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ARTICLE

Factors affecting the use of weather station data in predicting surface soil moisture for agricultural applications

Umesh Acharya, Aaron Lee M. Daigh, and Peter G. Oduor

Abstract: Weather stations often provide key information related to soil moisture; temperature and evaporation are used by farmers to decide farm operations of nearby agricultural fields. However, the site conditions at the weather stations where data are recorded may not be similar with these nearby fields. The objective of this study was to determine the level of discrepancies in surface soil moisture between weather stations and nearby agricultural fields based on (*i*) the soil texture, crop residue cover, crop type, growth stages and (*ii*) temporal dependency of soil moisture to recent rainfall and evaporation rates. Soil moisture from 25 weather stations in the North Dakota Agricultural Weather Network (NDAWN) and 75 nearby fields were measured biweekly during the 2019 growing season in Red River Valley. Field characteristics including soil texture, crop residue cover, crop type, and growth stages along with rainfall and PET were collected during the study period. The regression analysis between surface soil moisture at weather station and nearby field showed higher values for corn at V10 stage (r^2 = 0.92) and for wheat at flowering stage (r^2 = 0.68) and opposite was observed with soybean. We found the regression coefficient of soil moisture with 4-d cumulative rainfall slightly increased to 0.51 with an increase in percent residue cover resulting in a decreased root mean square error (RMSE) to 0.063 $m^3 \cdot m^{-3}$. In general, we observed that surface soil moisture at weather stations could reasonably predict moisture in nearby agricultural fields considering crop type, soil type, weather, and distance from weather station.

Key words: rainfall, potential evapotranspiration, Red River Valley of the North, temporal relationship, residue cover.

Résumé : Les stations météorologiques procurent souvent des informations essentielles sur la teneur en eau du sol, la température et l'évaporation que les agriculteurs utilisent pour décider des mesures à appliquer aux cultures voisines. Toutefois, il se pourrait que les conditions à l'endroit où la station enregistre les données diffèrent de celles qu'on observe au champ. Les auteurs voulaient préciser l'importance de l'écart entre la teneur en eau dans le sol de surface établie par les stations météorologiques et celle mesurée dans les cultures à proximité d'après (*i*) la texture du sol, la couche de résidus culturaux, la nature de la culture et le stade de croissance et (*ii*) la dépendance temporelle entre la teneur en eau du sol et les précipitations récentes, de même que le taux d'évaporation. À cette fin, ils ont recueilli les données sur la teneur en eau du sol des 25 stations météorologiques du North Dakota Agricultural Weather Network (NDAWN) et ont mesuré ce paramètre dans 75 champs voisins, toutes les deux semaines durant la période végétative de 2019, dans la vallée de la rivière Rouge. Au nombre des paramètres agronomiques établis pendant la période à l'étude figuraient la texture du sol, la couche de déchets culturaux, la nature de la culture et le stade de croissance ainsi que l'importance des précipitations et l'évapotranspiration potentielle. L'analyse de régression de la teneur en eau dans le sol de surface établie par la station météorologique et de celle mesurée dans le champ voisin révèle des valeurs supérieures pour le maïs au stade V10 (r^2 = 0,92) et pour le blé au stade de la floraison (r^2 = 0,68), avec la situation inverse pour le soja. Le coefficient de régression de la teneur en eau du sol après quatre jours cumulatifs de pluie augmente légèrement pour passer à 0,51, la couche plus importante de résidus en pour cent entraînant une diminution de l'écart-type, qui s'établit à 0,063 $m^3 \cdot m^{-3}$. En général, les auteurs estiment que la teneur en eau dans le sol de surface relevée aux stations météorologiques pourrait raisonnablement prédire celle dans les cultures voisines, selon la nature de ces dernières, le type de sol, les conditions météorologiques et l'éloignement de la station. [Traduit par la Rédaction]

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Mots-clés : précipitations, évapotranspiration potentielle, nord de la vallée de la rivière Rouge, relation temporelle, couche de résidus.

Introduction

Soil moisture is an important variable in hydrology and climate studies due to its strong influence on water infiltration, runoff, evaporation, erosion, and heat and gas fluxes (Verstraeten et al. 2007; Amani et al. 2017). Similarly, soil moisture plays a key role in farm activities such as crop selection and the timing of tilling, planting, applying fertilizers, and harvesting (Helms et al. 1996; Hamman et al. 2002). However, the heterogeneity of soil moisture within and across spatial scales creates difficulties for both research efforts and land management decisions. The most accurate methods for representing soil moisture are point measurements (e.g., gravimetric sampling, in situ electromagnetic sensors). These methods are limited in terms of spatial extent and are time consuming and labor intensive (Brocca et al. 2007; LaGuardia and Niemeyer 2008). Other methods with larger spatial extents include proximal and remote sensing technologies as well as hydrologic simulations to model soil moisture on the landscape (Babaeian et al. 2019). In contrast to point measurements, the larger spatial extents innately result in lower resolution and a loss of information in landscapes with complex physical attributes (e.g., topography, parent materials), land management (e.g., crop rotations and diversity), and thus require adequate point-scale validation. Therefore, an efficient and reliable means to represent soil moisture in and across landscapes are highly desired by both the research and agricultural communities.

Researchers and farmers commonly use data from nearby weather stations to inform them on a location's soil moisture (if available), atmospheric conditions, and potential evapotranspiration (PET). The key assumption for using these weather station data is that they adequately represent the actual conditions of nearby fields for some task of interest, even though these fields may differ in physical (e.g., soil texture, slope) and crop (e.g., type, previous year's plant residues, growth stage) attributes (Dalton et al. 2011; Rosenbaum et al. 2012). In the United States, there are 122 weather stations managed by National Weather Services to provide weather related products in addition to state-managed mesonets (NWS 2020; NDAWN 2020). The North Dakota Agricultural Weather Network (NDAWN) is an example of a state-managed mesonet, which provides up to 32 measured weather and soil parameters from 117 weather stations in North Dakota (83 stations), Minnesota (28 stations), and Montana (6 stations) (NDAWN 2020). Similar state-level mesonets are also deployed in Kansas and Oklahoma (Kansas Mesonet 2020; Oklahoma Mesonet 2020).

