1 **Identifying Important Features for Downscaling Soil Moisture to 1-km in the Contiguous**
2 **United States**

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Abstract

Soil moisture is a fundamental state variable in climatology, meteorology, and hydrology. Many

of the available soil moisture products have a coarse spatial resolution that is not useful for

agricultural applications. This study used Random Forest to identify which features are most

helpful for accurately downscaling soil moisture to 1-km resolution. Fourteen features were

considered: precipitation, antecedent precipitation index, maximum daily air temperature,

minimum daily air temperature, mean daily air temperature, diurnal temperature range, dew

point temperature, elevation, slope, aspect, normalized difference vegetation index, leaf area

index (LAI), soil texture, and land use/land cover. The analysis of variable importance was

repeated using two different sources of soil moisture data (e.g., satellite-derived soil moisture

from NASA's Soil Moisture Active Passive (SMAP) and model-derived soil moisture from the

North American Land Assimilation System (NLDAS)) and ~~two different ways of representing

soil saturation (e.g., volumetric water content (VWC) and percentiles~~). We found that dew point

temperature is the most important variable for downscaling SMAP percentiles (0.18), NLDAS

VWC (0.27), and NLDAS percentiles (0.17) over CONUS, while elevation is the most important

variable for downscaling SMAP VWC (0.28). Dew point temperature is crucial for downscaling

in most regions of the United States, except in the South and WestNorthCentral, where elevation

is the most important feature. The accuracy of the downscaling varies by region. In the South,

SMAP VWC and NLDAS VWC downscaling are relatively accurate, both have mean absolute

errors of ~0.07. The MAE values in the South region are 0.196 for SMAP percentiles and 0.175

for NLDAS percentiles.

Keywords: Soil moisture, downscaling, SMAP, NLDAS, Random Forest

1. Introduction

37   Soil moisture is an important state variable in the climate system. Soil moisture is

38   essential for examining, monitoring, and forecasting drought and streamflow (Abbaspour et al.

39   2015; Keesstra et al. 2016), hydrological parameter distribution (Carrijo et al. 2019; Dobriyal et

40   al. 2012; Pittelkow et al. 2015), flash flood management (Brocca et al. 2014; Wanders et al.

41   2014), drought (Ruosteenoja et al. 2020; Wagner et al. 2013) and weather forecasting

42   (Seneviratne et al. 2010; Zhang et al. 2019). Soil moisture is also important for agriculture. It

43   influences crop yield, irrigation planning, disease outbreaks, pest control, and determining

44   optimal management practices, including irrigation (Dobriyal et al. 2012; Pittelkow et al. 2015).

45   Soil moisture is a small constituent of the total available freshwater (0.0015%) and the

46   global water cycle (0.05%) (Robinson et al. 2008). However, soil moisture is a critical element

47   of land-atmosphere interactions because it plays a significant role in modulating exchanges of

48   water between the land and atmosphere through evapotranspiration and transpiration (Ford et al.

49   2016; Zhang et al. 2019). Processes such as evapotranspiration, runoff, infiltration, and

50   groundwater recharge are influenced by the soil moisture and so it also has a significant part to

51   play in the hydrologic cycle (Vereecken et al. 2008).

52   Although soil moisture is useful for many purposes, national soil moisture data are not

53   readily available at high resolution (e.g., kilometer scale). For example, satellite soil moisture

54   products are limited to 1-km spatial resolution and model-derived products are limited to 12.5-

55   km, therefore often it is not sufficient for field-scale applications in the agricultural sector. To

56   make these datasets applicable to the finer scale, downscaling is necessary. It is possible to

57   conduct soil moisture downscaling in different ways. To assess soil moisture heterogeneity at a

58   finer scale, one approach is to combine ancillary data with low-resolution soil moisture

59   estimates. This has been implemented in several studies to obtain soil moisture at high spatial

60   resolution (Alemohammad et al. 2018; Srivastava et al. 2013). The spatial heterogeneity of soil

61   moisture is influenced by numerous factors, such as topography, precipitation, temperature, soil

62   texture, and vegetation. The purpose of this study is to identify which variables are most

63   important for downscaling soil moisture to 1-km spatial resolution. We downscaled SMAP and

64   NLDAS using Random Forest. We compared the importance of the ancillary variables for two

65   different data sources and two different methods for representing soil moisture (e.g., percentiles

66   and volumetric water content). To the best of our knowledge, this is the first study to evaluate

67   feature importance over CONUS using both satellite-derived and modeled soil moisture.

68   **2. Data**

69   **2.1 Soil moisture data**

70   **2.1.1   In-situ soil moisture**

71   In-situ datasets are useful for calibration and validation of the SMAP and NLDAS soil

72   moisture. In-situ measurements of soil moisture were used to validate the results of the

73   downscaling approach. The in-situ measurement of soil moisture is based on sensors installed in

74   various national and state networks. The networks used in this study include: the U.S. Climate

75   Reference Network (CRN), Delaware Environmental Observing System (DEOS), North Carolina

76   Environment and Climate Observing Network (ECONet), Illinois Climate Network (ICN),

77   Kansas Mesonet (KS Mesonet, New Jersey Weather and Climate Network (NJWCN), NOAA

78   Hydrometeorological Testbed (NOAA), New York Mesonet (NY Mesonet), Oklahoma Mesonet

79   (OK Mesonet), Soil Climate Analysis Network (SCAN), South Dakota Mesonet (SD Mesonet),

80   Snowpack Telemetry (SNOTEL), Texas Soil Observation Network (TxSon), Georgia Automated

81   Environmental Monitoring Network (GA AEMN), and West Texas Mesonet (WTX Mesonet). A

82   total of 1542 in-situ stations were used for this study. The number of stations varies from region

83   to region greatly. For example, the South has a lot of stations, while the NorthWest has few

84   stations. In-situ data from 2001 to 2021 were used for validating the downscaled soil moisture.

2.1.2 SMAP soil moisture

86   Remote sensing data provides gridded products instead of point-based soil moisture

87   measurements and improves spatial coverage. Ford and Quiring (2019) examined the remote

88   sensing soil moisture datasets provided by SMAP (SMAP L3 and SMAP L4), SMOS, and ESA-

89   CCI and they concluded that SMAP Level 3 products consistently performed best among the

90   four datasets. Though SMAP L3 products perform better than other remote sensing products, it

91   has a significant number of missing values and dates. For that reason, SMAP L4 data are used in

92   this study. The SMAP L4 product is a model-derived value-added products of surface and root

93   zone soil moisture that support key SMAP applications. SMAP produces Level 4 data products

94   that combine surface observations with a land surface model using a data assimilation system to

95   simulate root zone soil moisture. The SMAP L4 data are available from 2015 to the present and

96   they provide surface soil moisture (0-5 cm) and root zone soil moisture (0-100 cm). This study

97   used SMAP data from 2015 to 2021.

2.1.3   NLDAS soil moisture

99   Land surface models use climate inputs and parameterizations of the environment to

100 simulate soil moisture based on model-derived equations and assumptions. The model-derived

101 soil moisture products can be achieved consistently at the global scale because the model can be

102 operated seamlessly. However, model-simulated soil moisture has limitations because there is a

103 nonlinear relationship between climate parameters and soil water content. In addition, soils and

104   vegetation are spatially heterogeneous and this is not accurately captured by models (Xia et al.

105   2015). Ford and Quiring (2019) examined the NLDAS-2 and found that it performed better than

106   the CPC-modeled soil moisture when validated against in-situ measurements. Therefore, this

107   study uses NLDAS-2 model-simulated soil moisture. The soil moisture data are provided hourly

108   at 1/8° spatial resolution by the NLDAS-2 Noah model. The data are available at four soil layers:

109   0-10 cm, 10-40 cm, 40-100 cm, and 100-200 cm. To align the temporal granularity with in-situ

110   and satellite data, we averaged the hourly data to daily. NLDAS-2 data from 2001 to 2021 were

111   used in this study. The downscaling was done every day from 2001 to 2021 within the CONUS

112   to generate a 1-km soil moisture from NLDAS-2.

2.2 Ancillary variables

114   This study evaluated a total of 14 features: precipitation, antecedent precipitation index,

115   maximum daily air temperature, minimum daily air temperature, mean daily air temperature,

116   diurnal temperature range, dew point temperature, elevation, slope, aspect, Normalized

117   Difference Vegetation Index, Leaf Area Index, soil texture, and land use/land cover.

118   Soil texture (sand, silt, and clay percentage) came from the gridded soil survey

119   geographic database (SSURGO) provided by Natural Resources Conservation Services (NRCS)

120   (https://www.nrcs.usda.gov/). It has a spatial resolution of 10-30 m. Precipitation, mean

121   temperature, maximum temperature, minimum temperature, and dew point temperature were

122   obtained from Parameter-elevation Regressions on the Independent Slopes Model (PRISM) lab

123   (https://prism.oregonstate.edu/). The spatial resolution of PRISM is 4-km. The Antecedent

124   Precipitation Index (API) was calculated from the precipitation data for each day. The antecedent

125   precipitation index (API) formula is,

126 $$API = P_i * N * 0.98$$

127 where: P_i: daily precipitation i days before a storm, N: total number of days to consider before

128 the storm, K: a recession constant that is less than 1.0 (here, a value of 0.98 was used).

129   The diurnal temperature range (DTR) was calculated based on the difference between the

130 maximum to minimum temperature. Elevation data were extracted from GTOP30 provided by

131 the United States Geological Survey (USGS), and the spatial resolution is 1-km. Slope and

132 aspect were derived from the elevation data. The Normalized Difference Vegetation Index

133 (NDVI) and Leaf Area Index (LAI) are from the Advanced Very High-Resolution Radiometer

134 (AVHRR) satellite. The spatial resolution of the AVHRR satellite is 9-km. Land use data were

135 collected from the National Land Cover Dataset (NLCD). The native spatial resolution of NLCD

136 is 30-m. Table 1 provides a description of all of the ancillary variables.

