Relationship between topsoil and subsoil moisture content for various land uses

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Abstract

The ability of remote sensing to detect surface parameters at temporally and spatially consumable resolutions provides a potential avenue to estimate subsurface moisture based upon surface attributes. This paper explores the estimation and depth of moisture at the near surface and within the soil profile along with the physical and environmental relationships which influence the two for the agriculturally dominated state of Nebraska, United States. Root zone moisture content is estimated from five models based upon the evaporative fraction, surface moisture, temperature, and vegetation indices. A state-wide evaluation of ASCAT surface moisture index for ET Look root zone moisture estimation consisting of 45 stations representing various land types is performed. In addition to the ET Look model, three additional sets of root zone moisture estimations based upon a model relating soil moisture and evaporative fraction are included in this study, along with an adjusted model. Root zone depth is approximated by comparing subsurface moisture estimations to moisture profile simulations from the agro-hydrology model SWAP for three case study locations. The three case studies provide a basis for evaluating the models over varying land cover and water management schemes to resolve the hurdles which deter remotely sensed root zone moisture estimation from near surface factors.

Keywords: *Root zone soil moisture, SWAP, ASCAT SWI, ETLook, Evaporative fraction*

1. Introduction

Soil moisture is an integral flux of the land-atmosphere interface. It is responsible, in part, for the partitioning of mass and energy between the two boundaries (Jackson 1993; Robinson et al. 2008; Betts et al. 1996) and is variable in both space and time (Bell et al. 1980). Although it amounts to only ~0.001% of total water reserves and ~0.05% of freshwater reserves globally (Shiklomanov 1993; Dingman 2015), it is considered as one of the “Essential Climate Variables” (GCOS 2010). It is essential to understanding changes in climate as moisture content within the subsurface impacts both plant stress and productivity.

In order to effectively manage freshwater resources, the United Nations General Assembly recognizes the implementation of integrated water resources as one of the 17 Sustainability Development Goals to be achieved by 2030. One of the targets for achieving Sustainability Development Goal 06 (SDG06) is to reduce water stress (United Nations 2015). Water stress is linked to an over-reliance on freshwater resources and irrigation is a factor that intensifies water stress. The practice of integrated water resources management requires the sustainable allocation of water resources. Approximately 70% of global freshwater withdrawals are used to satisfy irrigation demands (Food and Agriculture Organization 2014). Knowledge of moisture availability in terms of quantity, depth, and timing is compulsory for the implementation of sustainable irrigation practices. Accurate estimation of soil moisture resources will improve water management by accounting for where and when the content is available.

This research focuses on determining local differences in agro-ecology as well as climate which impact soil moisture within the soil profile. The relationship between topsoil and subsoil is to be studied to provide a basis for evaluating subsurface moisture estimations. Identifying the factors which influence moisture content provide an avenue for improving and/or suggesting subsurface moisture estimation models. Various models will be compared to determine whether the models can be applied universally or are applicable to certain agro-ecological conditions.

Specific Research Questions

- What are the relationships between surface and subsurface soil moisture,
- How do physical and climatological changes influence moisture variability,
- Does the remotely sensed ASCAT SWI represent topsoil moisture well,
- Can SWAP simulate moisture within the soil profile to estimate subsurface moisture and evaluate the depth of estimated moisture content,
- Can root zone moisture content be estimated using the relationship between evaporative fraction and topsoil moisture content?

2. Study Area

The Texas A&M University (TAMU) North American Soil Moisture Database provides open-source access to soil moisture data from throughout the United States, Canada, and Mexico (Texas A&M Geoservices 2013). The Nebraska subnetwork is selected due to the availability of processed daily vegetation index and land surface data from the National Aeronautics and Space Administration's (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS) for the period of 2007-2010.

Merritt, Concord, and Grand Island are selected as case study sites to provide a variation of land cover types (natural pasture, maize) and agricultural water management schemes (rainfed, irrigation). Figure 1 depicts the locations of Nebraska stations available within the TAMU network along with the selected three case study sites. Land use and cover provided for Nebraska is provided by a historical land use categorization by the University of Nebraska for 2005 (Univeristy of Nebraska Lincoln 2007).