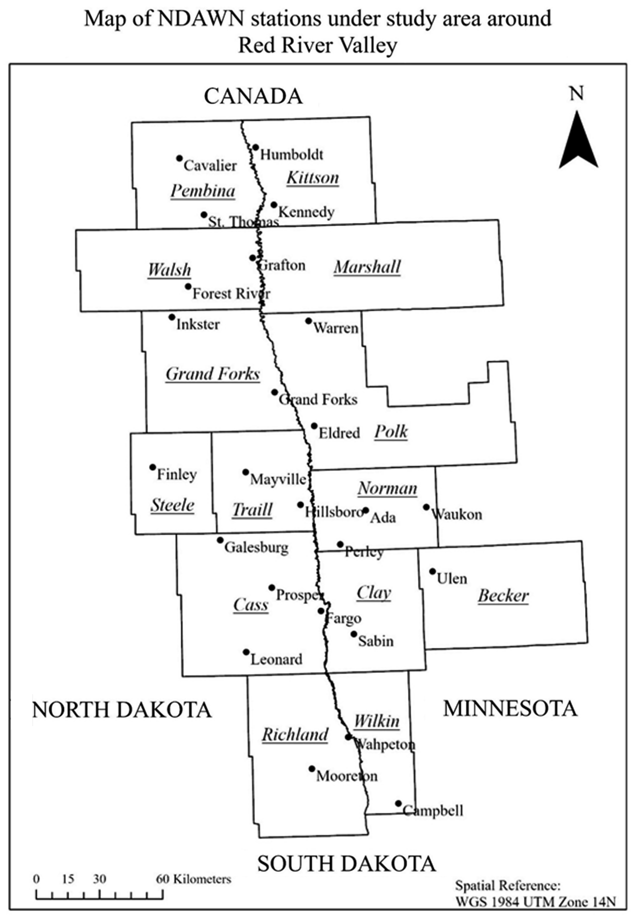
In agricultural fields with annual grain crops, soil moisture is likely more dynamic over time than when under perennial cover. For instance, the amount, type, and management (e.g., tillage) of crop residues left from previous growing season influence soil moisture evaporation and retention of soil moisture over time in the top soil (Dabney 1998; Gwak and Kim 2017). In addition, the live vegetation type and plant canopy cover modify the root-zone microclimate and affect evapotranspiration rates, while root morphologies and age strongly affect infiltration rates and patterns and water uptake into the plant (Fernandez-Illescas et al. 2001). Therefore, the dynamics of live vegetation strongly affects soil moisture (Thompson et al. 2010; Daigh et al. 2014). Soil moisture measurement at weather stations is typically taken under a mowed perennial grass (i.e., turf), which starkly differs from the characteristics of nearby cropped fields (Patrignani and Ochsner 2018). Moreover, if neighboring fields differ in soil texture, then soil moisture spatial variability and its dynamics over time will be impacted accordingly (Vereecken et al. 2007; Pan and Peters-Lidard 2008; Ivanov et al. 2010; Vivoni et al. 2010). Using linear correlation and empirical orthogonal function analysis, Gwak and Kim (2017) reported that soil particle size distributions were a more dominating factor than vegetation in the soil moistures distribution. At larger scales, Dong and Ochsner (2018) reported that the variation of soil particle size distributions across the landscape also controls soil moisture more than rainfall distributions during storm events.

The spatial extrapolation of measured soil and atmospheric conditions at weather stations is a major concern for representing nearby fields. However, most agricultural management decisions are also made based on inferences of what the conditions in those nearby fields will be in the following days or weeks. Weather forecasts of rainfall are likely the most obvious parameter to use for making such inferences. Rainfall history has a large impact on soil moisture and is a main determinant in farm activities (Western et al. 2002). Entekhabi and Rodriguez-Iturbe (1994) reported rainfall as the primary factor in controlling the state and subsequent evolution of soil moisture. Similarly, Pan et al. (2003) observed soil moisture to be a function of the time-weighted average of previous cumulative rainfall over a period of 14 d. However, evapotranspiration, air and soil temperatures, and wind speeds are also some of the more widely used weather data from stations to make inferences on near-future soil moisture conditions (Western et al. 2002). The variety of factors influencing soil moisture variability in space and time (e.g., soil physical properties, topography, microclimate, groundwater, evapotranspiration) presents a barrier for farmers and agricultural consultants to infer the representativeness of weather station data readily and efficiently to nearby fields (Famiglietti et al. 1998; Western et al. 2002;

Vereecken et al. 2007; Rosenbaum et al. 2012; McMillan and Srinivasan 2015).

Therefore, it is important to determine discrepancies in soil moisture between local weather stations and nearby agricultural fields. Moreover, identifying correlations of any discrepancies to differences in soil type, residue cover, or crop type and growth stage can then guide the development of simple quantitative relationships to extend weather station data to inform on-farm management decisions. Such discrepancies are intuitively expected. However, little to no evidence is currently reported in the literature. To our knowledge, the literature lacks any such evaluations for the upper interior plains of North America. Thus, our objectives are as follows: (*i*) determine the level of discrepancies in soil moisture between weather stations in the Red River Valley of the North (RRVN) and nearby agricultural fields; (*ii*) identify correlations of any discrepancies based on soil texture, crop type, residue cover, and crop growth stage; and (*iii*) determine the duration of temporal dependency of these soil moistures to recent rainfall and evapotranspiration rates.

Fig. 1. Map showing counties of North Dakota and Minnesota and weather stations under study area around Red River Valley. Black dots in map represent weather stations and words that are italicized and underlined represent counties. The counties outlines of North Dakota and Minnesota were retrieved from North Dakota Geographic Information System (www.gis.nd.gov). Figure created in ArcGIS (Environmental System Research Institute-ESRI).



Material and Methods

Study area, weather station network, and data collection

The study area was located in North Dakota and Minnesota within the RRVN. The Red River of North extends 885 km northward from its source near Breckenridge, Minnesota in the United States to Lake Winnipeg in Canada. The segment of river in the United States (634 km) forms most of the border between Minnesota and North Dakota. The Red River Valley is a glaciolacustrine lake bed formed by the ancient Lake Agassiz, which existed for about 4000 yr. The topography is minimal with a gradient of only 1:5000 (1 m per 5 km). The dominant soil orders in RRVN are Mollisols and Vertisols, whereas soil texture ranges from loamy sand to clay. The large range in textures can be attributed to variations in the lake deposits and formation of braided streams as the ancient lake drained to the north in around 8000 yr ago. The parent material is poorly drained and consists of gray, slickensided, flat clays of Brenna/Argusville formations, which are overlain by the tan-buff, laminated silty clays of the Sherack Formation. Shales within the parent materials commonly result in the shallow perched water tables being saline or saline-sodic. The major crops grown in this region are corn (*Zea mays* L.), soybean (*Glycine max* (L.) Merr.), wheat (*Triticum aestivum* L.), barley (*Hordeum vulgare* L.), sugar beet (*Beta vulgaris*) along with canola (*Brassica napus*), sunflower (*Helianthus annuus* L.), potato (*Solanum tuberosum* L.), dry beans (*Phaseolus vulgaris*), and oats (*Avena sativa* L.). Summers are long and warm, whereas winters are frigid, snowy, windy, and partly cloudy year-round. The average annual air temperature is 4 °C, typically varies from −16 °C to 29 °C and rarely below −27 °C or above 32 °C, whereas 30-yr mean annual rainfall is 60 cm and snowfall is 317 cm (NOAA/NCEI 2020).