137   Table 1: Spatial and temporal resolution of variables evaluated for downscaling soil moisture

Variable Name	Temporal Domain	Temporal Resolution	Spatial Resolution	Source
Elevation	2018	N/A	1-km	USGS EROS Archive - Digital Elevation - Global 30 Arc-Second Elevation (GTOPO30)
Slope	2018	N/A	1-km	USGS EROS Archive - Digital Elevation - Global 30 Arc-Second Elevation (GTOPO30)
Aspect	2018	N/A	1-km	USGS EROS Archive - Digital Elevation - Global 30 Arc-Second Elevation (GTOPO30)
Soil Texture	2021	N/A	10 to 30-m	Gridded Soil Survey Geographic (gSSURGO) Database
Land Use	2021	N/A	30-m	National Land Cover Dataset (NLCD)
Precipitation	2001 to 2021	Daily	4-km	Parameter-elevation Relationships on Independent Slopes Model (PRISM)
Antecedent Precipitation Index (API)	2001 to 2021	Daily	4-km	Parameter-elevation Relationships on Independent Slopes Model (PRISM)
Mean Temperature	2001 to 2021	Daily	4-km	Parameter-elevation Relationships on Independent Slopes Model (PRISM)
Maximum Temperature	2001 to 2021	Daily	4-km	Parameter-elevation Relationships on Independent Slopes Model (PRISM)
Minimum Temperature	2001 to 2021	Daily	4-km	Parameter-elevation Relationships on Independent Slopes Model (PRISM)
Dew Point Temperature	2001 to 2021	Daily	4-km	Parameter-elevation Relationships on Independent Slopes Model (PRISM)
~~Normalized ference Vegetation Index (NDVI)~~	~~2001 to 2021~~	~~Daily~~	~~4-km~~	~~Parameter-elevation Relationships on Independent Slopes Model (PRISM)~~
Normalized Difference Vegetation Index (NDVI)	2001 to 2021	Daily	9-km	Advanced very-high-resolution radiometer (AVHRR)
Leaf Area Index (LAI)	2001 to 2021	Daily	9-km	Advanced very-high-resolution radiometer (AVHRR)

138

2.3 Soil Moisture Standardization

140   Volumetric water content (VWC) varies according to weather conditions, soil properties,

141   vegetation cover, topographic features, and various other elements. Thus, it is not possible to

142   directly compare the VWC from different locations since a fine-textured soil will almost always

143   have a higher VWC than a coarse-textured soil. Therefore, VWC is commonly standardized

144   using an approach such as soil moisture percentiles (Ford et al. 2016; Zhang et al. 2019). In this

145   paper, we converted the soil moisture datasets to percentiles using the following approach. First,

146   the VWC data were converted to VWC anomalies ($m^3 m^{-3}$) by subtracting the climatological

147   mean from the daily VWC value (Crow et al. 2012). A moving window approach was used to

148   calculate the climatological mean. Following Chen et al. (2019), a 31-day moving window was

149   used surrounding the target day, and all years of data from the period of record from that window

150   were used to calculate the mean. Next, daily percentiles were calculated using the empirical

151   cumulative distribution function based on a 31-day moving approach that used the entire period

152   of record. According to Ford et al. (2016), at least 6 years of daily data are required to create

153   stable and robust percentiles. In our case, soil moisture percentiles were calculated based on 7

154   years of SMAP data and 21 years of NLDAS data.

155   **3. Methods**

156   The NLDAS and SMAP soil moisture data were downscaled using Random Forest. This

157   algorithm was applied separately to the SMAP soil moisture (9-km) and the NLDAS soil

158   moisture (12.5-km) to generate a 1-km soil moisture dataset over CONUS. Figure 1 provides a

159   summary of the methods used to identify the most important features for downscaling soil

160   moisture. The first step was to retrieve from different sources and aggregate the ancillary

161   variables by applying nearest-neighbor interpolation. Then an RF model was generated for

162   downscaling SMAP and NLDAS soil moisture products. The third step was to summarize feature

163   importance. Each step is described in detail below.

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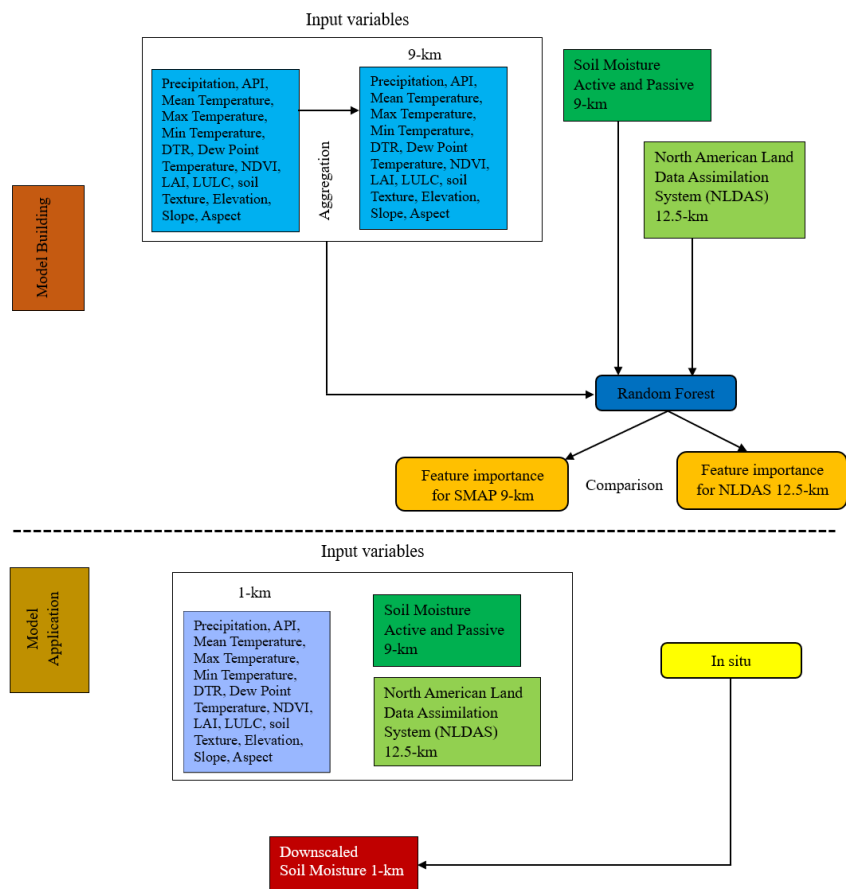
Figure 1: Schematic representation of the methodology used in this study

166   **3.1 Nearest neighbor interpolation**

167   All ancillary data are first aggregated to a resolution of 9-km and 12.5-km to construct

168   the downscaling models. Nearest neighbor interpolation is used to resample the ancillary data

169   (Table 1). Nearest neighbor is a method of spatial resampling that calculates the value of a new

170   pixel based on the value of its nearest neighbor. This method was selected because it is

171   computationally efficient and previous soil moisture downscaling studies have applied the

172   nearest neighbor method (Alemohammad et al. 2018; Li et al. 2016; Liu et al. 2020, 2011). This

173   method was applied twice, once to generate features at the same resolution as SMAP (9-km) and

174   to generate features at the same resolution as NLDAS (12.5-km).

3.2 Downscaling soil moisture with random forest

175

176   Soil moisture downscaling to 1-km from the native SMAP (9-km) and NLDAS (12.5-km)

177   resolutions was done using Random Forest. Random Forest (RF) was first developed by

178   (Breiman 2001) and then later advanced by (Cutler et al. 2012). RF is an integrated learning

179   algorithm that can be used for both classification of a categorical response and regression for

180   continuous variables (Li et al. 2013; Lu et al. 2014). The advantages of RF are that it is very fast

181   to train and predict, it only depends on a few tuning parameters, and it can be used for high-

182   dimensional problems, outlier detection, and visualization (Cutler et al. 2012). The regression

183   model in RF was used for downscaling soil moisture in this study.

184   The dataset was randomly split into 80% training and 20% testing for model evaluation.

185   To optimize the model, we performed randomized search cross-validation over a set of

186   hyperparameters, including the number of trees (n_estimators): {20, 40, 60, …, 200}, maximum

187   depth of trees (max_depth): {10, 20, 30, …, 110, None}, maximum number of features per split

188   (max_features): {'auto', 'sqrt'}, minimum number of samples per split (min_samples_split): {2,

189   5, 10}, minimum number of samples per leaf (min_samples_leaf): {1, 2, 4}, and bootstrap

190   sampling method: {True, False}. The hyperparameter tuning is the same for each region.

191   The RF model for SMAP was generated using data from 2015 to 2021, and the RF model

192   for NLDAS was generated using data from 2001 to 2021. A 3-fold cross-validation was used for

193   cross-validation, each fold randomly selected 80% of the data for training and the remaining

194   20% was used for validation. The RF model with the highest accuracy was selected based on the

195 cross-validation. This model was used to downscale the soil moisture to 1-km resolution and this

196 downscaled soil moisture was validated using the in-situ measurements. This process was

197 repeated separately for SMAP and NLDAS.

3.3 Model evaluation

199 The correlation coefficient (R), coefficient of determination (R^2), mean absolute error

200 (MAE), mean squared error (MSE), and root mean square error (RMSE) were used for validating

201 the downscaled soil moisture data. R and R^2 measure the goodness-of-fit of the model. MAE,

202 MSE and RMSE measure the error between the actual and downscaled soil moisture values.

$$R = \frac{Cov\ (SM_o, SM_p)}{\sqrt{Var[SM_o]Var[SM_p]}}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}[(SM_p - SM_{mp})(SM_o - SM_{mo})]^2}{\sum_{i=1}^{n}(SM_p - SM_{mp})^2 \sum_{i=1}^{n}(SM_o - SM_{mo})^2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|SM_o - SM_p|$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(SM_o - SM_p)^2$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(SM_o - SM_p)^2}{n}}$$

208 Where n is the number of observations, SM_o, SM_p, SM_{mo}, SM_{po} represent the observed soil

209 moisture value, predicted soil moisture value, mean observed soil moisture value, and mean

210 predicted soil moisture value.

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4 Results

4.1 Feature importance for SMAP downscaling

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212

213 There are two measures that can be used to quantify the predictive power of individual

214 features in RF Regression: (1) an increased mean squared error (IncMSE) and, (2) an increase in

215 the number of nodes purified (IncNudePurity). IncMSE measures how an individual feature

216 changes when it is permuted at random. IncMSE measures the degree to which the accuracy of

217 Random Forest decreases when a feature is removed. Fourteen features were used to downscale

218 the coarse resolution of soil moisture products to 1-km resolution. The IncMSE was calculated

219 for each feature in each of the 9 regions to determine feature importance.