Climate parameters including air temperature, wind, surface pressure, are provided on an hourly basis from the North American Land Data Assimilation System Phase 2 (NLDAS-2) primary forcing data (FORA0125). NLDAS FORA0125 is available at approximately 14 km spatial resolution (NASA 2017). Sub-daily downward longwave radiation data is provided by the Climate Forecast System Reanalysis (CFSR) at about 38 km resolution (National Centers for Environmental Prediction 2017). Daily precipitation data is available by way of the Climate Hazard Group InfraRed Precipitation (CHIRP) data archive at 5 km (Climate Hazards Group 2016). Mualem van Genuchten soil physical properties are available from the Hihydrosoil database at 1 km resolution from FutureWater (de Boer 2016). Soil content and classification is provided by TAMU (Texas A&M Geoservices 2013) and confirmed via soil surveys that also provide information regarding the nature of surface ponding and runoff (United States Department of Agriculture 2016). Downscaled MODIS Normalized Difference Vegetation Index (NDV) and Land Surface Temperature (LST) are provided on a scale 1 km (Espinoza-Dávalos et al. n.d.).

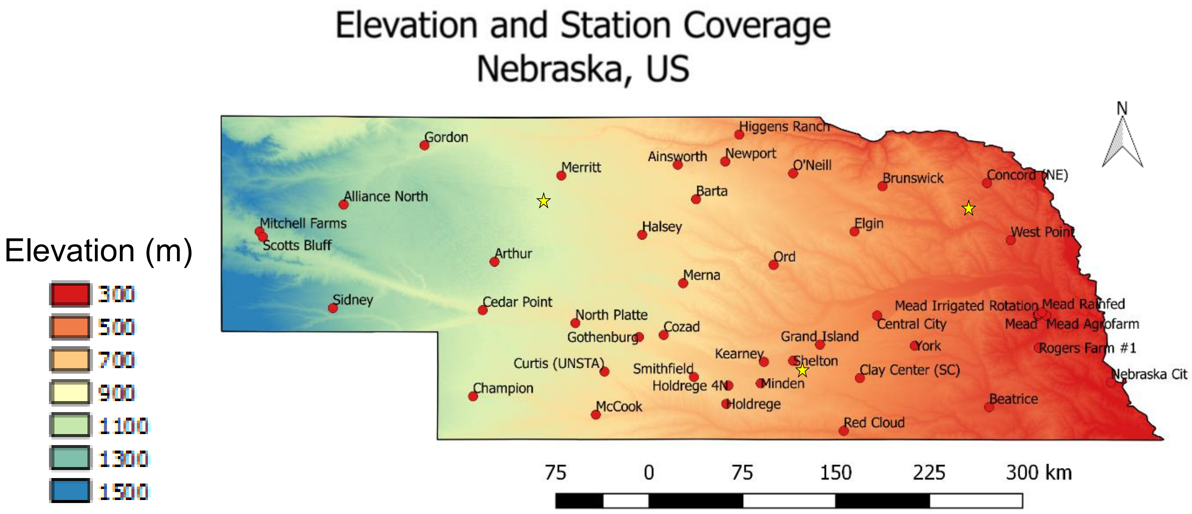

Figure 1 Map of Nebraska featuring TAMU network stations and elevation data.

2.1. Merritt, Nebraska: Rainfed Pasture

Merrit, Nebraska represents natural land use, vegetation cover, and low moisture conditions. The moisture range is consistently between 0.05- 0.2 cm^3/cm^3 volumetric moisture content and precipitation low with an average of 87 cm per year (Texas A&M Geoservices 2013; Climate Hazards Group 2016). Soil record provided in Table 2 indicates a profile consisting of sandy horizons (Texas A&M Geoservices 2013).

Concord, Nebraska represents rainfed agricultural land use for maize production. Moisture availability is higher than at Merritt although average precipitation is nearly 10 cm lower at 78 cm (Climate Hazards Group 2016). Higher moisture content (0.15 – 0.4 cm3/cm3 within the first 100 cm) could be due to the moisture higher retention property silt, which is the predominant soil constituent at 67% (Texas A&M Geoservices 2013). Surface moisture is unlikely to pond or runoff (United States Department of Agriculture 2016). LST features an atypical trend in 2009, and is likely due to uncertainties regarding the daily downscaling from biweekly MODIS data.