The NDAWN was used for the study. NDAWN reports 32 weather parameters (e.g., air temperature, rainfall, wind direction, soil moisture) at 117 weather stations, which includes stations in North Dakota (N = 83), Minnesota (N = 28), and Montana (N = 6). A subset of these stations (i.e., those located in the RRVN) were selected for this study. This included a total of 25 stations, where 15 stations were located across 8 counties in North Dakota and 10 stations were located across 7 counties in Minnesota (Fig. 1).

Weather station data and measurements in nearby agricultural fields of the study area were collected during the cropping season from June to September in 2019. Three nearby agriculture fields (corn, soybean, wheat, sugarbeet, potato, dry bean, canola) within the

Table 1. Soil sampling date with corresponding weather station for soil moisture determination for year 2019.

Weather station	Date sampled
Campbell, Mooreton, Wahpeton	6/27, 7/13, 7/29, 8/14
Leonard, Sabin, Fargo, Ulen, Prosper, Galesburg, Perely, Hillsboro, Ada, Waukon, Mayville, Finley, Eldred, Grand Forks, Forest River, Inkster, Warren, Grafton, St. Thomas, Kennedy, Cavalier, Humboldt	6/18, 7/20, 8/5, 8/21
Grafton, St. Thomas, Kennedy, Cavalier, Humboldt	7/27

range of 30 m to 2 km were selected around each weather station (N = 75 fields). From each field, three different composite soil samples were randomly selected to determine soil moisture content. Soil samples were collected in 16 d intervals from the field and weather station between June and September 2019 (Table 1).

Determination of soil moisture

Soil moisture was measured using the gravimetric method for each location and sample date (N = 985). Soil samples were collected from all weather stations and nearby field to determine soil moisture. GPS coordinates for each station and sampling location were also recorded. From each field, three spots were randomly selected to determine soil moisture content. From each spot, three soil cores were collected using Uhland core sampler at 0–6 cm depth and mixed to get composite soil sample. Soil was sampled using core sampler with dimension (6 cm × 8 cm), the field-wet weight of the soil was recorded, and then oven dried at 105 °C for 48 h. The weight of dry soil was again recorded and gravimetric water content was determined as the mass of water lost due to drying. The soil's volumetric water content (VWC) was calculated by multiplying gravimetric water content with the soil bulk density (Reynolds 1970).

Crop type and growth stages

The major crops grown in RRVN are corn, soybean, wheat, barley, sugar beet along with canola, sunflower, potato, dry beans, and oats. For this study, the selected fields nearby the weather stations were planted with soybean (N = 24), wheat (N = 18), corn (N = 16), sugar beet (N = 6), dry beans (N = 5), oats (N = 2), barley (N = 1), potato (N = 1), canola (N = 1), and alfalfa (N = 1). Soil samples taken after crops were planted and germinated. Growth stages for each crop were recorded every 16 d throughout the growing period until harvest. The growth stages for each crop were determined using standards developed by the United States Department of Agriculture (USDA 2020). These coincided with the dates for soil sampling, and soil moisture values determined for each growth stage.

Antecedent site characteristics: Crop residue cover and soil texture

Crop residue cover was determined along eight transects per sample site using the rope method (i.e., residue presence at 100 points along 15 m oriented 45° to plant rows) (Daigh et al. 2019). Crop residue was then pooled into three categories: <10%, 20%–30% and 50%–60% crop residue cover. Crop residue was measured at the start of the growing season for this study. Soil texture was determined for each site (i.e., weather stations and nearby fields) using the pipette method described by Gee and Bauder (1986). All the weather stations in this study area have grasses covered around them with different bulk density of soil.

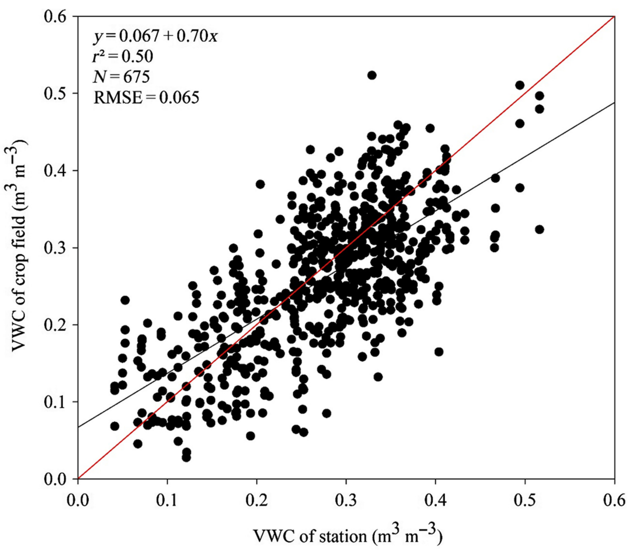
Rainfall and PET

Rainfall at the NDAWN stations was measured hourly at a 1 m height above the soil surface using TE525 tipping bucket rain gauges (Texas Electronics TR-525I, Dallas, Texas). Each bucket tip measures 0.254 mm of rainfall. The PET estimates of the maximum daily crop water loss when water is readily available. PET is calculated from solar radiation, dew point temperature, wind speed, and air temperature using the Penman (1948) equation and is based on alfalfa, which is called reference ET. Rainfall and PET (mm) for the preceding 10 d before soil sampling were downloaded from each weather station (https://ndawn.ndsu.nodak.edu/) and used to calculate cumulative values. Rainfall and PET recorded at each weather station also represent the values for nearby field in this study.