220 At the national (CONUS) scale, elevation is the most influential variable and dew point

221 temperature is the second most important feature (Figure 2). Maximum temperature is also

222 ranked as an important variable that improves the accuracy of downscaling of SMAP VWC over

223 CONUS. The least important features at the national scale are slope, aspect, and LAI.

224 In addition to evaluating feature importance for each region, the analysis was also

225 replicated by evaluating feature importance for different regions of CONUS. Figure 3 shows the

226 feature importance for SMAP VWC by region. The dew point temperature is the most important

227 feature in all regions, except the WestNorthCentral and South regions. Elevation is the most

228 important variable in these two regions. API is the second-most important variable in the

229 NorthWest, West, and SouthWest regions. Maximum, minimum, and mean temperature also play

230 a significant role in downscaling soil moisture. LAI is a feature that consistently is ranked as a

231 relatively unimportant feature for downscaling soil moisture (ranks from 0.1 to 0.2 across the 9

232 regions).

233   This study evaluates both VWC and soil moisture percentiles. Therefore, we can compare

234   the relative feature importance for downscaling soil moisture percentiles. At the CONUS scale,

235   dewpoint temperature is the most influential variable (Figure 4). This is followed by API and

236   elevation. The results at the CONUS scale are relatively consistent with the regional results.

237   Additionally, precipitation, maximum, mean temperatures, and DRT are all relatively important

238   variables for downscaling soil moisture percentiles at the CONUS scale (rank ranges from 3 to

239   6).

240   Similar to the results for SMAP VWC, dew point temperatures are the most influential

241   variable in all regions except the South (Figure 5). Elevation is the most influential feature in the

242   South. The second most important feature is either API or elevation. API is the second-most

243   influential variable in the NorthWest, SouthWest, and EastNorthCentral, NorthEast, SouthEast,

244   and Central regions. While elevation is the second most important feature of WestNorthCentral

245   regions. LAI, aspect, slope, NDVI, and LULC are the least important features for downscaling

246   soil moisture percentiles.

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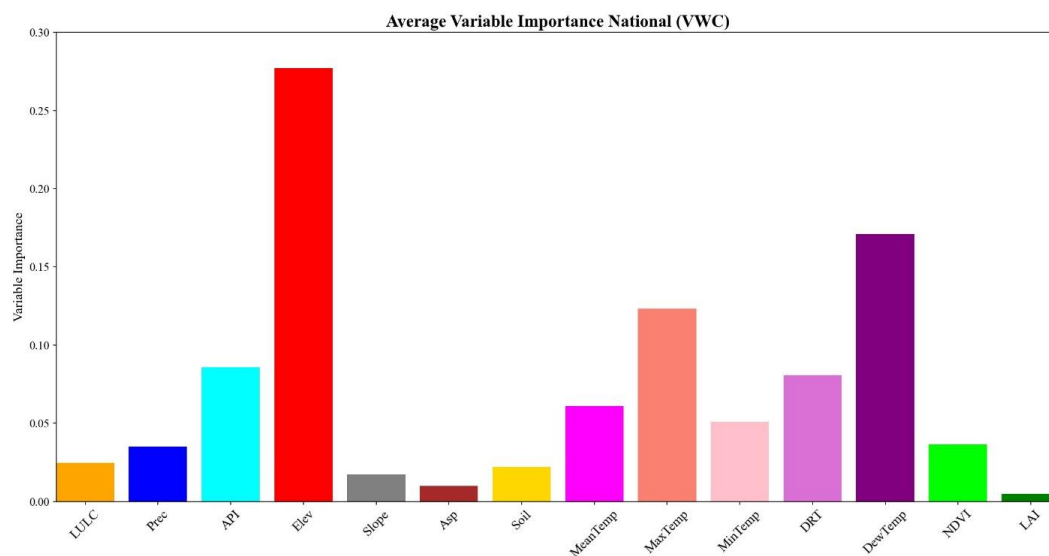
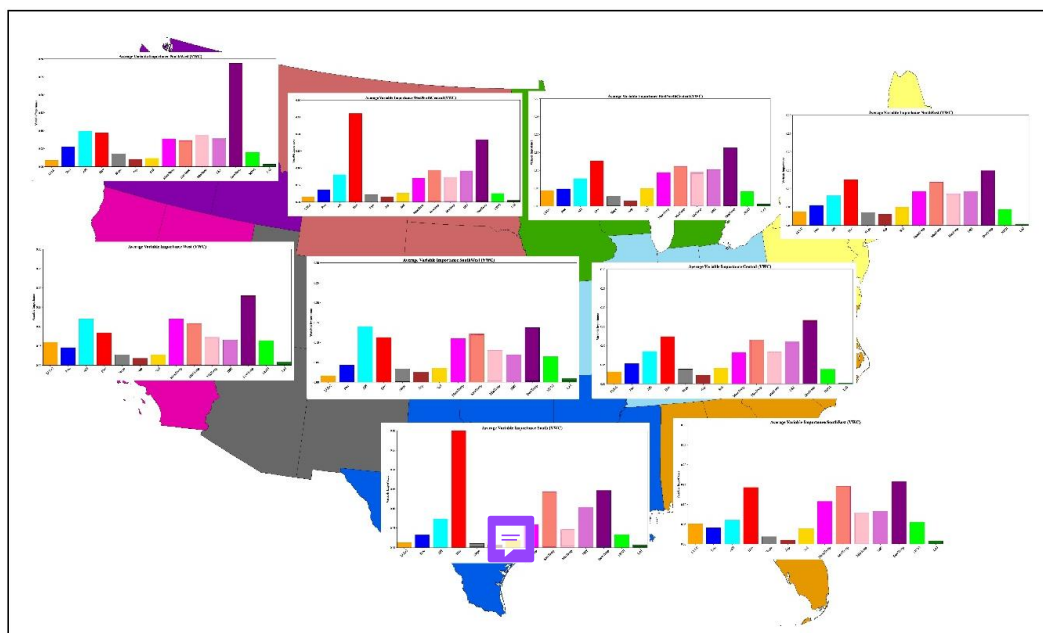

248   Figure 2: Feature importance (IncMSE%) for CONUS for SMAP VWC

249   Figure 3: Features importance (IncMSE%) by region for SMAP VWC

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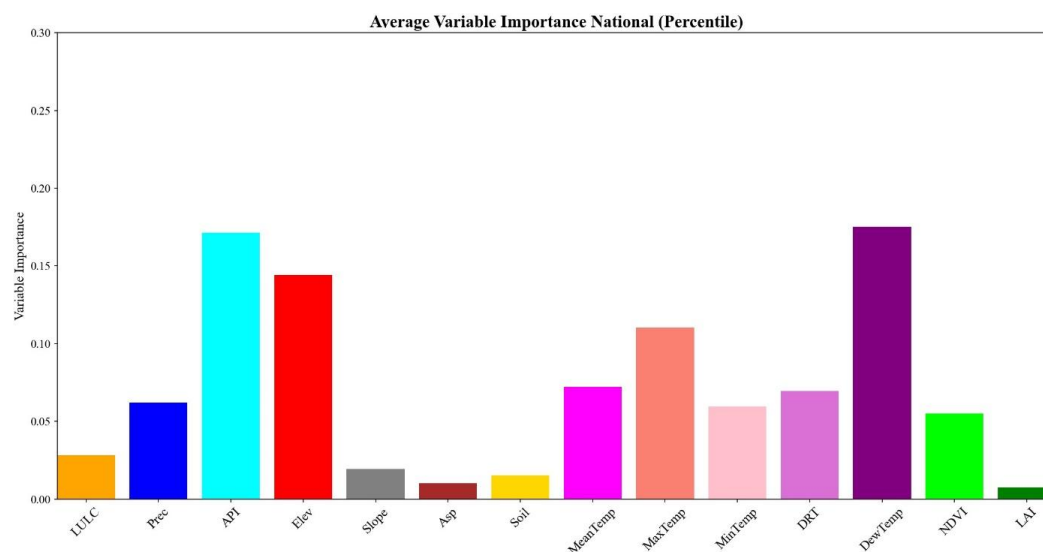
Figure 4: Feature importance (IncMSE%) for CONUS for SMAP percentile

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Figure 5: Feature importance (IncMSE%) by region for SMAP percentiles

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4.2 Feature importance for NLDAS downscaling

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256   At the CONUS scale, dew point temperature is the most important feature (Figure 6).

257   Elevation and maximum temperature have almost the same influence and are ranked as the

258   second and third most important features on the CONUS scale. Though elevation was the highest

259   influential variable for SMAP VWC, elevation is ranked second here. However, as SMAP VWC,

260   slope, aspect, LAI ranked the lowest.

261   Figure 7 shows the feature importance for downscaling NLDAS VWC in each region.

262   Dew point temperature is the most important feature in all regions. Elevation is the second-

263   highest important feature in all regions, except the NorthWest, West, SouthWest, and

264   EastNorthCentral regions. The second most important variable for the NorthWest, SouthWest,

265   and EastNorthCentral region is maximum temperature; for the West is mean temperature.

266   Maximum and mean temperature are also influential features for downscaling NLDAS VWC.

267   They typically rank as each region's 3rd or 4th most important features. While LAI and aspect

268   are generally the least important features. These results are quite consistent with the SMAP

269   feature importance.

270   At the CONUS scale, dewpoint temperature is again the most influential feature (Figure

271   8). This is followed by API and elevation. Maximum and mean temperatures are also influential

272   features at the CONUS scale. The results of the feature importance for NLDAS soil moisture

273   percentiles are consistent with NLDAS VWC. Dew point temperature is the most important

274   feature in all regions (Figure 9). API is the second most important feature in all regions, except

275   the NorthWest, West, WestNorthCentral. In these regions, elevation is the second most important

276   feature. LAI and aspect consistently have the lowest feature importance for downscaling NLDAS

277   soil moisture percentiles.