Table 1 Merritt Soil Physical Observations from the TAMU network.

Case Study Descriptions

	Merritt				**Concord**				**Grand Island**			
Depth (cm)	10	25	50	100	10	25	50	100	10	25	50	100
Sand (%)	96.3	96.3	96.3	96.3	11.3	11.3	11.3	11.3	27	27	27	27
Silt (%)	0.7	0.7	0.7	0.7	67.7	67.7	67.7	67.7	54	54	54	54
Clay (%)	3.0	3.0	3.0	3.0	21.0	21.0	21.0	21.0	19.0	19.0	19.0	19.0
Soil Type	s	s	s	s	sl	sl	sl	sl	si	si	si	si
Elevation (m)	948				445				507			
Latitude (˚)	42.45				42.38				40.88			
Longitude (˚)	-100.90				-96.95				-98.50			

*Sand (s), Silt (si), Silt loam (sl)

Grand Island, Nebraska represents irrigated agricultural land use for maize production. Moisture content within the top 100 cm lies between 0.15 – 0.40 cm3/cm3. At 77 cm, annual precipitation is only 1 cm less than under the rainfed maize condition at Concord (Climate Hazards Group 2016). Soils are predominantly silt, but have more clay and sand content than Concord (Texas A&M Geoservices 2013). Ponding and runoff are absent within the region (United States Department of Agriculture 2016). Table 1 provides a summary of the local environmental conditions at Merritt, Concord, and Grand Island.

3. Soil Moisture: Relationships and Remote Sensing

3.1 Soil Physical Properties and Moisture Content

Soils are neither static in space nor time. Deviation from traditional land use and/or land cover can lead to dramatic changes in topsoil properties. For instance, the transformation of pasture to cropland alters the soil matrix through changes in capillary structure. Disruption of the natural bioaccumulation process alters topsoil content and thickness. In addition, agricultural techniques to improve planting efficiency or promote biomass production also leads to physical changes in topsoil. The use of heavy or automated sowing machinery, rotation of crops, application of supplemental topsoil, or the practice of tilling alters soil matrix structure and capillary size. Changes to the topsoil may lead to variations in retention and capacity within the entire profile (Hillel 2004; Zhang et al. 2014; Manyiwa & Dikinya 2014).

Soil-specific parameters describe soil moisture retention, capacity, and flow. These properties are commonly referred to as the Mualem van Genuchten (MVG) parameters after the pore-size distribution model introduced by Mualem and the water-retention function presented by van Genuchten in 1976 and 1980, respectively (van Genuchten 1980). The six MVG parameters include θ_r θ_s, K, α, n, and m. Upper and lower limits of moisture content (cm^3/cm^3) within the layer are described by the residual water content, θ_r and saturated water content, θ_s. The ease in which water can flow through the soil is the hydraulic conductivity, K (cm/d). Alfa, α is the inversely related to the air-entry pressure in cm^{-1} while n corresponds to the pore-size distribution within the layer and m is the exponent in the soil water retention equation equal to 1 – 1/n. The parameters relate in the MVG hydraulic conductivity function:

Equation 1

$$K(S_e) = \begin{cases} K_o S_e^L \cdot [1 - \left(1 - S_e^{1/m}\right)^m]^2, & h \leq 0 \\ K_o & , \; h > 0 \end{cases},$$

Where h is a range of pressure heads (cm), L is the pore-connectivity parameter, the subscript $_o$ relates to the parameter at a matching point of saturation, and S_e is the effective saturation defined:

Equation 2

$$S_e(h) = \frac{\theta(h) - \theta_r}{\theta_s - \theta_r} \quad .$$

MVGs can only describe the soil physical interactions that control moisture content. Overlying vegetative conditions and climate also affect moisture uptake and replenishment, respectively.