Statistical analysis

Linear and non-linear regression was performed and Pearson correlation coefficients determined to describe the relationships between soil moisture at the weather stations (independent variable) and the nearby cropped fields (dependent variable) using Proc Reg in SAS software version 9.4 (SAS 2017). The analysis was repeated by pooling the data for each factor (i.e., crop type, crop growth stage, crop residue cover, soil texture, distance from weather station, and their interactions) separately. The recent cumulative rainfall and PET history at the weather station were compared with the current soil moisture using non-linear regression using Proc Reg in SAS software version 9.4 (SAS 2017). The analysis was repeated by pooling the data for each factor (i.e., crop type, crop growth stage, crop residue cover, soil texture, distance from weather station, and their interactions) separately. The regression parameters (slopes and intercept), correlation coefficients, and root mean square error (RMSE) are reported and discussed below.

Fig. 2. Linear relationship between volumetric water content (VWC) of crop fields with nearby weather stations in the Red River Valley during 2019. RMSE, root mean square error. [Color online.]



Results

VWC discrepancies between crop field and weather station

Soil moisture ranged from 0.028 to 0.523 $m^3 \cdot m^{-3}$ across the study area of the RRVN and sampling time frame (May to September 2019). VWC at weather stations and nearby agricultural fields were linearly correlated, with the weather station VWC explaining 50% ($r^2 = 0.50$, $N = 675$, slope = 0.7, RMSE = 0.0654 $m^3 \cdot m^{-3}$) of the variance for the nearby fields (Fig. 2). Distances up to 2 km from the weather station moderately affected this relationship (see Supplementary Table S1[1]). The correlation coefficient was higher ($r^2 = 0.55$, $N = 215$) for fields nearer (0–100 m) as compared with fields farther (1200–2000 m) from weather stations ($r^2 = 0.40$, $N = 42$).

VWC discrepancy due to crop type and their growth stage

Discrepancies associated with crop types and growth stage were apparent between VWC at the weather stations and nearby fields (Fig. 3, Supplementary Table S2[1]). Fields planted to dry beans ($r^2 = 0.69$, $N = 33$, RMSE = 0.041 $m^3 \cdot m^{-3}$) had the highest correlation, followed by wheat ($r^2 = 0.56$, $N = 159$, RMSE = 0.06 $m^3 \cdot m^{-3}$) and corn ($r^2 = 0.46$, $N = 156$, RMSE = 0.068 $m^3 \cdot m^{-3}$), whereas, the lowest correlations were in sunflower ($r^2 = 0.41$, $N = 9$, RMSE = 0.061 $m^3 \cdot m^{-3}$) and barley ($r^2 = 0.18$, $N = 9$, RMSE = 0.052 $m^3 \cdot m^{-3}$), which also had the lowest sample size. Moreover, the slope of all the linear regression equations was less than 1 (i.e., corn = 0.81; wheat = 0.72; sugarbeet = 0.70; soybean = 0.69; alfalfa = 0.45) (Supplementary Table S1[1]).

Regression coefficients increased with corn growth stage [V10 stage ($r^2 = 0.92$), V11 stage ($r^2 = 0.99$)] until the silking reproductive phase and then declined [tasseling ($r^2 = 0.59$), grain filling ($r^2 = 0.78$)]. Wheat expressed a similar trend [tillering ($r^2 = 0.17$); flowering ($r^2 = 0.68$); hard dough ($r^2 = 0.590$) and after harvest ($r^2 = 0.24$)], whereas correlations in soybean continued to increase [V1 stage ($r^2 = 0.11$); V2 stage ($r^2 = 0.15$); flowering ($r^2 = 0.51$); podding ($r^2 = 0.70$)].

VWC discrepancy due to residue cover and soil texture

Crop residue cover and soil texture had a moderate influence on the disparity between the weather stations and nearby fields. Crop fields with the lowest amount of crop residue cover (<10%) had the highest correlation ($r^2 = 0.63$, $N = 275$, RMSE = 0.058 $m^3 \cdot m^{-3}$) with the VWC of weather station as compared with higher residue-covered fields [20%–30% residue ($r^2 = 0.44$, $N = 198$, RMSE = 0.066 $m^3 \cdot m^{-3}$); 50%–60% residue ($r^2 = 0.46$, $N = 198$, RMSE = 0.067 $m^3 \cdot m^{-3}$)] (Fig. 4). Soils with a relatively high clay content, such as clay ($r^2 = 0.63$, $N = 48$, RMSE = 0.061 $m^3 \cdot m^{-3}$), clay loam ($r^2 = 0.57$, $N = 69$, RMSE = 0.063 $m^3 \cdot m^{-3}$), silty clay loam ($r^2 = 0.52$, $N = 117$, RMSE = 0.054 $m^3 \cdot m^{-3}$), and silty clay ($r^2 = 0.46$, $N = 153$, RMSE = 0.073), had higher correlation coefficients as compared with soils with a high sand content (Fig. 6).