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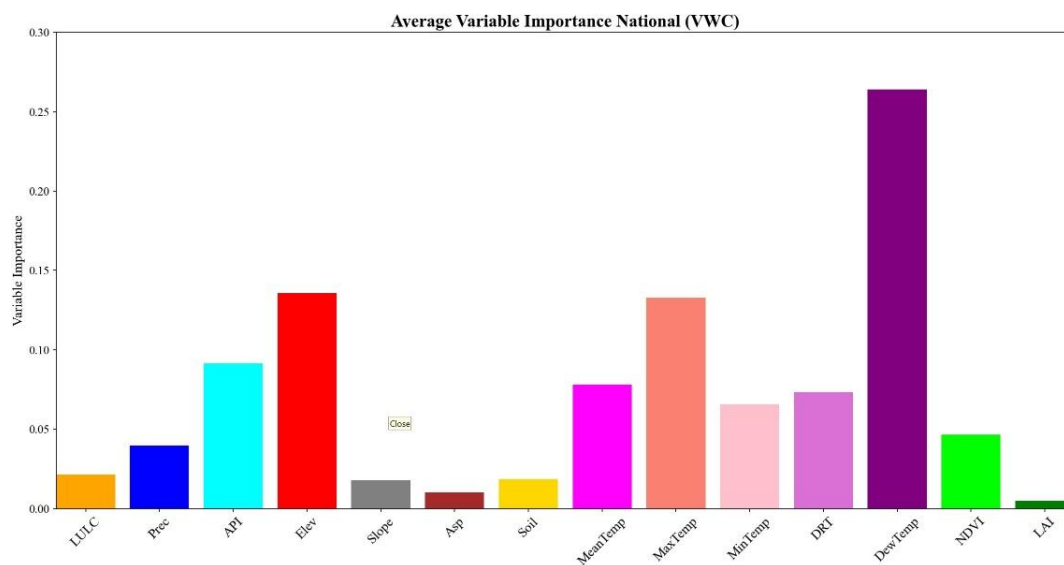
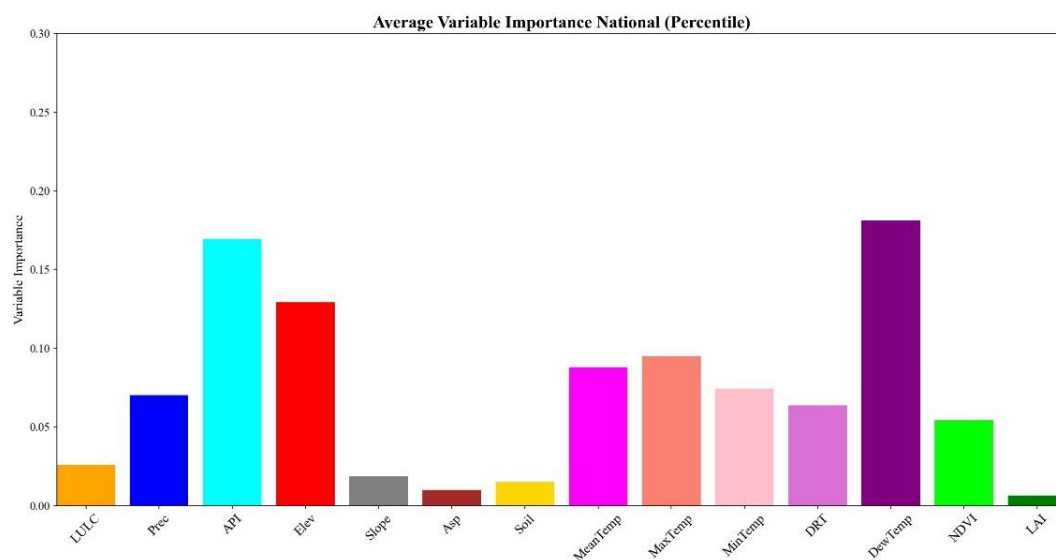
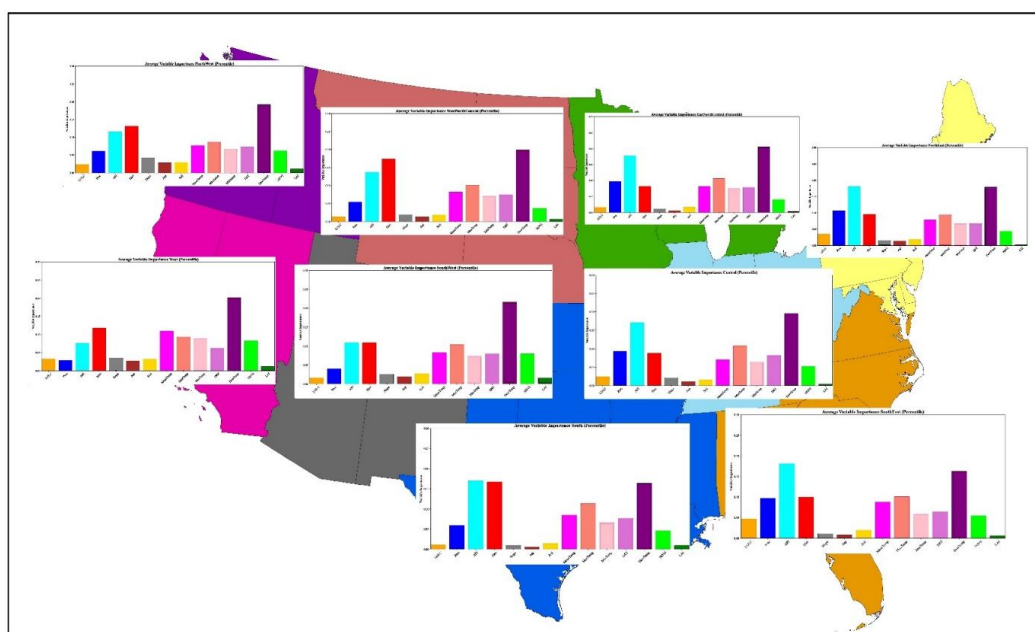


Figure 6: Feature importance (IncMSE%) for CONUS for NLDAS VWC

280

Figure 7: Feature importance (IncMSE%) by region for NLDAS VWC

282   Figure 8: Feature importance (IncMSE%) for CONUS for NLDAS percentiles

283   Figure 9: Feature importance (IncMSE%) by region for NLDAS percentile

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4.3 Partial dependence plot (PDP) of variables

285

286  Figure 10 represents the relationship between predicted soil moisture and the other

287 variables (dew point temperature, elevation, API, and maximum temperature).

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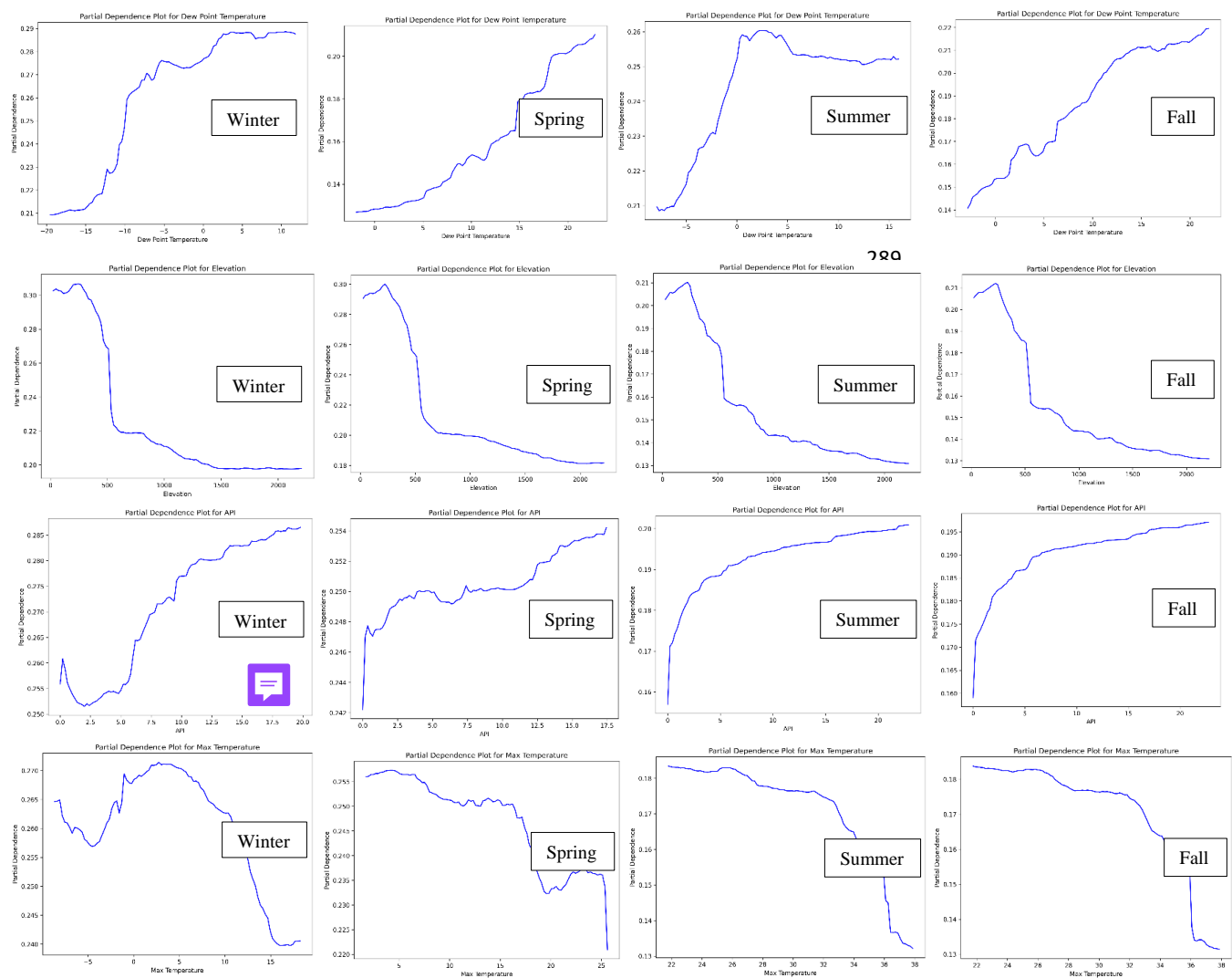
300

301      Figure 10: Partial dependence plot for the four most important variables

302 The higher dew point temperature is related to the high soil moisture values in all seasons. The

303 lower elevation seems to have high soil moisture values in four seasons which is reasonable

304 because in the high elevation, the water content in the soil is low. If the API value is increasing,

305 the value of water content in the soil will be high and vice versa. On the other hand, with the

306 increasing maximum temperature, the soil moisture will be decreasing.