3.2 Vegetation and Soil Moisture

Vegetation stress and productivity are driven by the availability of soil moisture (Emanuel et al. 2007). Not only is the moisture requirement variable during the vegetative development period, but the resource must also be available at an accessible depth for plant root uptake. Vegetative productivity as a function of leaf area or vegetation index reflects moisture availability within the subsurface meeting minimum vegetation development requirements (Koeksal 2008). Vegetation development as a function of root growth stage is key to understanding at what depth sufficient moisture resources are available to maintain plant productivity.

Remote sensing of surface vegetation growth is commonly performed by observing changes in a vegetation cover, for instance the Normalized Difference Vegetation Index (NDVI) or the Leaf Area Index (LAI) (Scott et al. 2003). NDVI is a contrast between the reflectance of light in the near infrared, ρ_{NIR} (841-876 cm) and red, ρ_{RED} (620-670 nm) bands (Wang et al. 2011; Kouadio et al. 2014):

Equation 3

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} \ .$$

Moderate-Resolution Imaging Spectroradiometer (MODIS) provides spatial information for vegetation monitoring at various resolutions according to band range in the electromagnetic spectrum. MODIS ρ_{NIR} and ρ_{RED} portions of the spectrum are available for download at 1 kilometer resolution every 16 days (U.S. Geological Survey 2014). Unfortunately, MODIS' temporal resolution is too coarse for direct application of NDVI to estimate volumetric soil moisture. Since MODIS is only available every 16 days, temporal downscaling must be performed to fill in data gaps. The work of Espinoza-Dávalos et al. showed that Harmonic Time Series Analysis (HANTS) can be applied to downscale NDVI and land surface temperature (LST) for 45 monitoring stations in Nebraska (Espinoza-Dávalos et al. n.d.).

3.3 Remote Sensing of Soil Moisture

Remote sensing involves the detection of changes in soil dielectric properties auxiliary information such as temperature and leaf area index to indirectly monitor soil moisture content. The use of remote sensing for soil moisture has improved greatly in terms of resolution and accuracy. Notable surface soil moisture products include the Advanced Scatterometer Soil Water Index at 12.5 km spatial resolution, the Soil Moisture Active Passive mission at varied spatial resolution (Entekhabi et al. 2010), and the Soil Moisture and Ocean Salinity Satellite (Vereecken et al. 2008; Vereecken et al. 2016). Brocca et al. (2017) suggests that dedicated evaluation of ASCAT SWI is. The product featured poor performance in Nebraska and reanalysis was considered (Brocca et al. 2017).

4. Models for Soil Moisture Estimation

Topsoil moisture content can be used to estimate subsurface moisture content using the Scott et al. relationship (2003). The work of Bett (2017) incorporated the substitution of vegetation indices the Temperature Vegetation Dryness Index (TVDI) and Water Deficit Index (WDI) for the evaporative fraction in the Scott et al. model. A separate model, the *ETLook 1.0* also aims to estimate subsurface moisture content. The latter relates subsoil moisture content to evapotranspiration and topsoil moisture. The current foci are to define depth of subsurface moisture estimations and quantify the saturation.

4.1 TVDI and WDI Methods

The TVDI is based upon the relationship of NDVI and land surface temperature (LST). TVDI is associated with soil moisture estimations as vegetation is a proxy for moisture content (Chen et al. 2011; Chen et al. 2012; Kasim & Usman 2016). Higher NDVI values are associated with a smaller range of LST while lower NDVI can be associated with a larger range of LST. This is due to vegetation growth limits such as water stress at higher LSTs. Under bare soil conditions (low NDVI) and low LST, soil moisture availability is higher. When crop biomass is high (high NDVI) and LST is low, the vegetation is well watered. Conditions with bare soil and high LST indicate residual moisture contents.

To perform the Triangle Method, the TVDI is calculated from rescaled values of MODIS NDVI and MODIS LST between 0 and 1. NDVI values below 0.2 are removed, as they represent conditions where vegetation cover is low. For LST, outliers are removed and the maximum temperature is used to scale the remaining measurements between 0 and 1. Upon scaling, LST values are sans units. Then, the relative difference between daily LST (LST_i) and minimum LST (LST_{min}) is calculated (N) and is related to the difference in LST range ($D = LST_{max} - LST_{min}$):

Equation 4

$$TVDI = \frac{LST_i - LST_{min}}{LST_{max} - LST_{min}} = \frac{N}{D}.$$

LST_{min} and LST_{max} represent values within the tails of the LST distribution (upper and lower 5%) associated with a specific NDVI value. Trendlines can be used to represent each case. Thus, the “warm edge” estimates NDVI-dependent LST_{max} and the “cold edge” approximates NDVI-dependent LST_{min}.