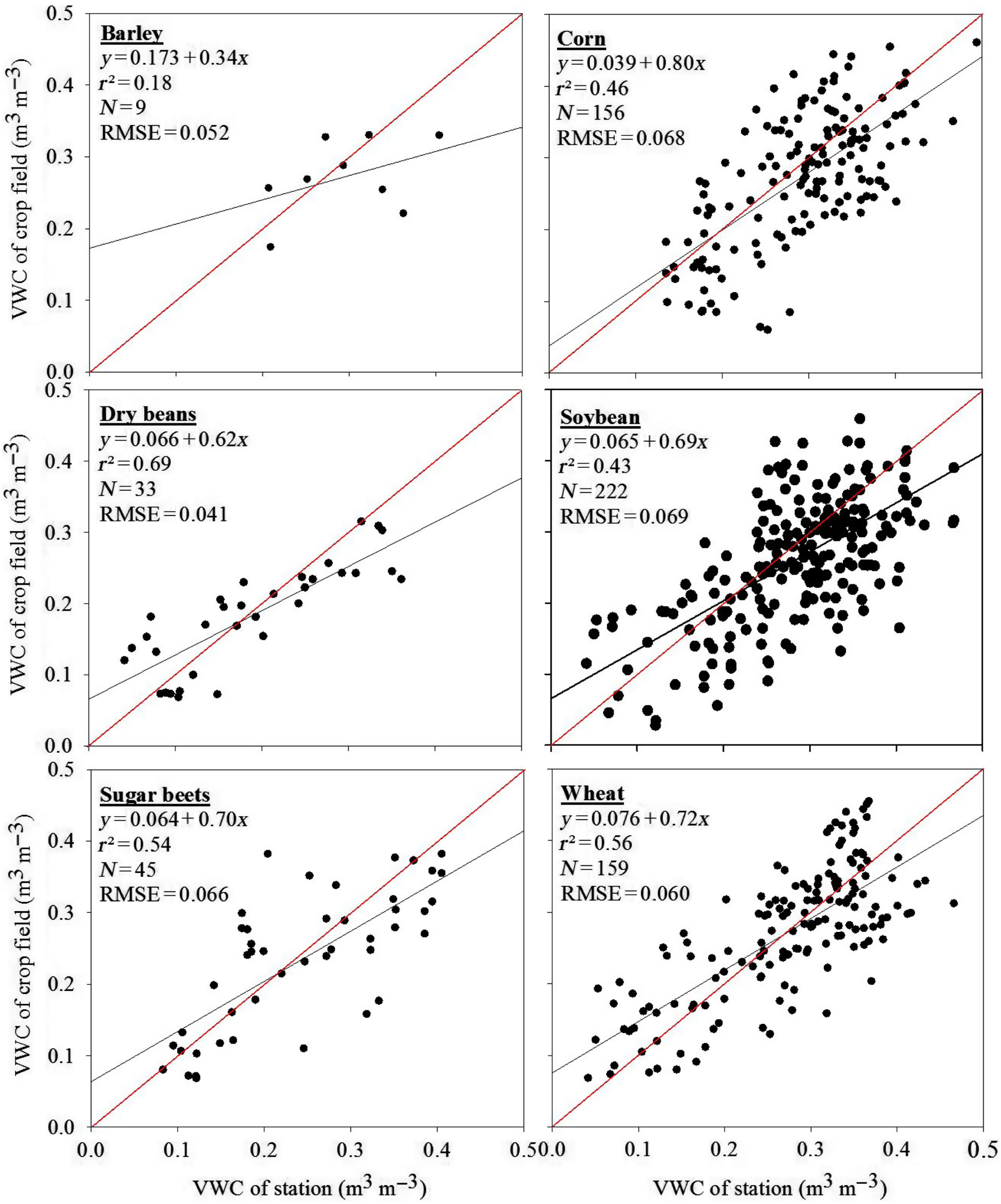
Temporal dependency of soil moisture in crop fields to recent rainfall and PET rates

Soil moisture expressed a non-linear (cubical) relationship with past cumulative rainfall and PET (5 d) measured from the weather station. The highest correlation ($r^2 = 0.49$) was observed between soil moisture and a 4 d cumulative rainfall that was improved significantly from a 1 d cumulative rainfall ($r^2 = 0.16$). Similarly, the highest correlation ($r^2 = 0.29$) was observed between soil moisture and a 4 d cumulative PET (Supplementary Table S3[1]).

The non-linear relationship between soil moisture with 4 d cumulative rainfall had various weak to strong influences by crop residue cover, crop type, distance from weather station and soil texture (Fig. 6; Supplementary Table S4[1]). The regression coefficient of soil moisture with 4 d cumulative rainfall slightly increased with an increase in the crop residue cover percentage (<10, 20–30, 50%–60%) from 0.48 to 0.51, and RMSE decreased from 0.068 to 0.063 $m^3 \cdot m^{-3}$. The highest correlation coefficient between soil moisture and a 4 d cumulative rainfall was observed with alfalfa ($r^2 = 0.93$), followed by oats ($r^2 = 0.86$), sugarbeet ($r^2 = 0.71$), dry beans ($r^2 = 0.65$), wheat ($r^2 = 0.56$), corn ($r^2 = 0.48$) and lowest in soybean ($r^2 = 0.45$). The non-linear relationship between soil moisture and 4 d cumulative rainfall shows crop fields near to weather station (100–200 m) had higher correlation coefficient ($r^2 = 0.65$), whereas fields further away (1200–2000 m) had a lower coefficient

[1]Supplementary data are available with the article at https://doi.org/10.1139/CJSS-2021-0034.

Fig. 3. Linear relationship between volumetric water content (VWC) of crop fields with nearby weather stations under different crop types. RMSE, root mean square error. [Color online.]

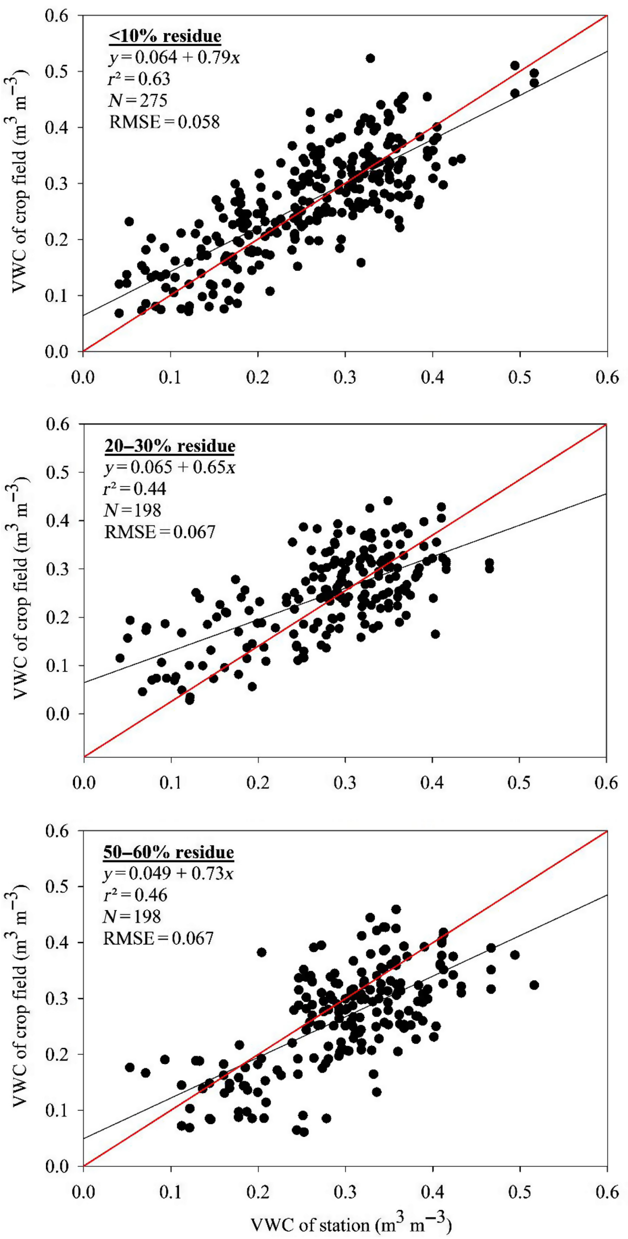


(r^2 = 0.25). A strong non-linear relationship was observed between soil moisture and 4 d cumulative rainfall for soils having high clay content [clay (r^2 = 0.75), silty clay loam (r^2 = 0.65), and clay loam (r^2 = 0.52)], whereas a weak relationship was observed with soils having high sand content.