307 **4.3 Accuracy of VWC downscaling**

308 Table 2 shows the accuracy of the VWC downscaling in each region based on the

309 validation against in situ measurements. As shown in the table, the R-value is < 0.5 and $R^2 <$

310 0.25 for NLDAS downscaling. The ~~average~~ absolute difference between the SMAP downscaling

311 and observed value (MAE) ranges from 0.074 to 0.092. The Central region has a relatively low

312 MAE of 0.074, indicating a small average absolute difference between the predicted and actual

313 values. The highest value of MSE is 0.014 corresponding to SouthEast and 0.013 to

314 EastNorthCentral and the lowest value is 0.008 corresponding to South. The ubRMSE for the

315 South is 0.082 which is the lowest and for the SouthEast is 0.109 which is the highest. Although

316 the R^2 values are relatively low, the errors (MAE and ubRMSE) are also low. This indicates that

317 the downscaling is skillful.

318 Table 2: Accuracy of 1-km downscaled soil moisture (VWC) by region for SMAP and

319 NLDAS

	R		R2		MAE		MSE		RMSE		ubRMSE		Bias	
	SMAP	*NLDAS*	*SMAP*	*NLDAS*	*SMAP*	*NLDAS*	*SMAP*	*NLDAS*	*SMAP*	*NLDAS*	*SMAP*	*NLDAS*	*SMAP*	*NLDAS*
Central	0.451	0.352	0.204	0.146	0.074	0.086	0.009	0.011	0.093	0.104	0.089	0.091	-0.008	-0.021

EastNorthCentral	0.403	0.494	0.157	0.248	0.092	0.072	0.013	0.010	0.115	0.097	0.093	0.087	0.053	-0.017
NorthEast	0.323	0.337	0.104	0.131	0.075	0.084	0.009	0.010	0.095	0.100	0.089	0.085	0.001	-0.017
NorthWest	0.268	0.298	0.065	0.090	0.080	0.085	0.009	0.010	0.097	0.100	0.092	0.089	0.022	0.014
South	0.568	0.551	0.323	0.304	0.072	0.069	0.008	0.007	0.091	0.086	0.082	0.080	-0.033	-0.020
SouthEast	0.419	0.622	0.176	0.386	0.094	0.084	0.014	0.010	0.116	0.101	0.109	0.090	0.034	0.010
SouthWest	0.364	0.622	0.132	0.073	0.078	0.091	0.010	0.012	0.098	0.108	0.093	0.097	-0.020	-0.004
West	0.308	0.270	0.099	0.081	0.075	0.084	0.009	0.010	0.094	0.099	0.092	0.090	0.016	0.025
WestNorthCentral	0.520	0.494	0.270	0.248	0.073	0.080	0.008	0.010	0.091	0.097	0.085	0.087	-0.011	0.004
National	0.514	0.509	0.192	0.259	0.082	0.083	0.010	0.010	0.102	0.100	0.100	0.095	-0.015	-0.011

320

4.4 Accuracy of percentile downscaling

322 Table 3 provides the evaluation metrics of soil moisture downscaling for percentiles by

323 region. The South region has the lowest MAE of 0.195, indicating the smallest average absolute

324 difference between predicted and actual values among all the regions. The MSE is also the

325 lowest which is 0.061 for this region, indicating a higher average squared difference. The RMSE

326 of 0.248 is also the lowest among the regions, indicating the smallest average absolute

327 difference. On the other hand, the NorthWest and SouthWest regions are characterized by the

328 highest MAE of 0.223, which indicates a greater average absolute difference between the

329 predicted and actual values compared to other regions. As indicated by the MSE value of ~0.076,

330 there is a greater average squared difference between the two regions. RMSE of ~0.275 indicates

331 Table 3: Accuracy of 1-km downscaled soil moisture (percentiles) by region for SMAP

332 and NLDAS

	R		R²		MAE		MSE		RMSE		ubRMSE		Bias	
	SMAP	*NLDAS*	*SMAP*	*NLDAS*	*SMAP*	*NLDAS*	*SMAP*	*NLDAS*	*SMAP*	*NLDAS*	*SMAP*	*NLDAS*	*SMAP*	*NLDAS*
Central	0.423	0.536	0.187	0.297	0.200	0.177	0.065	0.050	0.256	0.224	0.222	0.198	-0.055	-0.016

EastNorthCentral	0.411	0.429	0.198	0.304	0.207	0.195	0.065	0.056	0.256	0.236	0.216	0.189	-0.026	-0.045
NorthEast	0.269	0.307	0.085	0.120	0.207	0.211	0.066	0.068	0.257	0.261	0.226	0.220	-0.048	-0.034
NorthWest	0.229	0.194	0.050	0.048	0.223	0.237	0.076	0.084	0.276	0.291	0.249	0.252	0.0276	-0.058
South	0.442	0.488	0.195	0.238	0.195	0.175	0.061	0.049	0.248	0.223	0.224	0.208	-0.068	-0.019
SouthEast	0.394	0.437	0.156	0.195	0.207	0.189	0.066	0.055	0.258	0.236	0.227	0.212	-0.081	-0.027
SouthWest	0.229	0.229	0.053	0.058	0.223	0.228	0.077	0.079	0.278	0.281	0.256	0.253	0.000	-0.042
West	0.238	0.180	0.062	0.047	0.216	0.226	0.072	0.076	0.268	0.276	0.245	0.245	-0.015	-0.025
WestNorthCentral	0.363	0.367	0.141	0.144	0.215	0.218	0.073	0.074	0.270	0.272	0.253	0.244	-0.021	-0.054
National	0.425	0.370	0.029	0.138	0.217	0.226	0.073	0.080	0.270	0.284	0.260	0.262	-0.033	-0.080

333

a greater average absolute difference among the regions. The lowest MAE value is 0.175 in the

South region. The lowest MAE value indicates the closer alignment between actual and predicted

values. The average squared difference between the expected and actual values ranges from

0.050 to 0.086. Similar patterns can be observed between MSE and RMSE values. The lowest

value of RMSE is 0.223 indicating good predictions for South regions.

5 Discussion

5.1 Feature importance

A complex interaction between pedologic, topographic, vegetative, and meteorological

factors is responsible for the extensive horizontal variability in surface soil moisture fields

(Mohanty and Skaggs 2001). It is difficult to isolate and measure these factors, however,

understanding their magnitude is critical for determining soil moisture upscaling strategies

(Crow et al. 2012).

Topography is another crucial factor that influences the spatial organization of soil

moisture at various scales. The topographic attributes such as slope, aspect affect the movement

of water through gravity-driven processes, such as runoff and infiltration, leading to variations in

349   soil moisture across the landscape (Crow et al. 2012). This research also complements that

350   topography is an important factor because elevation is the most influential factor and second

351   highest factor relatively in SMAP VWC and NLDAS VWC downscaling over CONUS. In

352   addition, elevation ranks third for percentile downscaling for both data sources. Understanding

353   the role of topography is essential for accurately characterizing and predicting soil moisture

354   patterns. Charpentier and Groffman (1992) suggested that variations in topography play a

355   significant role in shaping the spatial distribution of soil moisture, with more diverse topographic

356   features leading to increased variability in soil moisture. This study shows the South and

357   WestNorthCentral regions have the influences of slope regardless of data sources and units of

358   measurement. Since the WestNorthCentral region includes portions of the Rocky Mountains, and

359   the mountainous area has high variability in elevation. It has been demonstrated that relative

360   slope position significantly impacts determining soil moisture variation. When considering

361   different time scales, a straightforward averaging of soil moisture values across a slope is likely

362   to produce errors (Mohanty et al. 2000; Jacobs 2004). Here, this research shows differences

363   because slope has a relatively low impact on the downscaling for both data sources and both

364   units of measurement (VWC and percentile). In addition, the aspect (direction of slope) also has

365   less impact on the downscaling in all the regions and over CONUS too. The effects of slope on

366   soil moisture are more localized and dependent on other factors rather than being significant. It is

367   important to mention that slope influences soil moisture in various ways, including its length and

368   direction (aspect). Although these effects are generally less pronounced than those that elevation

369   has on the local microclimate and hydrology, they can be observed (Bennie et al. 2008).

370   Among these meteorological factors, precipitation is considered the single most

371   important forcing factor for soil moisture content and its distribution (Crow et al. 2012). This

372   research agrees with Crow et al. (2012) because the precipitation index (API) ranks second in

373   terms of SMAP percentile downscaling over the CONUS. Furthermore, API is also a dominant

374   factor for the South, WestNorthCentral, NorthWest, SouthWest regions. Sivapalan et al. (1987)

375   and Famiglietti et al. (1999) found the mean soil moisture trend changed with the precipitation

376   gradient. The soil moisture storage, drainage, and water budget for different climate patterns

377   changed with the intensity of rainfall (Kim et al. 1997; Salvucci 2001). To date, there has not

378   been any research that has shown that dew point temperature is useful for downscaling soil. The

379   present study found that dew point temperature is the most important feature for downscaling

380   soil moisture for both products and both measurements, except SMAP VWC over the CONUS.

381   Although elevation has the highest impact on SMAP VWC downscaling over the CONUS, dew

382   point temperature has the highest influence over all the regions except the South, and

383   WestNorthCentral regions both for SMAP VWC and percentile downscaling. For NLDAS VWC

384   and percentiles, only the South region is different.

385   There are a number of ways that the dew point temperature can influence soil moisture.

386   First, when the air temperature cools to the dew point temperature water vapor will condense,

387   forming dew on the soil surface and vegetation (Monteith, 1957, Jacobs et al. 2000). Second,

388   dew point temperature can also affect the transpiration rates of plants (Ambrose et al. 2009). Soil

389   evaporation and plant transpiration will increase as a function of the vapor pressure gradient.

390   Therefore, dew point temperature fluctuations can influence the wetting and drying cycles of the

391   soil (Zhou et al. 2008).

392   Precipitation, mean, maximum, and minimum temperatures also have an impact on soil

393   moisture. Higher temperatures tend to be associated with an increased vapor pressure deficit

394   between the soil surface and the air, and this leads to a higher evaporation rate from the soil.

395 Higher temperatures can cause the soil to dry out more rapidly, particularly from the surface of

396 the soil (Balugani et al. 2014). They can also cause vegetation to utilize more soil water and so

397 they can cause the depletion of soil moisture (Oren et al. 1999).

