii* Vitman), little bluestem (*Schizachyrium scoparium* (Michx.) Nash), indiangrass (*Sorghastrum nutans* (L.) Nash) and switchgrass (*Panicum virgatum* L.). Despite similari-

Table 1. Leaf area index (LAI) and biomass measurements for the study sites. These data were taken from Hollinger and Daughtry (1999).

Site	LAI	Green Standing Biomass			Brown Standing Biomass			Surface Residue (Litter)		
		Wet	Dry	Water Content	Wet	Dry	Water	Wet	Dry	Water Content
		----(gm^{-2})----		-(%-)-	----(gm^{-2})----		-(%)-	----(gm^{-2})----		-(%)-
ER01	4.7	1403	460	67	133	97	26	967	510	47
LW02	2.2	350	161	53	184	158	19	160	141	14
LW06	0.9	112	41	62	22	18	17	18	12	10
LW11	3.6	940	246	73	67	44	43	494	319	35

Table 2. Soil particle fractions and texture of the soil profile and taxonomy of the soils for each site.

Site	Sand	Silt	Clay	Texture	Soil taxonomy
	--------------- (%) ---------------				
ER01 silty,	22	60	18	Silt loam	Pond Creek silt loam (fine- mixed, thermic Pachic Argiustolls)
LW02	26	48	26	Loam	Lucien-Nash complex (loamy, mixed, thermic, shallow Udic Haplustolls)
LW06	73	17	10	Sandy loam Haplustalfs)	Dougherty loamy fine sand (loamy, mixed, thermic, Arenic
LW11	54	24	22	Sandy clay loam	Nash loam (coarse-silty, mixed, thermic Udic Haplustolls)

ties in species composition, Hollinger and Daughtry (1999) showed that other vegetation conditions varied widely between sites during the study period. For example, the leaf area index at ER01 was 4.7, while that at LW06 was 0.9. Additionally, litter mass at ER01 measured 510 g m^{-2} (on a dry matter basis), which is about 1.5 times that measured at site LW11 and 42 times that at LW06 (Table 1).

The soil profile at each site was sampled to a depth of 60 cm in 15 cm depth intervals using a coring tool with a 5 cm inside diameter. Depth intervals were divided into 7.5 cm long sub-samples. One subsample was used to determine soil texture using the hydrometer method (Day 1965). Soil texture for the total soil profile was calculated as the average of the sand, silt, and clay fractions of the four subsamples (Table 2). The remaining sub-sample was used to determine the soil water release curve at each depth interval using the procedure given in Ahuja et al. (1985). Soil water release curves allow conversion of soil matric potential (ψ), the measure of the soil matrix capillary and absorptive forces exerted on water, into estimates of θ_V. Laboratory determination of the soil water release curves provided direct measurement of bulk density and the required model parameters of θ_V at saturation (θ_{VS}), field capacity (θ_{VFC}), and wilting point (θ_{VWP}) (Table 3).

Table 3. Surface (0-5cm) and soil profile (0-60cm) volumetric soil water contents (θ_v) at field capacity (FC), wilting point (WP) and saturation (S) used in the model.

Site	Layer	θ_{VFC}	θ_{VWP}	θ_{VS}
		-------------------------	m^3m^{-3}	-------------------------
ER01	Surface	0.32	0.24	0.41
	Soil profile	0.32	0.24	0.40
LW02	Surface	0.32	0.17	0.38
	Soil profile	0.31	0.11	0.35
LW06	Surface	0.17	0.02	0.44
	Soil profile	0.17	0.02	0.41
LW11	Surface	0.29	0.05	0.38
	Soil profile	0.29	0.06	0.42

Meteorological and θ_v Field Measurements

Air temperature, rainfall, relative humidity, wind speed, incoming solar radiation, and barometric pressure were recorded at meteorological stations located at or near each study site. These data were used in a Penman-Monteith equation to calculate potential ET (ET_p) at sites LW06 and LW11. Actual ET (ET_a) was calculated at sites ER01 and LW02 using the Bowen ratio/energy balance approach (Rosenberg et al. 1983).