Similarly, the highest correlation coefficient of soil moisture with 4 d cumulative PET (r^2 = 0.37) was observed with 20%–30% crop residue cover followed by the 50%–60% (r^2 = 0.31) and lowest observed with <10%. The RMSE was also lowest with 20–30% crop residue cover (0.071 $m^3 \cdot m^{-3}$) followed by 50%–60% (0.076 $m^3 \cdot m^{-3}$) and <10% (0.083 $m^3 \cdot m^{-3}$) (Supplementary Table S5[1]). For different types of crops, similar trends were evident between soil moisture and a 4 d PET as with 4 d cumulative rainfall. In contrast to cumulative rainfall, the opposite was observed between soil moisture and 4 d cumulative PET, where farther crop fields (800–1200 m) had higher correlation coefficients (r^2 = 0.57) and the nearest fields (0–100 m) had a lower coefficient (r^2 = 0.33).

Similarly, correlation between soil moisture and 4 d cumulative PET for soils was higher with high clay content [clay (r^2 = 0.59), clay loam (r^2 = 0.59), and silty clay (r^2 = 0.51)] as compared with soils having high sand content [loamy sand (r^2 = 0.09)] as with cumulative rainfall.

Fig. 4. Linear relationship between volumetric water content (VWC) of crop field with weather stations at different residue percentage (<10%, 20%–30%, 50%–60%). RMSE, root mean square error. [Color online.]



Discussion

In general, we observed that soil moisture at weather stations could reasonably predict moisture in nearby agricultural fields (Fig. 2) considering crop, soil, rainfall, PET, and distance from weather station. This corroborates findings by Famiglietti et al. (1998) regarding correlations between topographical attributes, soil properties, and soil moisture measured along distances of 200 m. Therefore, the discrepancies in soil moisture observed in the present study are likely due to spatial heterogeneities of soil characteristics (Hu et al. 1997), vegetation characteristics (Qiu et al. 2001), and land management practices (Daigh et al. 2018).

As expected, the analysis showed that the moisture prediction weakens with an increase in distance from the weather stations. This is likely due to change in soil moisture spatial patterns caused by the field variations in the landscape as well as other autocorrelated factors (soil texture, vegetation, rainfall, evapotranspiration) that influence local hydrologic processes (Bardossy and Lehmann 1998; Famiglietti et al. 1998; Western et al. 1999, Brocca et al. 2007). The large spatial and temporal variability of the study area might have resulted in the lower prediction value, which can be improved by considering those factors in a prediction model (McMillan and Srinivasan 2015). The changes in the spatial pattern of soil moisture were studied by Hawley et al. (1983) in the flat areas of Central Italy under different soil wetness conditions, Cunningham et al. (1978) in a 10 yr long revegetating study in Australia, and Dunin and Reyenga (1978) in an evaporation study of subhumid grassland of Australia. The Red River Valley has diverse crop rotations that include canola, sunflower, lentil along with soybean, corn, wheat, and oats (O'Brien et al. 2020). This diversity of crops made it difficult to predict soil moisture of nearby field using weather station because of their nature of growth and canopy cover (Wright et al. 2017).

Crop type and their growth stages showed weak to strong relationships in the soil moisture prediction from the weather stations (Fig. 3). Crops with dense, closed leaf canopies at their peak vegetative growth stage showed higher regression coefficients compared with thin, open leaf canopies. This is consistent with studies showing that cropping system and crop growth stage influence soil water storage (Daigh et al. 2014) and impact soil hydrology (McIsaac et al. 2010; Kravchenko et al. 2011; Steele et al. 2012). The type of crop and their growth stage influences small-scale soil moisture variability due to the pattern of (*i*) throughfall imposed by the canopy (Zheng et al. 2019), (*ii*) shading the soil surface and affecting rate of evaporative drying (Todd et al. 1991), (*iii*) moderating or inducing turbulence airflows and corresponding evapotranspiration rates (Katul et al. 2012), and (*iv*) affecting soil Ksat through root distributions and their activity with extracting soil moisture for plant transpiration (Schymanski et al. 2008). The degree to which these factors affect the soil moisture depends upon plant species, density, and season (Reynolds 1970b; Famiglietti et al. 1998; Lull and Reinhart 1995). These results are in accordance with Hawley et al. (1983), Francis et al. (1986), Ozkan and Gokbulak (2017) who found significant difference in soil moisture content due to difference in vegetation cover. For instance, row crop systems tend to have lower water storage capacities than natural or restored perennial systems (Brye et al. 2000; Qi et al. 2011; Mitchell et al. 2012), which is linked with soil moisture contents. Similarly,

Fig. 5. Linear relationship between volumetric water content (VWC) of crop field with weather station at different type of soil texture in the study area. RMSE, root mean square error. [Color online.]