398 The distribution of soil moisture is significantly affected by soil heterogeneity, due to

399 variations in soil properties such as texture, organic matter content, porosity, and structure. As a

400 result of these variations, soil moisture can significantly differ over small spatial distances,

401 influencing local hydrological processes. The color of the soil can also influence the rate of

402 evaporative drying for bare or lightly vegetated soils by affecting the albedo. Soil hydraulic

403 conductivity affects processes such as water infiltration, redistribution, and drainage, which in

404 turn impact the distribution of soil moisture across a given area (Moore et al. 1988; Kim and

405 Barros 2002). Although previous research concluded that soil type has a significant impact on

406 soil moisture, this research found that soil type has minimal impact on downscaling soil

407 moisture. In addition, whether over the CONUS or for all the regions, soil type is one of the least

408 influential variables. The reason could be that other factors like elevation, prevailing climate, and

409 precipitation patterns have a greater impact than the soil texture.

410 Previous work has concluded that variations in soil moisture are more strongly influenced

411 by vegetation than by soil and topography (Crow et al. 2012). Our results do not support this

412 conclusion (at least for 1-km soil moisture) since the vegetation variables (NDVI and LAI) were

413 less important than topography. Soil moisture is spatially variable as a result of various processes

414 that involve water uptake, transpiration, and the surface energy budget. The influence of land

415 cover characteristics must be understood to accurately model and predict soil moisture dynamics.

416 Land cover affected soil moisture distribution significantly at the satellite footprint during the

417 NAFE'05 field campaign in Australia (Panciera et al. 2008). The regional distribution of soil

418 moisture was noted to be impacted by variations in land cover (Cosh et al. 2004; Joshi and

419 Mohanty 2010). However, the results of our study indicated that land cover was not an important

420 feature for downscaling soil moisture to 1-km resolution. It had minimal impact on the

421 downscaling regardless of the data sources or soil moisture measurement. These results were

422 consistent over the CONUS and all regions.

423   Drawing broad conclusions regarding the impact of soil, topography, land cover,

424 vegetation, and meteorological forcing can be challenging because feature important is strongly

425 influenced by the spatial scale of analysis and the region of interest (Crow et al. 2012). Our study

426 results demonstrate that there can be substantial region variations in feature importance and that

427 feature importance is also a function of the data source, unit of measurement and spatial

428 resolution.

429   Regions may differ in terms of climatic, geographic, and soil characteristics, which can

430 have a significant impact on the relationship between the input features and soil moisture.

431 Regions with limited or incomplete data may be difficult to predict accurately. Our analysis

432 demonstrates that other than elevation, temperature is an important feature in the South. This

433 region includes Texas, Louisiana, Mississippi, Arkansas, Kansas, and Oklahoma. It is

434 characterized by a warm and humid climate. Soil moisture is influenced by precipitation and

435 topography. Periodic droughts have a strong influence on soil water content (Bond et al. 2008;

436 Engle et al. 2008).

437   The northeastern region includes New York, Pennsylvania, Connecticut, Delaware,

438 Maine, Maryland, Massachusetts, New Hampshire, New Jersey, Vermont, and Rhode Island. It

439 has a temperate climate with distinct seasonal patterns. Seasonal variations in precipitation and

440 snowmelt can significantly impact soil moisture patterns (Daly et al. 2008). Our results

441   demonstrate that API, dew point temperature, and temperature influence soil moisture. The

442   northwestern region includes Idaho, Oregon, and Washington. It has a diverse climate ranging

443   from maritime to continental. The EastNorthCentral includes Iowa, Michigan, Minnesota, and

444   Wisconsin. It has a humid continental climate with distinct seasonal changes. The region is

445   dominated by the Great Lakes. Soil moisture depends on temperature and precipitation patterns

446   (Kunkel et al. 2013). Our results demonstrate that API and temperature have a significant impact

447   on soil moisture.

448   The WestNorthCentral includes Montana, Nebraska, North Dakota, South Dakota, and

449   Wyoming. It is characterized by a continental climate with hot summers and cold winters.

450   Snowmelt and spring rains can increase soil moisture levels (Kunkel et al. 2013). Temperature

451   and dew point temperature are important features for accurately downscaling soil moisture. The

452   West includes California and Nevada. It has a diverse range of climates, from Mediterranean to

453   arid and semi-arid. This region with mountainous terrain may experience higher soil moisture

454   levels due to increased precipitation (Nielsen et al. 2024). The SouthWest includes Arizona,

455   Colorado, New Mexico, and Utah. It has an arid to semi-arid climate. However, soil moisture is

456   lower in this region (Huxman et al. 2004) and API has an impact on the soil moisture. Moreover,

457   topographic features such as mountains and valleys can cause localized variations in soil

458   moisture (Seager et al. 2007), which is evident in the present study.

459   **5.3 Model evaluation**

460   Abbaszadeh et al. (2019) downscaled SMAP 9-km (SMAP level 3) soil moisture to 1-km

461   over the CONUS using ensemble learning methods and they found overall the ubRMSE between

462   downscaled and in-situ observations met the SMAP accuracy requirement of 0.04. The

463   downscaled soil moisture data showed a strong correlation (R=0.325 to 0.997, average 0.715)

464   and high accuracy (ubRMSE=0.010 to 0.141 m³/m³, average 0.041 m³/m³) compared to the in-

465   situ soil moisture measurements (Xu et al. 2022). Our study shows that the ubRMSE value for

466   SMAP VWC is 0.100 m³/m³. The reason could be the different methods of downscaling because

467   our analysis used RF, while Xu et al. (2022) used an ensemble approach. In addition, Xu et al.

468   (2022) used SMAP level 3, while this analysis used SMAP level 4.

469   Sun and Cui (2021) downscaled VWC in the central United States using support vector

470   machine (SVM). The correlation between their downscaled soil moisture and the in-situ

471   measurements ranged from 0.174 to 0.754, and their RMSE ranged from 0.063 to 0.101. In our

472   study, the correlation between the downscaled soil moisture and in-situ measurements in the

473   central region was 0.452 for SMAP VWC and 0.352 for NLDAS VWC. The RMSE was 0.093

474   for SMAP VWC and 0.104 for NLDAS VWC. Therefore, our results are relatively comparable

475   in terms of correlation and error.

476   Guevara and Vargas (2019) downscaled the soil moisture from 27-km to 1-km by

477   training the kernel-weighted nearest neighbors across the conterminous United States. They

478   showed that the downscaled soil moisture had an R^2 value of 0.46. Our results generally have

479   lower correlations for all the regions, except the South. It is possible that this is because Guevara

480   and Vargas (2019) used different methods of downscaling such kernel-weighted nearest

481   neighbors, while our approach was based on. There is also the difference of spatial native

482   resolutions of soil moisture products that were used for downscaling.

483   Liu et al. (2020) downscaled soil moisture using six methods over different regions

484   including Oklahoma. The R^2 value for their Oklahoma region ranged from 0.287 to 0.714, and

485   the MAE ranged from 0.027 to 0.055. The MAE in the South region in our study ranged from

486   0.069 to 0.195. A similar study in Oklahoma state was done by Jiang and Cotton (2004) applying

487   the artificial neural network (ANN). Their RMSE was <0.04. Xu et al. (2021) downscaled SMAP

488   36-km soil moisture to 3-km and 1-km by applying the convolution neural network in Oklahoma.

489   Xu et al. (2021) had a correlation of 0.659 and ubRMSE of 0.052 for their 1-km downscaled soil

490   moisture using SMAP level 3 products from 1ˢᵗ January 2018 to 30ᵗʰ December 2018. While

491   these studies had lower errors than our analysis, this is likely because they focused on a single

492   state, while our region encompasses multiple states. In addition, they downscaled only one year

493   soil moisture, but we downscaled daily soil moisture from 2015 to 2021 and evaluated

494   performance using this entire period. In addition, Xu et al. (2021) utilized a convolutional neural

495   network (CNN) and we used RF for downscaling.

496   Warner et al. (2021) downscaled VWC in Delaware to 100-m resolution using kernel k-

497   nearest neighbor (KKNN) based on SSM estimates from the European Space Agency's Climate

498   Change soil moisture products. They had an MAE of 0.048 (Warner et al. 2021). In comparison,

499   our MAE in the NorthEast region, which includes Delaware, ranged from 0.076 to 0.082. Warner

500   et al. (2021) likely had greater accuracy because they their study area is a single state

501   (Delaware), while our NorthEast region includes Delaware, Connecticut, Maine, Maryland,

502   Massachusetts, New Hampshire, New York, Pennsylvania, Rhode Island, and Vermont. In

503   addition, Warner et al. (2021) downscaled different soil moisture data than our study.

504   Overall, the soil moisture downscaling is more accurate in the South, Central, and

505   NorthEast regions, as they have lower error than in other regions. The downscaling was not as

506   accurate in the NorthWest, SouthWest, West, and WestNorthCentral regions.

507   **6   Conclusions**

508   This study evaluated and compared feature importance for downscaling satellite and

509 model-derived soil moisture products across different regions. Random forest was applied to

510 predict the soil moisture products (SMAP and NLDAS) to 1-km resolution over CONUS and in-

511 situ data were used to validate the model. The conclusions are:

512   1) Results indicated that dew point temperature is the most important feature and elevation

513   is the second most important feature for downscaling soil moisture in the United States.

514   In general, the atmospheric features (e.g., temperature) have more impact on the

515   downscaling than vegetation features. Vegetation features such as NDVI and LAI, as well

516   as topographic features such as slope and aspect were not important for downscaling soil

517   moisture to 1-km resolution.

518   2) Based on the accuracy metrics, downscaling VWC is more accurate than soil moisture

519   percentiles.

520   3) Downscaled SMAP and NLDAS VWC was most accurate in the South and

521   WestNorthCentral regions.

522   Our results can be used to improve feature selection for soil moisture downscaling.

523 However, it is likely that the optimal features for downscaling soil moisture are strongly

524 dependent on the spatial resolution of the analysis and the climatic, topographic and edaphic

525 characteristics of the study region.