A Soil Heat and Water Measurement System (SHAWMS) was installed at each of the 4 sites prior to SGP '97. Each SHAWMS was placed inside a fenced enclosure measuring about 3.7 m on a side and about 1.3 m high. The vegetation within the enclosure was monitored regularly and managed to match surrounding field conditions as closely as possible. The SHAWMS instrumentation includes soil heat dissipation sensors (HDS) (Model 229, [1]Campbell Scientific, Inc., Logan, Utah) which provided hourly measurements of ψ with 3 replications at 5 cm and 1 replication each at 10, 15, 20, 25, and 60 cm below the soil surface. All HDSs were calibrated according to the method outlined in Starks (1999). Conversion of ψ to θ_V was based on the site- and depth-specific soil water release curves. The SHAWMS HDS output at 1200 hours (CST) was used to represent daily θ_V since it was nearly co-incident with the time that the remotely sensed data were obtained over the area. Measured θ_{VBL} was calculated as a weighted average of the HDS readings.

Elliott et al. (1999), Humes et al. (1999), Schneider et al. (1999), and Starks et al. (1999) found good correspondence between θ_V derived from HDSs and gravimetrically-based values, and to values obtained from various types of electronic sensors. The HDS-derived θ_V tended to overestimate gravimetrically obtained values by about 0.02 m^3m^{-3}, on average, at 3 study sites in Oklahoma (Starks 1999). When a sandy site was eliminated from the analysis, the overestimation was ≤ 0.01 m^3m^{-3}. Humes (personal communication) compared θ_V derived from both HDS and that determined gravimetrically from soil cores at a number of locations in Oklahoma and found that the HDS values

[1]Names are necessary to report factually on available data; however, the USDA neither guarantees or warrants the standard of the product, and the use of the name by the USDA implies no approval of the product to the exclusion of others that may also be suitable.

were within about 0.05 m^3m^{-3} of those obtained from the soil cores.

The HDSs tend to lose hydraulic contact with sandy soils and do not yield consistently reliable data under those conditions (Starks 1999). Therefore, at sites LW06 and LW11, gravimetric and time-domain reflectometry (TDR) measurements were used to determine θ_{vSL} and θ_{vBL}, respectively. The TDR measurements at these 2 sites were obtained daily (weather permitting) during the 16 June–18 July experimental period within 2 hours of the remotely sensed data. An Environmental Sensors' MoisturePoint TDR (G.S. Gabel Corporation, British Columbia, Canada), utilizing 4-segment profiling rods, was used to sample the soil profile at 0–15, 15–30, 30–45 and 45–60 cm. Three readings were acquired per site per layer and were averaged to represent daily θ_{vBL}. The manufacturer's stated accuracy of the TDR is ± 3% of the instrument reading.

Nine soil samples, representing the 0–5 cm surface layer, were collected once daily over a 20 m by 20 m grid at each site. Gravimetric soil water content was determined for each sample, averaged and multiplied by the respective soil's bulk density to obtain a representative value of θ_{vSL} for each site. Standard deviations of the gravimetric soil water contents ranged between 0.01 and 0.04 m^3m^{-3}.

Remotely Sensed Data

Remotely sensed images of surface microwave brightness temperatures (T_B) were acquired over the 10,000 km^2 SGP '97 study area using the Electronically Scanned Thinned Array Radiometer (ESTAR). The ESTAR is an L band, synthetic aperture, passive microwave radiometer operating at a center frequency of 1.413 GHz (21 cm) and a bandwidth of 20 MHz. The ESTAR instrument was flown onboard a NASA P3B aircraft at an altitude of 7.5 km. Postprocessing of the remotely sensed data produced a pixel size of 800 m by 800 m. Because of weather conditions and equipment failures, the ESTAR was only able to collect data on 16 days of the 29 day study period. Nominal time over target was 0930 to 1130 hours local time.