The WDI method relates NDVI, LST, and air. It is the ratio of the difference between measured LST and air temperature (Tair), “T_{AB}” at a daily NDVI and the range of LST-Tair difference, “T_{AC}” associated with the NDVI (Wang et al. 2011; Sun 2016):

Equation 5

$$WDI = AB/AC .$$

The WDI model is based on the principle that plant water stress can be detected as a difference between canopy and air temperature. Differences in LST-Tair and NDVI give rise to warm and cold edges and represent the four conditions: well-watered vegetation, water stressed vegetation, bare soil with residual moisture, and saturated bare soil. Table 1 provides a summary of the relationship between temperature and NDVI on moisture content.

4.2 ETLook 1.0

ETLook 1.0 model from Bastiaanssen et al. (2012) is based upon the relationship of surface moisture content and vegetation cover on subsurface moisture content. It mirrors the relationship between net radiation for the bare soil, $R_{n,soil}$ and net radiation in the canopy, $R_{n,canopy}$ as a function of vegetation growth, LAI:

Equation 6

$$R_{n,soil} = \{(1 - \propto_0)R_{short} - L_{n,long} - I\}e^{-a*LAI} ,$$

Equation 7

$$R_{n,canopy} = \{(1 - \propto_0)R_{short} - L_{n,long} - I\}(1 - e^{-a*LAI}) ,$$

From Beer's law where $\propto_0$ is the surface albedo, R_{short} is incoming shortwave radiation (W/m^2), $L_{n,long}$ is the net longwave radiation (W/m^2), *I* is the canopy interception (W/m^2), and *a* is the vegetation-specific, net radiation light extinction coefficient (Bastiaanssen et al. 2012).

To monitor the state of vegetation, changes in MODIS NDVI are compared to threshold values for fully vegetated surfaces and bare soil, $NDVI_{FV}$ = 0.8 and $NDVI_{BC}$ = 0.125, respectively. From NDVI, the state of vegetation cover (VC) is estimated:

Equation 8

$$VC = 1 - (\frac{NDVI_{FC} - NDVI}{NDVI_{FC} - NDVI_{BC}}).$$

VC is then used to estimate the Leaf Area Index (LAI), along with the same light extinction coefficient mentioned earlier, *a* which ranges between 0.40 to 0.65:

Equation 9

$$LAI = -ln(\frac{1 - VC}{a})$$

a was not expected to vary widely amongst the vegetation types included in the Bastiaanssen et al. (2012) study for India and ranged between 0.40 and 0.65. Since estimations were not readily available, a value of 0.50 was adopted to represent the local vegetation types.

From LAI and topsoil moisture saturation, θ_{top} (cm^3/cm^3), the subsoil saturation content, θ_{sub} (cm^3/cm^3) is calculated:

Equation 10

$$\theta_{sub} = 0.1LAI + (1 - 0.1LAI)(1 - \mathrm{e}^{\theta_{top}(-0.5LAI-1)}) .$$

The *ETLook 1.0* method requires knowledge of topsoil moisture content, NDVI, and *a* to calculate subsurface moisture content. Model sensitivity and uncertainty are related to the input parameter resolution and estimation accuracy.