526   Future research can advance this work in the following ways. First, we can increase the

527 validity of the accuracy assessment by using more in-situ data to validate the downscaling. This

528 study compares the 1-km downscaled soil moisture to a single station. A better approach would

529 be to use a dense network of stations to upscale the in-situ data to match the resolution of the soil

530 moisture products. Second, given the substantial regional variations in performance, future work,

531   would benefit from including a more comprehensive set of features that account for soil moisture

532   dynamics in each region. Third, the method of upscaling the features can be improved. Last, this

533   study only used a single method for downscaling. Using other downscaling approaches may

534   result in increased accuracy and provide additional insights.

535   **Author Contributions:**

536   **EAE-**Conceptualization, methodology, formal analysis, validation, visualization, writing-
537   original draft, **ZL-** Data acquisition, validation **ID-** Data acquisition, validation **SQ-**Funding
538   acquisition, supervision, writing-review, editing.

539   **Funding:** This research was funded by the United States Department of Agriculture (USDA)
540   under Grant AQD-109872.

541   **Acknowledgments:** The authors thank the anonymous reviewers for providing such valuable
542   comments.

543   **Conflicts of Interest:** The authors declare no conflict of interest.

544

References

Abbaspour, K. C., E. Rouholahnejad, S. Vaghefi, R. Srinivasan, H. Yang, and B. Kløve, 2015: A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. *Journal of Hydrology*, **524**, 733–752, https://doi.org/10.1016/j.jhydrol.2015.03.027.

Abbaszadeh, P., H. Moradkhani, and X. Zhan, 2019: Downscaling SMAP Radiometer Soil Moisture Over the CONUS Using an Ensemble Learning Method. *Water Resources Research*, **55**, 324–344, https://doi.org/10.1029/2018WR023354.

Alemohammad, S. H., J. Kolassa, C. Prigent, F. Aires, and P. Gentine, 2018: Global downscaling of remotely sensed soil moisture using neural networks. *Hydrology and Earth System Sciences*, **22**, 5341–5356, https://doi.org/10.5194/hess-22-5341-2018.

Ambrose, A. R., S. C. Sillett, and T. E. Dawson, 2009: Effects of tree height on branch hydraulics, leaf structure and gas exchange in California redwoods. *Plant, Cell & Environment*, **32**, 743–757, https://doi.org/10.1111/j.1365-3040.2009.01950.x.

Baldwin, D., K. J. Naithani, and H. Lin, 2017: Combined soil-terrain stratification for characterizing catchment-scale soil moisture variation. *Geoderma*, **285**, 260–269, https://doi.org/10.1016/j.geoderma.2016.09.031.

Balugani, E., M. Lubczynski, and K. Metselaar, 2014: A framework for sourcing of evaporation between saturated and unsaturated zone in bare soil condition. *Hydrological Sciences Journal*, **61**, 150527103244004, https://doi.org/10.1080/02626667.2014.966718.

Bennie, J., B. Huntley, A. Wiltshire, M. Hill, and R. Baxter, 2008: Slope, aspect and climate: Spatially explicit and implicit models of topographic microclimate in chalk grassland. *Ecological Modelling*, **216**, 47–59, https://doi.org/10.1016/j.ecolmodel.2008.04.010.

Bond, B. J., F. C. Meinzer, and J. R. Brooks, 2008: How Trees Influence the Hydrological Cycle in Forest Ecosystems. *Hydroecology and Ecohydrology*, P.J. Wood, D.M. Hannah, and J.P. Sadler, Eds., Wiley, 7–35.

Breiman, L., 2001: Random Forests. *Machine Learning*, **45**, 5–32, https://doi.org/10.1023/A:1010933404324.

Brocca, L., and Coauthors, 2014: Soil as a natural rain gauge: Estimating global rainfall from satellite soil moisture data. *Journal of Geophysical Research: Atmospheres*, **119**, 5128–5141, https://doi.org/10.1002/2014JD021489.

Carrijo, D. R., C. Li, S. J. Parikh, and B. A. Linquist, 2019: Irrigation management for arsenic mitigation in rice grain: Timing and severity of a single soil drying. *Science of The Total Environment*, **649**, 300–307, https://doi.org/10.1016/j.scitotenv.2018.08.216.

Charpentier, M. A., and P. M. Groffman, 1992: Soil moisture variability within remote sensing pixels. *Journal of Geophysical Research: Atmospheres*, **97**, 18987–18995, https://doi.org/10.1029/92JD00882.

Chen, S., D. She, L. Zhang, M. Guo, and X. Liu, 2019: Spatial Downscaling Methods of Soil Moisture Based on Multisource Remote Sensing Data and Its Application. *Water*, **11**, 1401, https://doi.org/10.3390/w11071401.

Cosh, M., T. Jackson, and R. Bindlish, 2004: Watershed scale temporal and spatial stability of soil moisture and its role in validating satellite estimates. *Remote Sensing of Environment*, **92**, 427–435, https://doi.org/10.1016/j.rse.2004.02.016.

Crow, W. T., and Coauthors, 2012: Upscaling sparse ground-based soil moisture observations for the validation of coarse-resolution satellite soil moisture products. *Reviews of Geophysics*, **50**, https://doi.org/10.1029/2011RG000372.

Cutler, A., D. R. Cutler, and J. R. Stevens, 2012: Random Forests. *Ensemble Machine Learning: Methods and Applications*, C. Zhang and Y. Ma, Eds., Springer US, 157–175.

Daly, C., M. Halbleib, J. I. Smith, W. P. Gibson, M. K. Doggett, G. H. Taylor, J. Curtis, and P. P. Pasteris, 2008: Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *International Journal of Climatology*, **28**, 2031–2064, https://doi.org/10.1002/joc.1688.

Dobriyal, P., A. Qureshi, R. Badola, and S. A. Hussain, 2012: A review of the methods available for estimating soil moisture and its implications for water resource management. *Journal of Hydrology*, **s 458–459**, 110–117, https://doi.org/10.1016/j.jhydrol.2012.06.021.

Engle, D., B. Coppedge, and S. Fuhlendorf, 2008: From the Dust Bowl to the Green Glacier: Human Activity and Environmental Change in Great Plains Grasslands. Vol. 196 of, 253–271.

Famiglietti, J. S., and Coauthors, 1999: Ground-based investigation of soil moisture variability within remote sensing footprints During the Southern Great Plains 1997 (SGP97) Hydrology Experiment. *Water Resources Research*, **35**, 1839–1851, https://doi.org/10.1029/1999WR900047.

Fang, B., V. Lakshmi, R. Bindlish, and T. J. Jackson, 2018: Downscaling of SMAP Soil Moisture Using Land Surface Temperature and Vegetation Data. *Vadose Zone Journal*, **17**, 170198, https://doi.org/10.2136/vzj2017.11.0198.

Ford, T. W., Q. Wang, and S. M. Quiring, 2016: The Observation Record Length Necessary to Generate Robust Soil Moisture Percentiles. *Journal of Applied Meteorology and Climatology*, **55**, 2131–2149, https://doi.org/10.1175/JAMC-D-16-0143.1.

Guevara, M., and R. Vargas, 2019: Downscaling satellite soil moisture using geomorphometry and machine learning. *PLoS ONE*, **14**, e0219639, https://doi.org/10.1371/journal.pone.0219639.

Huxman, T. E., and Coauthors, 2004: Precipitation pulses and carbon fluxes in semiarid and arid ecosystems. *Oecologia*, **141**, 254–268, https://doi.org/10.1007/s00442-004-1682-4.

I. D. Moore, G. J. Burch, and D. H. Mackenzie, 1988: Topographic Effects on the Distribution of Surface Soil Water and the Location of Ephemeral Gullies. *Transactions of the ASAE*, **31**, 1098–1107, https://doi.org/10.13031/2013.30829.

618 Im, J., S. Park, J. Rhee, J. Baik, and M. Choi, 2016: Downscaling of AMSR-E soil moisture with MODIS
619   products using machine learning approaches. *Environ Earth Sci*, **75**, 1120,
620   https://doi.org/10.1007/s12665-016-5917-6.

621 Jacobs, A. F. G., B. G. Heusinkveld, and S. M. Berkowicz, 2000: Dew measurements along a longitudinal
622   sand dune transect, Negev Desert, Israel. *Int J Biometeorol*, **43**, 184–190,
623   https://doi.org/10.1007/s004840050007.

624 Jacobs, J., 2004: SMEX02: Field scale variability, time stability and similarity of soil moisture. *Remote
625   Sensing of Environment*, **92**, 436–446, https://doi.org/10.1016/j.rse.2004.02.017.

626 Jiang, H., and W. Cotton, 2004: Soil moisture estimation using an artificial neural network: A feasibility
627   study. *Canadian Journal of Remote Sensing*, **30**, https://doi.org/10.5589/m04-041.

628 Joshi, C., and B. P. Mohanty, 2010: Physical controls of near-surface soil moisture across varying spatial
629   scales in an agricultural landscape during SMEX02. *Water Resources Research*, **46**,
630   2010WR009152, https://doi.org/10.1029/2010WR009152.

631 Keesstra, S. D., and Coauthors, 2016: The significance of soils and soil science towards realization of the
632   United Nations Sustainable Development Goals. *SOIL*, **2**, 111–128, https://doi.org/10.5194/soil-
633   2-111-2016.

634 Kim, C. P., J. N. M. Stricker, and R. A. Feddes, 1997: Impact of soil heterogeneity on the water budget of
635   the unsaturated zone. *Water Resources Research*, **33**, 991–999,
636   https://doi.org/10.1029/97WR00364.

637 Kim, G., and A. Barros, 2002: Downscaling of remotely sensed soil moisture with a modified fractal
638   interpolation method using contraction mapping and ancillary data. *Remote Sensing of
639   Environment*, **83**, 400–413, https://doi.org/10.1016/S0034-4257(02)00044-5.

640 Kim, M., J. Im, H. Han, J. Kim, S. Lee, M. Shin, and H.-C. Kim, 2015: Landfast sea ice monitoring using
641   multisensor fusion in the Antarctic. *GIScience & Remote Sensing*, **52**, 239–256,
642   https://doi.org/10.1080/15481603.2015.1026050.

643 Krueger, E. S., T. E. Ochsner, and S. M. Quiring, 2019: Development and Evaluation of Soil Moisture-
644   Based Indices for Agricultural Drought Monitoring. *Agronomy Journal*, **111**, 1392–1406,
645   https://doi.org/10.2134/agronj2018.09.0558.