Brightness temperatures measured by ESTAR are affected by a number of surface conditions which must be taken into account before a final θ_{vSL} can be determined. Figure 2 is a diagram of the soil moisture retrieval algorithm used to convert T_B to θ_{vSL}. Input requirements for the model are soil temperature at 15 cm, vegetation type, vegetation water content, soil roughness, and soil texture. The model corrects T_B for vegetation cover and surface roughness, and then estimates the soil's dielectric constant. Soil texture effects are then taken into account before inverting the dielectric mixing model (Wang and Schmugge 1980) to provide the final remote sensing images of θ_{vSL}. For additional details of the soil moisture algorithm see Jackson (1993).

Study site latitude and longitude coordiates were used in an image processing system to locate and extract θ_{vSL} values from the ESTAR images, which were subsequently assimilated into the model.

The Model

The model is a one-dimensional soil water budget algorithm based on the force-restore concept presented by Bhumralkar (1975) for soil temperature, later adapted to soil water movement by Deardorff (1977). The model is divided into a surface layer (the remote sensing depth, 0-5 cm for this study) and a layer that extends from the soil surface to a user-defined depth (termed bulk layer by Ragab). In the remainder of this paper the term bulk layer will be used in preference to soil profile.

The model operates on a daily time step and the required meteorological data are daily values of rainfall and ET_p. The ET_p values are adjusted within the model by a stress factor to estimate ET_a. The stress factor is the ratio of actual available to maximum available soil water content. The model was modified to bypass the stress adjustment when measured ET_a values are used. Required soil parameters include depth of the surface and bulk layers; and, for each layer, θ_{vFC} (θ_v corresponding to ψ of -33 kPa), θ_{vWP} (θ_v corresponding to ψ of -1500 kPa), antecedent θ_v (initial soil water content at the beginning of the model run), and maximum and minimum model-allowed θ_v (prevents model estimates from being unrealistically wet or dry). The user can partition a portion of incident rainfall into runoff through the "surface runoff percentage" variable. This variable is initialized at the beginning of the model run and all subsequent rainfall events are partitioned in the same fashion. Since most rainfall events that occurred in this study were light, this variable was set to zero (i.e., no runoff). The "uptake ratio" variable is used to define the surface layer's contribution to ET_a. In this study the uptake ratio was set to 0.25 at all sites.

Dynamically, θ_{vSL} is determined as a function of rainfall, runoff, ET_a, and the amount of water in the bulk layer. The rate of exchange of water between the surface and bulk layer is governed by a pseudo-diffusivity coefficient (C), which depends upon surface soil texture and θ_{vBL}. The value of C at our four study sites was empirically determined by running the model at sites with similar soils and making adjustments to C until the best match between model output and measured data was achieved.

Calculation of θ_{vBL} is independent of surface layer computations and is a simple water budget requiring only daily values of rainfall, runoff, and ET. Thus, assimilation of surface θ_{vSL} measurements into the original model will not affect bulk layer calculations. Therefore the original model was re-written in order that measurements of θ_{vSL} could be assimilated into the model to infer θ_{vBL}. To this end, we adapted the statistical procedure outlined in Ragab (1995) for determining model initialization values for the bulk layer from surface measurements. This procedure utilizes site-specific linear regression equations, developed from field