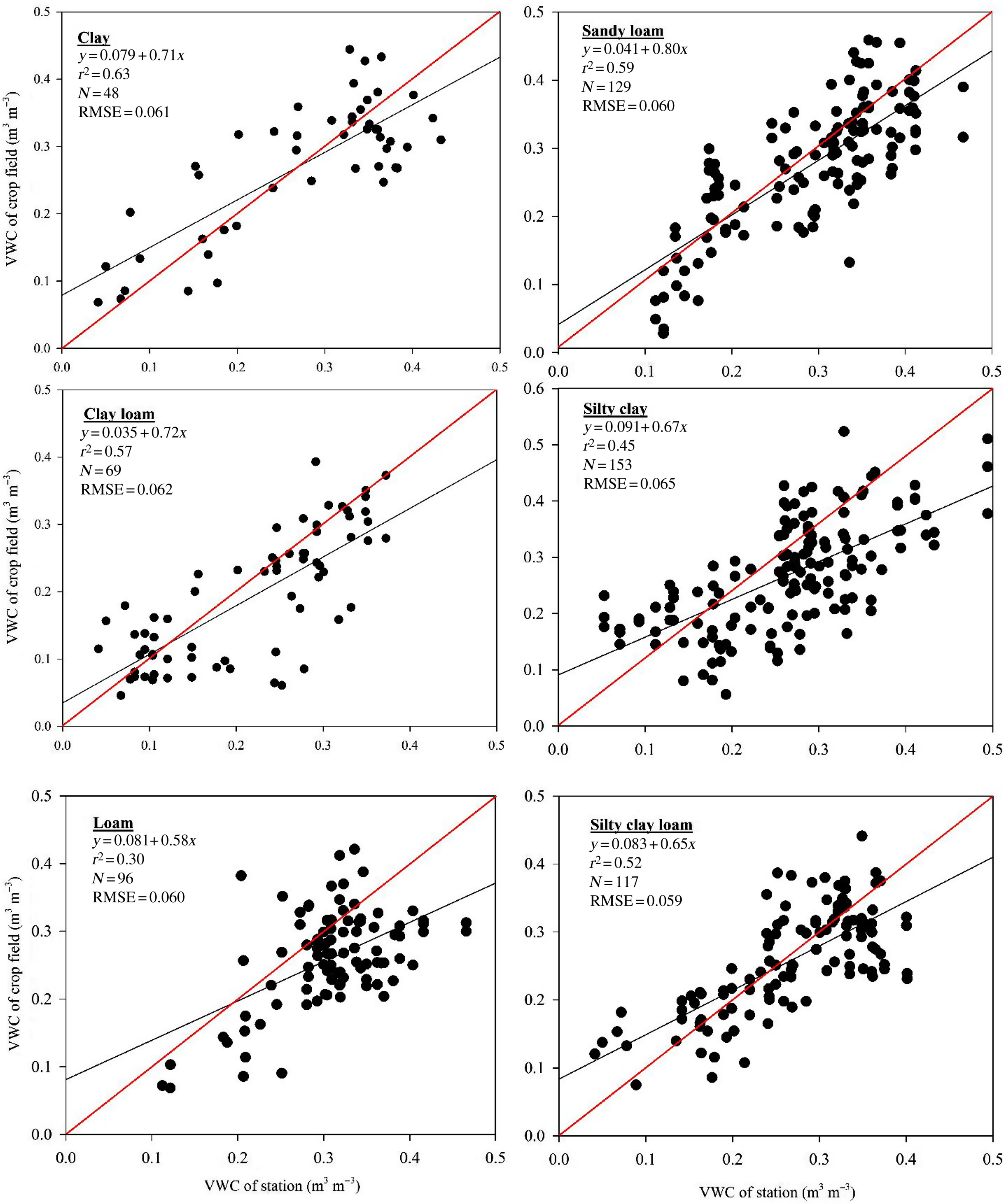
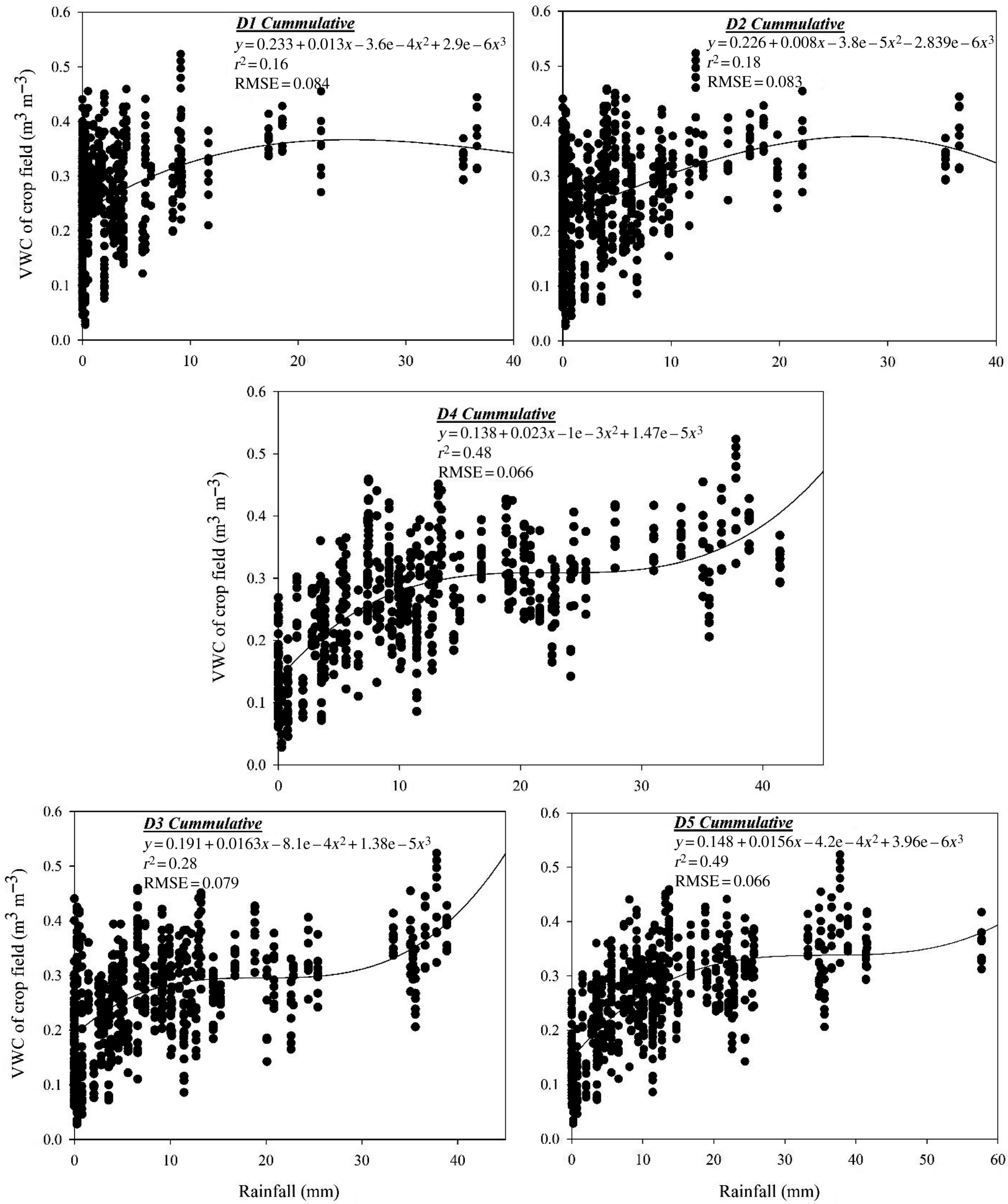


Fig. 6. Non-linear relationship between volumetric water content (VWC) of crop field (N = 675) with cumulative rainfall for past 5 d (D1, D2, D3, D4, and D5) for the study area. RMSE, root mean square error. [Color online.]