646 Kunkel, K. E., L. E. Stevens, S. E. Stevens, and L. Sun, Regional Climate Trends and Scenarios for the
647   U.S. National Climate Assessment Part 4. Climate of the U.S. Great Plains.

648 Li, M., J. Im, and C. Beier, 2013: Machine learning approaches for forest classification and change
649   analysis using multi-temporal Landsat TM images over Huntington Wildlife Forest. *GIScience &
650   Remote Sensing*, **50**, 361–384, https://doi.org/10.1080/15481603.2013.819161.

651 Li, X., W. Chen, X. Cheng, and L. Wang, 2016: A Comparison of Machine Learning Algorithms for
652   Mapping of Complex Surface-Mined and Agricultural Landscapes Using ZiYuan-3 Stereo
653   Satellite Imagery. *Remote Sensing*, **8**, 514, https://doi.org/10.3390/rs8060514.

Liu, J., F. Rahmani, K. Lawson, and C. Shen, 2022: A multiscale deep learning model for soil moisture integrating satellite and in-situ data. *Geophysical Research Letters*, **n/a**, e2021GL096847, https://doi.org/10.1029/2021GL096847.

Liu, Q., and Coauthors, 2011: The Contributions of Precipitation and Soil Moisture Observations to the Skill of Soil Moisture Estimates in a Land Data Assimilation System. *Journal of Hydrometeorology*, **12**, 750–765.

Liu, Y., W. Jing, Q. Wang, and X. Xia, 2020: Generating high-resolution daily soil moisture by using spatial downscaling techniques: a comparison of six machine learning algorithms. *Advances in Water Resources*, **141**, 103601, https://doi.org/10.1016/j.advwatres.2020.103601.

Lu, Z., J. Im, J. Rhee, and M. Hodgson, 2014: Building type classification using spatial and landscape attributes derived from LiDAR remote sensing data. *Landscape and Urban Planning*, **130**, 134–148, https://doi.org/10.1016/j.landurbplan.2014.07.005.

Mohanty, B. P., and T. H. Skaggs, 2001: Spatio-temporal evolution and time-stable characteristics of soil moisture within remote sensing footprints with varying soil, slope, and vegetation. *Advances in Water Resources*, **24**, 1051–1067, https://doi.org/10.1016/S0309-1708(01)00034-3.

Mohanty, B. P., T. H. Skaggs, and J. S. Famiglietti, 2000: Analysis and mapping of field-scale soil moisture variability using high-resolution, ground-based data during the Southern Great Plains 1997 (SGP97) Hydrology Experiment. *Water Resources Research*, **36**, 1023–1031, https://doi.org/10.1029/1999WR900360.

Nielsen, M., B. I. Cook, K. Marvel, M. Ting, and J. E. Smerdon, 2024: The Changing Influence of Precipitation on Soil Moisture Drought With Warming in the Mediterranean and Western North America. *Earth's Future*, **12**, e2023EF003987, https://doi.org/10.1029/2023EF003987.

Oren, R., J. S. Sperry, G. G. Katul, D. E. Pataki, B. E. Ewers, N. Phillips, and K. V. R. Schäfer, 1999: Survey and synthesis of intra- and interspecific variation in stomatal sensitivity to vapour pressure deficit. *Plant, Cell & Environment*, **22**, 1515–1526, https://doi.org/10.1046/j.1365-3040.1999.00513.x.

Panciera, R., J. P. Walker, J. D. Kalma, E. J. Kim, J. M. Hacker, O. Merlin, M. Berger, and N. Skou, 2008: The NAFE'05/CoSMOS Data Set: Toward SMOS Soil Moisture Retrieval, Downscaling, and Assimilation. *IEEE Trans. Geosci. Remote Sensing*, **46**, 736–745, https://doi.org/10.1109/TGRS.2007.915403.

Park, S., J. Im, E. Jang, and J. Rhee, 2016: Drought assessment and monitoring through blending of multi-sensor indices using machine learning approaches for different climate regions. *Agricultural and Forest Meteorology*, **216**, 157–169, https://doi.org/10.1016/j.agrformet.2015.10.011.

Peng, J., A. Loew, O. Merlin, and N. E. C. Verhoest, 2017: A review of spatial downscaling of satellite remotely sensed soil moisture: Downscale Satellite-Based Soil Moisture. *Rev. Geophys.*, **55**, 341–366, https://doi.org/10.1002/2016RG000543.

Pittelkow, C. M., and Coauthors, 2015: Productivity limits and potentials of the principles of conservation agriculture. *Nature*, **517**, 365–368, https://doi.org/10.1038/nature13809.

693   Rhee, J., S. Park, and Z. Lu, 2014: Relationship between land cover patterns and surface temperature in
694   urban areas. *GIScience & Remote Sensing*, **51**, 521–536,
695   https://doi.org/10.1080/15481603.2014.964455.

696   Robinson, D. A., and Coauthors, 2008: Soil Moisture Measurement for Ecological and Hydrological
697   Watershed-Scale Observatories: A Review. *Vadose Zone Journal*, **7**, 358–389,
698   https://doi.org/10.2136/vzj2007.0143.

699   Ruosteenoja, K., T. Markkanen, and J. Räisänen, 2020: Thermal seasons in northern Europe in projected
700   future climate. *International Journal of Climatology*, **40**, 4444–4462,
701   https://doi.org/10.1002/joc.6466.

702   Salvucci, G., 2001: Estimating the moisture dependence of root zone water loss using conditionally
703   averaged precipitation. *Water Resources Research - WATER RESOUR RES*, **37**, 1357–1366,
704   https://doi.org/10.1029/2000WR900336.

705   Seager, R., and Coauthors, 2007: Model Projections of an Imminent Transition to a More Arid Climate in
706   Southwestern North America. *Science*, **316**, 1181–1184, https://doi.org/10.1126/science.1139601.

707   ——, A. Tzanova, and J. Nakamura, 2009: Drought in the Southeastern United States: Causes, Variability
708   over the Last Millennium, and the Potential for Future Hydroclimate Change.
709   https://doi.org/10.1175/2009JCLI2683.1.

710   Seneviratne, S. I., T. Corti, E. L. Davin, M. Hirschi, E. B. Jaeger, I. Lehner, B. Orlowsky, and A. J.
711   Teuling, 2010: Investigating soil moisture–climate interactions in a changing climate: A review.
712   *Earth-Science Reviews*, **99**, 125–161, https://doi.org/10.1016/j.earscirev.2010.02.004.

713   Sivapalan, M., K. Beven, and E. F. Wood, 1987: On hydrologic similarity: 2. A scaled model of storm
714   runoff production. *Water Resources Research*, **23**, 2266–2278,
715   https://doi.org/10.1029/WR023i012p02266.

716   Srivastava, P. K., D. Han, M. R. Ramirez, and T. Islam, 2013: Machine Learning Techniques for
717   Downscaling SMOS Satellite Soil Moisture Using MODIS Land Surface Temperature for
718   Hydrological Application. *Water Resour Manage*, **27**, 3127–3144,
719   https://doi.org/10.1007/s11269-013-0337-9.

720   Sun, H., and Y. Cui, 2021: Evaluating Downscaling Factors of Microwave Satellite Soil Moisture Based
721   on Machine Learning Method. *Remote Sensing*, **13**, 133, https://doi.org/10.3390/rs13010133.

722   Vereecken, H., J. A. Huisman, H. Bogena, J. Vanderborght, J. A. Vrugt, and J. W. Hopmans, 2008: On
723   the value of soil moisture measurements in vadose zone hydrology: A review. *Water Resources
724   Research*, **44**, https://doi.org/10.1029/2008WR006829.

725   Wagner, W., and Coauthors, 2013: The ASCAT Soil Moisture Product: A Review of its Specifications,
726   Validation Results, and Emerging Applications. *Meteorologische Zeitschrift*, **22**, 5–33,
727   https://doi.org/10.1127/0941-2948/2013/0399.

728   Wanders, N., D. Karssenberg, A. de Roo, S. M. de Jong, and M. F. P. Bierkens, 2014: The suitability of
729   remotely sensed soil moisture for improving operational flood forecasting. *Hydrol. Earth Syst.
730   Sci.*, **18**, 2343–2357, https://doi.org/10.5194/hess-18-2343-2014.

731 Warner, D., M. Guevara, J. Callahan, and R. Vargas, 2021: Downscaling satellite soil moisture for
732   landscape applications: A case study in Delaware, USA. *Journal of Hydrology: Regional Studies*,
733   **38**, 100946, https://doi.org/10.1016/j.ejrh.2021.100946.

734 Xu, M., N. Yao, H. Yang, J. Xu, A. Hu, L. Goncalves, and G. Liu, 2022: Downscaling SMAP soil
735   moisture using a Wide & Deep learning method over the Continental United States. *Journal of
736   Hydrology*, **609**, 127784, https://doi.org/10.1016/j.jhydrol.2022.127784.

737 Xu, W., Z. Zhang, Z. Long, and Q. Qin, 2021: Downscaling SMAP Soil Moisture Products With
738   Convolutional Neural Network. *IEEE Journal of Selected Topics in Applied Earth Observations
739   and Remote Sensing*, **14**, 4051–4062, https://doi.org/10.1109/JSTARS.2021.3069774.

740 Zhang, N., S. M. Quiring, and T. W. Ford, 2019: *Blending SMAP, Noah and In Situ Soil Moisture Using
741   Multiple Methods*. Vadose Zone Hydrology/Modelling approaches,.

742 Zhao, W., N. Sánchez, H. Lu, and A. Li, 2018: A spatial downscaling approach for the SMAP passive
743   surface soil moisture product using random forest regression. *Journal of Hydrology*, **563**, 1009–
744   1024, https://doi.org/10.1016/j.jhydrol.2018.06.081.

745 Zhou, X., H. S. Lin, and E. A. White, 2008: Surface soil hydraulic properties in four soil series under
746   different land uses and their temporal changes. *CATENA*, **73**, 180–188,
747   https://doi.org/10.1016/j.catena.2007.09.009.

748 Dew - Monteith - 1957 - Quarterly Journal of the Royal Meteorological Society - Wiley Online Library.
749   https://rmets.onlinelibrary.wiley.com/doi/10.1002/qj.49708335706 (Accessed June 6, 2024).

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