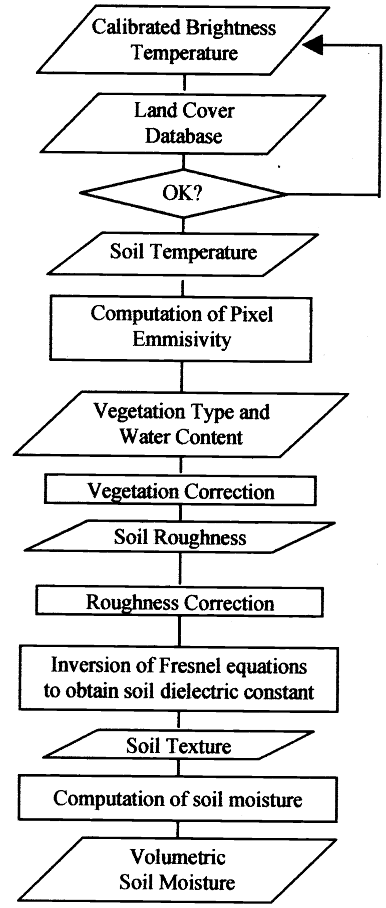

Fig. 2. Schematic of the soil moisture retrieval algorithm (adapted from Jackson, 1993).

Table 4. Slope, intercept and coefficient of determination (r^2) of linear regression equations used to convert remotely sensed surface θ_v to root zone soil water storage (mm). Root zone soil water storage is divided by depth of the root zone to estimate root zone θ_v.

Site	slope	intercept	r^2
ER01	387.76	67.13	0.60
LW02	309.58	67.02	0.74
LW06	409.96	43.21	0.96
LW11	307.96	86.33	0.90

measurements, which relate θ_{vSL} (in m^3m^{-3}) to the depth of water stored (in mm) in the bulk layer. Soil water storage values from the regression equations are divided by the bulk layer depth to yield updated values of θ_{vBL}. Correlation coefficients from the linear regressions (Table 4) are similar to those reported by Ragab (1995) for 2 soils in southern England.

The model was run for 4 scenarios. The first scenario examines the original model's ability to simulate θ_{vBL} for the meteorologic, soil, and vegetation conditions at each of the study sites. In this scenario the initial θ_{vBL} values are supplied from field-measured data. The model then produces a time series of θ_{vBL} based only upon the meteorological drivers of rainfall and ET_a and the measured soil and vegetation parameters initially supplied to the model. In the second scenario, field measurements of θ_{vSL} are assimilated into the model at 2-day intervals to determine if model simulations of θ_{vBL} are improved over that of scenario 1. The 2-day interval was chosen in response to the frequency of surface soil moisture products that may become available on future satellite platforms. For example, the European Space Agency's ENVISAT has a primary repeat coverage cycle of 35 days, but will have coverage subcycles of 1, 3, and 17 days (http://envisat.esa.int/ accessed 7 Jan. 2002). In scenario 3, field measurements are again used to update the model but only on those days corresponding to the times when the ESTAR was used to collect data during the study period. Since the ESTAR did not fly every day during the study period, this scenario examines the effect of irregular and/or infrequent data assimilation on model simulations during the study period. In the fourth scenario, ESTAR data, which represents a 800 m by 800 m spatial average of θ_{vSL}, are assimilated into the model.

Statistical Analysis

Willmott and Wicks (1980) and Willmott (1981, 1982) raised concerns about the exclusive use of r and r^2 in the context of evaluating model performance. Willmott (1981) noted that very dissimilar values of measurements and estimates can produce an *r* very near 1, while small differences between measured and estimated quantities can produce a low or even negative r (Willmott and Wicks 1980). Willmott (1982) proposed the d-index of model agreement which, when used in conjunction with other common statistical measures, aids in evaluating the accuracy of models. A d = 1 indicates complete agreement between modeled and measured values, and d = 0 indicates complete disagreement. The d-index is used herein to evaluate how well model output agrees with measured field data for each of the 4 scenarios. In addition, the mean error (ME) and root mean square error (RMSE) were used to describe the average difference between modeled and measured values and to describe the average total error in the estimating procedure, respectively. A no-intercept linear regression analysis was used to determine r^2 and regression coefficients (slope, designated β_1) between measured and modeled values. A *t*-test was used to determine if the modeled values are significantly different from measured values by testing the null hypothesis, Ho: $\beta_1 = 1$. Preliminary analy-