Gomez-Plaza et al. (2000) argued vegetated areas and vegetation cover improves soil structure and capacity of water retention into the soil compared with drier with low vegetation cover in southeastern Spain. The vegetation and land use could have significant effects on the temporal and spatial dynamics of soil moisture (Qiu et al. 2001; Fu et al. 2003; Jun et al. 2010). However, Zhao et al. (2010) postulated that correlation analysis showed that soil properties were important factors controlling temporal stability of soil moisture spatial patterns for any cropping practices or vegetation cover in a semi-arid region.

Soil physical properties (bulk density, Ksat, soil texture) are well-known parameters that significantly affect soil moisture. The regression analysis for soil moisture prediction showed higher r^2 values for soils with higher clay percentage as compared with sand percentage. Variation in soil texture, organic matter and macro porosity affect the water retention of soils, thereby causes the soil moisture variation (Crave and Gascuel-Odoux 1997; Famiglietti et al. 1998; Dong and Ochsner 2018). Similar to our findings, English et al. (2005) found sand-rich soil throughout the soil profile increases gravimetric water and soil water potential compared with clay-rich soils. Soil texture influences soil moisture through its direct effects on pore spaces governing evaporation and drainage rates, which are two main factors for controlling soil drying (Dexter 2004; Pan and Peters-Lidard 2008). Roy et al. (2018) have compared soil water release curves for three soils in the Red River Valley and found the difference in water content between two fitted curves for Fargo silty clay was higher (5%) due to shrinkage and swelling that Glyndon silty loam and Hecla sandy loam soils (<2%). This characteristic of Fargo clay soil has higher correlations. The irrigation cycle study conducted by Li et al. (2014) showed soil moisture content was significantly and consistently correlated with soil texture and bulk density. Similarly, both principal component analysis and multiple linear regression identified soil texture as the primary physical process controlling variability in soil moisture content of an agriculture field (Manns et al. 2014). Gao et al. (2011) in their study in Loess plateau, China, reported strong correlation between soil texture and surface soil moisture in gullies. Gao et al. (2011) also reported clay and silt content were both positively correlated with soil moisture during and regression values decrease with rainfall events. In the study of eleven textural classes, Vereecken et al. (2007) found that standard deviation of soil moisture peaked between 0.17 and 0.23 $m^3 \cdot m^{-3}$ for most textual classes such as, silt loam to clay loam soils. In contrast, they found standard deviation increases with increase in soil moisture for sandy loam and loamy sand soils.

Residue cover was also correlated with soil moisture prediction. We observed high r^2 values in areas with low residue cover (<10%) and lower r^2 values in areas with high residue cover. Residue cover on the soil surface not only limits soil erosion due to water and air but also changes soil moisture spatial patterns within fields (Dabney 1998; Daigh et al. 2019). Studies have shown that the reduction of soil evaporation due to residue cover maintains higher soil moisture contents at field level over time (Dabney 1998; Unger and Vigil 1998). Partial residue covers in the field contribute to a slower, but still positive effect on soil moisture recharge as compared with completely covered soils; this difference in water recharge at different residue covers affects the prediction of soil moisture at field level (Patrignani and Ochsner 2018). Farmers are gradually shifting toward the minimum tillage to zero tillage with government subsidies and concern to improve the soil health condition (Acharya et al. 2019). This changes the representation of soil moisture from nearby agricultural field to weather station.

As previously discussed, many of the plant and soil characteristics in fields not only induce spatial variability but also influence soil moisture over time. We observed that a 4 d cumulative rainfall and PET had the highest non-linear regression coefficient and lowest RMSE as compared with other cumulative periods. Several studies have established similar relationships between soil moisture with the rainfall at larger spatial scales than the RRVN (Yoo et al. 1998; Entin et al. 2000; Cosh et al. 2004; Brocca et al. 2007; Ziadat and Taimeh 2013). With the application of satellite data, Brocca et al. (2013) also established that 4 d cumulative rainfall can effectively predict soil moisture with correlation value close to 0.8, which is similar to this finding. Additionally, Brocca et al. (2007) reported that higher correlation coefficients for soil moisture as the antecedent precipitation increased, which were in accordance with Western et al. (1999) and Gomez-Plaza et al. (2001). Rainfall, as well as incoming solar radiation, is a key factor affecting soil moisture at point scale measurements (Vivoni et al. 2010). Entekhabi and Rodriguez-Iturbe (1994) and Pan et al. (2003) in their extensive studies on predicting surface soil moisture from rainfall observed that time-weighted averages of previous cumulative rainfall over a given period resulted in high correlation coefficients with soil moisture.

Conclusion

The results shown in this study offer evidence that soil moisture can be reasonably represented by using information obtained at nearby weather stations despite large differences in soil and crop characteristics. The correlation between the soil moisture at weather stations and nearby agricultural fields is affected by crop type and their growth stages, crop residue, soil texture, and distance from the weather station. In Red River Valley, crops with thick canopy cover showed higher correlations compared with sparse crop canopies. Similar associations were observed when crop growth stages were at peak vegetative and reproductive stages. However, higher correlations were observed with lower crop residue cover of the soil surface and vice versa. The correlation between soil moisture at weather stations and nearby fields decreases as the distance from weather stations increases. Rainfall and evapotranspiration measured at weather stations can be used to estimate soil moisture in these nearby agricultural fields. The 4 d cumulative rainfall and PET showed higher correlations with field soil moisture as compared with other durations. This shows that rainfall and precipitation data can be effectively used in the prediction on soil moisture in the nearby fields despite discrepancies in soil and crop characteristics. This study showed promising results on estimation of soil moisture on agricultural fields using nearby weather station data when considering key field variables. However, the level of effect of each of the variables on the soil moisture prediction using soil moisture of weather station needs further exploration. The use of different multivariate or machine learning algorithms to model and evaluate the influence of variables also needs further exploration.

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