4.3 Empirically Derived Evaporative Fraction and Soil Moisture Relationship

Subsoil moisture saturation has been empirically related to the evaporative fraction, Λ for locations in Kansas and Spain featuring grazed and ungrazed grassland as well as Mediterranean crops (Scott et al. 2003). Root zone moisture content, θ_{RZ} (cm^3/cm^3) is scaled between 0 and 1 with the curve fitting parameter, *a* = 1.0 so that the relationship is independent of soil type. θ_{RZ} is a function of Λ, the saturated moisture content (cm^3/cm^3) within the root zone, θ_s, and the curve-fitting parameter *b.* The latter is the slope of the fitted curve between the evaporative fraction and absolute soil moisture (*b = 0.421)*. When Λ is between 0 and 1.0, the soil moisture content should lie within the residual content and the saturated moisture content. The relationship is then

Equation 11

$$\theta_{RZ} = (e^{\frac{\Lambda - a}{b}})/\theta_s \,.$$

Λ is related to the energy flux as a function of the latent heat, λE, net radiation, R_N and soil heat flux, G or sensible heat flux, H as well as the Bowen ratio:

Equation 12

$$\Lambda = \frac{\lambda E}{R_N - G} = \frac{\lambda E}{\lambda E + H} = \frac{1}{1+\beta} \,.$$

4.3 Agro-hydrology SWAP Modeling

Agro- and ecohydrology models integrate local ecology with hydrology to simulate water flow. Land surface properties, meteorological factors, and land use parameters are incorporated to simulate overlying conditions and predict moisture responses. The Soil Water Atmosphere Plant model from Wageningen Environmental Research group Alterra addresses the need to integrate vegetation dynamics such as water dependency and crop development, precipitation and soil moisture content, evapotranspiration and radiation, to understand the relationships which impact ecosystems on a local level (Kroes et al. 2008). Simulation in the vertical allows for moisture inputs from precipitation and irrigation and losses due to evaporation and the atmosphere and as recharge to be simulated. Interception, evaporation, transpiration, and runoff modules allow for a simulation of the water budget.

4.4 Proposing the Root Zone Model

The Empirical model produces an evaporative fraction that is already associated with the curve fitting b parameter, which in other words is the slope of the fitted curve. The Scott et al. (2003) model estimates saturated moisture content, θ_s from topsoil moisture content θ through an exponential relationship of the evaporative fraction, the b parameter at 0.421 and a soil moisture normalizer of a = 1. Since the evaporative fraction is already related to b, it may already be internalized in within the parameter. To evaluate whether b is doubly emphasized, the Scott et al. (2003) is adjusted:

Equation 13

$$\frac{\theta}{\theta_s} = e^{\Lambda - a}$$

Adjusting the relationship should provide soil moisture estimations associated with the uppermost 50 cm. The Root Zone moisture model is based on the concept that the relationship can between evaporative fraction and soil moisture content can be described. Soil moisture sensors have a range of influence along the length of the probe and the evaporative fraction is then linked to the depths of sensor coverage for moisture content is measured. In the case of the Empirical model, the depth of sensors included in the study are between 0-50 cm. If the relationship between topsoil and subsoil moisture is determined, subsoil moisture can be estimated using the Root Zone moisture model.

4. Results and Discussions

4.1 ASCAT SWI

Estimations of topsoil moisture content from ASCAT SWI and HHS θs performed poorly at representing in situ observations during the study period 2007-2010. The target threshold of 0.05 cm3/cm3 RMSE is exceeded when in situ moisture at 10 cm is compared to estimated SWI moisture contents with and without time delay factors. ASCAT SWI products do not represent topsoil moisture well and cannot be incorporated further in the study. For the three study locations, ASCAT SWI 001 estimations according to HHS and calculated pedotransfer function θs are provided until table 8. Adopting locally calculated pedotransfer function θs did not improve ASCAT SWI 001 performance.

Table 2 ASCAT SWI 001 RMSE according to varying Saturated Soil Moisture Content values.

Site	HHS θs	RMSE	PF θs min	RMSE	PF θs max	RMSE	Calibrated θs	RMSE
Grand Island	0.43	0.08	0.01	0.39	0.01	0.39	0.39	0.13
Merritt	0.43	0.09	0.35	0.07	0.30	0.05	0.38	0.06
Concord	0.42	0.09	0.01	0.27	0.01	0.27	0.38	0.08

* RMSE (cm3/cm3) according to saturated water content, θs estimations from HiHydroSoil (HHS), the pedotransfer functions (PF) at minimum and maximum bulk density range, and for the final calibration.