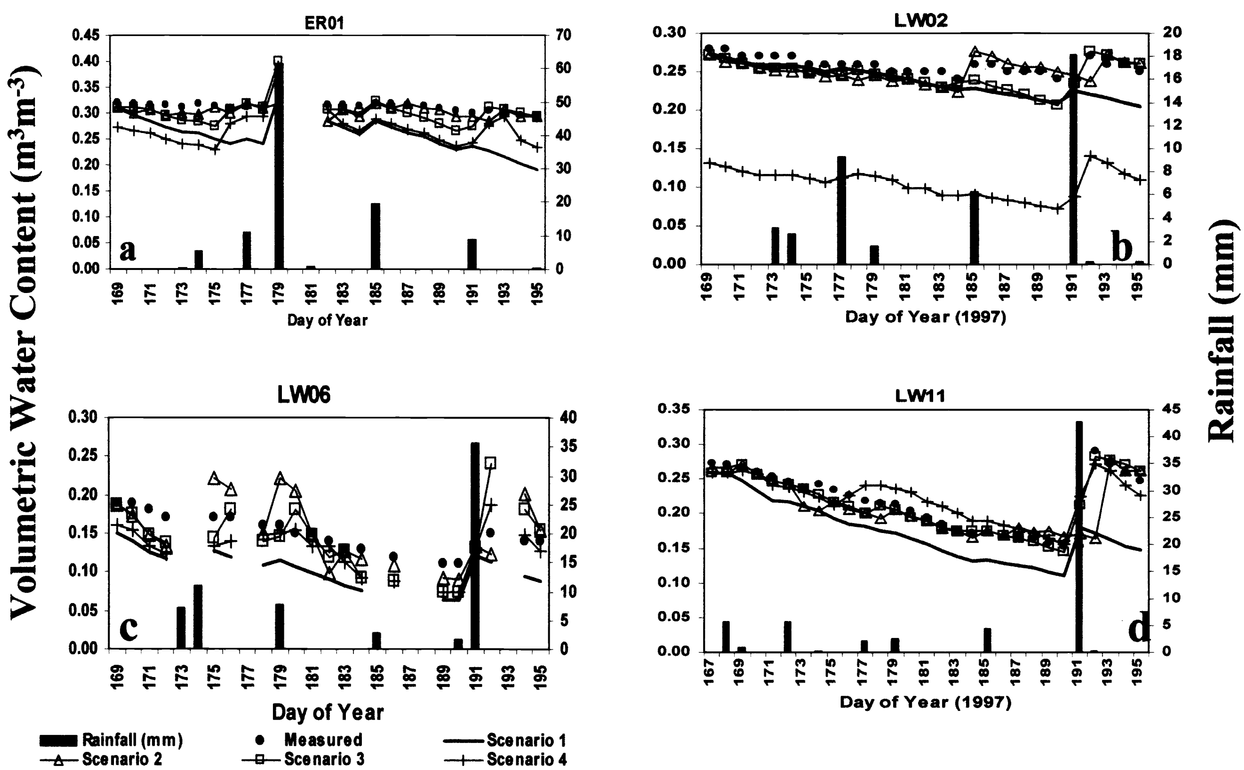

Fig. 3. Time series plots of measured and modeled bulk layer volumetric soil water content for study sites ER01 (a), LW02 (b), LW06 (c), and LW11 (d) during the experimental period. Gaps in the time series reflect days when measured values were unavailable for comparison with modeled output.

Table 5. Results from the statistical analysis of the comparison of modeled and measured bulk layer soil water content for each scenario.

	Scenario 1					Scenario 2				
Site ID	d[1]	ME[2]	RMSE	β_1	r^2	d	ME	RMSE	β_1	r^2
		-----(m^3m^3)------					------(m^3m^3)-----			
ER01	0.25	0.05	0.06	1.201**	0.990	0.58	0.01	0.01	1.028	0.999
LW02	0.52	0.02	0.03	1.088**	0.996	0.59	0.01	0.01	1.018	0.997
LW06	0.56	0.04	0.05	1.399**	0.985	0.78	0.00	0.02	1.000	0.972
LW11	0.69	0.05	0.06	1.235**	0.973	0.88	0.01	0.03	1.014	0.984
	Scenario 1					Scenario 2				
Site ID	d[1]	ME[2]	RMSE	β_1	r^2	d	ME	RMSE	β_1	r^2
		-----(m^3m^3)------					------(m^3m^3)-----			
ER01	0.37	0.01	0.02	1.021	0.995	0.23	0.04	0.05	1.142**	0.989
LW02	0.66	0.01	0.02	1.037	0.997	0.12	0.15	0.15	2.371**	0.982
LW06	0.72	0.01	0.03	0.984	0.956	0.73	0.02	0.03	1.123**	0.986
LW11	0.97	0.00	0.02	0.995	0.998	0.91	0.00	0.02	0.984	0.991

**Significant at the 0.01 level

[1]d = 1 - [Σ(Modeled - Measured)^2/Σ(|Modeled - Mean of Measured|^2 + |Measured - Mean of Measured|^2)]

[2]ME = Σ(Measured - Modeled) / n

[3]RMSE = [Σ(Modeled - Measured)^2/n]1/2

sis showed that the residual lack of fit in the no-intercept regression analyses was small and not a realistic estimate of the true error because of the extremely good fit of the model output to the measured data. Thus, an error of 0.03 m^3m^{-3} in the HDS and TDR measurements is assumed and is used as an approximation of the standard error of the estimate in the *t*-equation. Since the study objective relates to the bulk layer, only the results from that layer are reported.

Results

Scenario 1 - Original Model

The range of measured θ_{vBL} over the course of the study period was about 0.04 m^3m^{-3} at sites ER01 and LW02, 0.08 m^3m^{-3} at LW06, and 0.14 m^3m^{-3} at LW11. These ranges of measured θ_{vBL} represent 50, 20, 93, and 61% of the total plant available water (defined as the difference in water content at field capacity and wilting point) at these sites, respectively. Time series simulations from the original model exhibit the general patterns portrayed by the measured data, but the model consistently underestimated measured values at all sites (Figs. 3a–3d). The differences between measured and modeled θ_{vBL} generally increase with time at sites ER01 and LW02, while at sites LW06 and LW11 there appears to be a constant offset or bias in the model simulations (Figs. 3a–3d).

The r^2 values indicate that the variation in the modeled values is strongly associated with the variation in the measurements at all sites (Table 5), but the β_1 are significantly different from a slope of 1, indicating that the modeled output does not approximate measured values well. The d-index (Table 5), however, indicates weak agreement between measured and modeled values at ER01, moderate agreement at sites LW02 and LW06, and stronger agreement at LW11. The ME reveals that the model underestimated measured values from 0.02 m^3m^{-3} at site LW02 to 0.05 m^3m^{-3} at site ER01. Only site LW02 had a RMSE $\leq$ 0.05 m^3m^{-3}.

Scenario 2

Assimilation of field-measured θ_{vSL} values into the model at frequent, evenly-spaced intervals brings the model estimates of θ_{vBL} into close agreement with measured values (Figs. 3a–3d). Neither the steadily increasing differences or constant offset from measured values noted in the simulations of scenario 1 is observed here.

The d-index increased at all sites, with the greatest improvement observed at ER01. At all study sites, the RMSE were $\leq$ 0.03 m^3m^{-3}, a two-fold reduction at each site compared to scenario 1 (Table 5). The absolute values of ME were all $\leq$ 0.01 m^3m^{-3}, a reduction of at least 0.04 m^3m^{-3} at all sites, except at LW02 where the ME was reduced by 0.01 m^3m^{-3}. The β_1 values at all sites were not significantly different from a slope of 1, indicating that the model output closely approximates the measured values.