4.2 Vegetation Index based Models

TDVI, WDI, and Empirical model estimations of topsoil moisture content did not provide temporal moisture curves within range or exhibiting similar shape to the observations. ETLook was able to produce topsoil moisture estimations only at the Merritt site. While ETLook model produced estimations that were successful in predicting subsurface moisture content, the model failed to achieve similar results at Concord and Grand Island. Since the main input parameter of the model is LAI, perhaps the model is not suitable for locations where moisture content regularly meets and even exceeds the NDVI boundary condition of 0.80. As is, the ETLook model may not be suitable for vegetation cover with high biomass production that achieves the set threshold for NDVI. Further work or calibration on the model may lead to successful moisture estimations like those achieved at Merritt.

Table 3 ETLook topsoil and root zone moisture estimation performance metrics.

Performance Metric	Depth (cm)				Predicted*
	10-25	10-50	25-50	50-100	50-100 (cm)
NSE	0.59	0.88	-0.04	0.56	0.92
RMSE (cm3/cm3)	0.03	0.04	0.11	0.11	0.02
R^2	0.75	0.75	0.69	0.60	0.60

4.3 Root Zone Model

The Root Zone model performs best at Grand Island and is marked by high performance metrics corresponding most to the 10-50 cm depth. Performance at Concord is linked to a depth of 10-50 cm as well. The negative Concord NSEs indicate the Empirical model may not adequately describe conditions at Concord, however the relationship between evaporative fraction and soil moisture still holds as the moisture content has low RMSE and high R^2. Likewise, the low NSE and higher RMSE support the notion that the Empirical method should be either be a) evaluated on a local scale prior to subsurface moisture application or b) improved to include a wider range of datasets for application across a variety of agro-ecological conditions.

Table 4 Performance metrics for proposed Root Zone model for all three study sites.

Study Site	Performance Metric		Depth (cm)			
			10-25	10-50	25-50	50-100
Merritt	**RMSE**	(cm3/cm3)	0.10	0.10	0.09	0.09
	R^2		0.99	0.97	0.91	0.67
	NSE		-6.6	-8.8	-21.1	-21.1
Concord	**RMSE**	(cm3/cm3)	0.06	0.05	0.03	0.03
	R^2		0.99	0.97	0.91	0.67
	NSE		-1.74	-1.33	-0.32	-0.15
Grand Island	**RMSE**	(cm3/cm3)	0.06	0.05	0.05	0.04
	R^2		0.89	0.83	0.47	0.26
	NSE		0.30	0.98	0.98	0.99

4.4 Subsurface Moisture Estimations

ETLook subsoil predictions (50-100 cm) based on the topsoil estimations and empirically-derived relationship between topsoil and subsoil moisture content at Merritt performed well with very high Nash Sutcliffe Error (NSE), low Root Mean Square Error (RMSE), and moderate Coefficient of Determination R^2, as shown in Table 3. Performance of the Root Zone model (Tables 4, 5) indicate that the model is capable of estimating topsoil moisture (10-50 cm). The topsoil moisture can be applied to estimate subsoil moisture (50-100 cm) using local empirical relationships for topsoil and subsoil moisture.

Table 5 Performance metrics for Root Zone model subsurface estimation at 50-100 cm in the root zone.

Study Site	Moisture Depth (cm)	Estimation Performance for 50-10 cm		
		RMSE (cm3/cm3)	R^2	NSE
Merritt	10-50	0.05	0.43	0.10
Concord	10-50	0.04	0.67	0.20
Grand Island	10-50	0.02	0.28	0.14

5. Conclusions

Locally derived relationships for topsoil and subsoil moisture content can be used to estimate root zone moisture (50-100 cm) using the *ETLook* and Root Zone models. The performance of these models varies due to the local agro-hydrological characteristics regarding soil, vegetation, land use, and climate. Agro-hydrological model SWAP was used to estimate topsoil moisture in lieu of poor performing ASCAT SWI topsoil moisture estimates in Nebraska. TDVI, WDI, and Empirical model were found to poorly estimate soil moisture content with the Scott et al. (2003) model for subsurface moisture saturation. Further application of the Root Zone model is recommended to determine the applicability over various agro-hydrological areas with differing topsoil-subsoil moisture relationships.

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