Scenario 3

Assimilation of field-measured θ_{vSL} into the model at irregular intervals produced mixed results. At site ER01, the d-index decreased considerably in comparison to scenario 2, although the ME remained unchanged and the RMSE increased by only 0.01 m^3m^{-3} to 0.02 m^3m^{-3} (Table 5). Comparison of the time series plots (Fig. 3a) shows that scenarios 2 and 3 produced similar output except during consecutive days when assimilation data were unavailable (DOY 172-175, 185-191). At site LW02, the d-index increased slightly over that observed in scenario 2, the ME remained unchanged and the RMSE increased by 0.01 m^3m^{-3}. The largest discrepancies between measured and modeled data at site LW02 occurred during the 7 days from DOY 185–191 (Fig. 3b) when field measurements of θ_{vSL} were not available to the model. The effect of assimilating θ_{vSL} data at irregular intervals had a small negative effect at site LW06 (Fig. 3c) as indicated by a slight decrease in the d-index and an increase of 0.01 m^3m^{-3} in the ME and RMSE (Table 5) over that observed in scenario 2. At site LW11 (Fig. 3d) the d-index (Table 5) indicates near-perfect agreement between modeled and measured values. Additionally, the ME and RMSE decreased by 0.01 m^3m^{-3} from those observed in scenario 2. It should be noted that the statistical analysis from this scenario shows improved simulations at all sites over that obtained in scenario 1; all d-indices are larger and all ME and RMSE values smaller than their counterparts in scenario 1. As in scenario 2, the β_1 values were found to be statistically similar to a slope of 1.

Scenario 4

Model output at sites ER01 and LW02 did not agree well with measured data (d-index $\leq$ 0.23) (Figures 3a–d, Table 5). At site ER01, both the ME and RMSE increased by 0.03 m^3m^{-3} over that observed in scenario 3. Regression coefficients at these 2 sites are statistically different from a slope of 1, suggesting that modeled θ_{vBL} does not adequately approximate measured values. At site LW02, assimilation of remotely sensed θ_{vSL} into the model produced ME and RMSE values larger than any others encountered in the study. In contrast, the d-index, ME and RMSE values at sites LW06 and LW11 are comparable to those in scenarios 2 and 3, indicating good agreement with measured values. However, the β_1 at LW06 is statistically different from a slope of 1.

Summary and Conclusions

The objective of this paper was to examine the feasibility of inferring θ_{vBL} by combining remotely sensed estimates of surface water content, in situ measurements, and modeling techniques. The model of Ragab (1995) was selected for this study because of its simplicity and because it does not require detailed soil physical and hydraulic and vegetation properties to parameterize the model–properties that are not generally available or easily measured over large and/or spatially variable watersheds. This is particularly advantageous for applications where little is known about an area's soil physical properties, since the required model inputs may be estimated from general soil texture information (e.g., Rawls et al. 1982).

The original model was able to reproduce the time series patterns of θ_{vBL}, but consistently underestimated measured values from 0.02 to 0.05 m^3m^{-3}, on average, depending upon study site. Under-estimation of θ_{vBL} may be a result of overestimation of daily ET_a. The simplistic stress factor adjustment used in the model, to reduce the user-supplied daily ET_p values to more closely approximate ET_a, is calculated as the ratio of actual water available in a given layer of the soil to the maximum amount of water that layer could hold. This adjustment algorithm does not explicitly take into account the various resistances that may reduce the flow of water from the soil, through the plant and into the atmosphere. At 2 study sites, measured values of ET_a were used in place of ET_p, and the stress factor adjustment bypassed in the model. Even at these sites, ET_a may have been overestimated since the values supplied from the Bowen ratio measurements may have reflected contributions from below the 0–60 cm layer that was modeled.

Since numerical algorithms are approximations of complex physical processes, the model was re-written to determine if assimilation of θ_{vSL} observations could improve model estimates of θ_{vBL}. The data assimilation technique used either field-measured or remotely sensed θ_{vSL} values in site-specific linear regression equations to infer θ_{vSL} within the model. When field observations of θ_{vSL} were assimilated at regular and frequent intervals (scenario 2), the model simulations were improved and model output agreed well with measurements at all sites. When the field observations were assimilated at irregular intervals (scenario 3), model output agreed well with measured data at all but 1 site. However, scenario 3 simulations at all study sites showed improvement over that provided by the original model (scenario 1). In general, assimilation of field-measured θ_{vSL} into the model resulted in θ_{vSL} estimates that compared well to measured values.

Remotely sensed observations of θ_{vSL} were assimilated into the model to determine the effects on estimation of θ_{vBL} (scenario 4). Modeling results at sites LW06 and LW11 were similar to those produced by scenarios 2 and 3 (i.e., good agreement between measured and modeled values as indicated by the d-index, ME and RMSE statistics). Results from the *t*-tests showed that the β_1 obtained at LW06 was statistically different from a slope of 1, suggesting that the modeled output did not agree well with the measured data. The reason for this is not clear since the statistics (d-index, ME and RMSE) from scenario 4 are very similar to those from scenario 3 at this site. It is not likely that the vegetation adversely affected the remotely sensed data (discussed below) because LW06 had the lowest leaf area index of all the study sites. It is possible that the measured θ_{vBL} data (obtained at a point) did not adequately represent the 800 x 800 m area observed by the remotely sensed data.

When remotely sensed data were assimilated into the model at sites ER01 and LW02, the model output underestimated measurements throughout the study period. At site ER01, the modeling results were similar to those observed in scenario 1, but the simulation at site LW02 underestimated measured values by about 0.15 m^3m^{-3} throughout the study period. Underestimation of θ_{vBL} at these 2 sites is apparently a result of vegetational effects on the ESTAR data. Jackson et al. (1999) noted that tall grasses and heavy litter deposits will cause the ESTAR moisture retrieval algorithm to underestimate θ_{vSL}. Site ER01 was the most densely vegetated of the study sites and possessed the heaviest litter layer. Although site LW02 was classified as a rangeland site, there are a number of trees in the area and, like tall grasses and dense litter layers, trees lead to underestimation of ESTAR θ_{vSL}. Thus, assimilated remotely sensed θ_{vBL} values from these sites probably led to underestimated bulk layer values. Jackson et al. (1999) indicated that adjustments to vegetational aspects of the ESTAR soil moisture retrieval algorithm can be made to better account for litter and trees. These adjustments will be necessary if microwave-based remote sensing techniques are to be widely used to assess soil water content. The results from scenario 4 suggest that it is feasible to infer θ_{vBL} in tallgrass prairies by combining remotely sensed observations of θ_{vBL} into a soil water budget model, provided that the remotely sensed data has not been corrupted by vegetational effects.

The assimilation procedure used in this study was based upon a linear regression approach suggested by Ragab (1995) for determining bulk layer model initialization values from surface measurements. This approach is simple, and worked well at the study sites over the course of the study period, but the approach is empirical and may not produce satisfactory results over longer periods or in the presence of layered soils (e.g., sandy textured surface soil overlaying clay). An alternate approach would be to use a multiple regression equation that would take into account time since the last rainfall event, precipitation amount, and soil texture. The linear equations developed here should not be expected to apply to other locations having different soil, vegetation, and climate conditions.

A remote sensing/modeling approach such as that described above could be integrated with weather forecasts and/or climate outlooks to project future soil water supplies, as well as assessing the current status of soil water content. Such assessments and predictions could be used by agricultural producers and others to schedule irrigation and predict crop or forage production rates, and by water resources managers to better manage watersheds and surface, soil, and groundwater water resources.

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