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RESEARCH ARTICLE

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Optimizing Drought Assessment for Soil Moisture Deficits

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Key Points:

- Optimal drought index timescales for soil moisture are relatively short (less than 100 days) and increase with increasing soil depth
- The Short-term Prediction Research and Transition Center, Topofire and Soil Moisture Active Passive L4 models are more accurate than time-scale optimized drought indices for soil moisture anomaly prediction
- Drought monitoring should favor the use of soil moisture models over meteorological drought indices for characterizing soil moisture drought

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Accurate drought assessments are critical for mitigating the deleterious impacts of water scarcity on communities across the world. In many regions, deficits in soil moisture represent a key driver of drought conditions. However, relationships between soil moisture and widely used drought indicators have not been thoroughly evaluated. In addition, there has not been an in-depth assessment of the accuracy of operational soil moisture models used for drought monitoring. Here, we used 2,405 observed time series of soil moisture from 637 long-term monitoring stations across the conterminous United States to test the ability of meteorological drought indices and soil moisture models to accurately characterize soil moisture drought. The optimal timescales for meteorological drought indices varied substantially by depth, but were ~30 days for depth averaged conditions; progressively longer timescales (~10–80 days) represent progressively deeper soil moisture (2–36 in.). However, soil moisture models (including Short-term Prediction Research and Transition Center, Soil Moisture Active Passive L4, and Topofire) significantly outperformed the meteorological drought indices for predicting standardized soil moisture anomalies and drought conditions. Additionally, soil moisture models represent near instantaneous conditions, implicitly aggregating antecedent data thereby eliminating the need for timescales, providing a more effective and convenient method for soil moisture drought monitoring. We conclude that soil moisture models provide a straightforward and favorable alternative to meteorological drought indices that better characterize soil moisture drought.

1. Introduction

Drought is a conceptually intuitive, yet technically complex phenomena (Lloyd-Hughes, 2014) that causes billions of dollars in damages annually in the United States (U.S.) alone (NCEI, 2021). While “drought” has many definitions, the phenomena generally starts with a lack of precipitation, but can be exacerbated by warmer temperatures that contribute to atmospheric aridity (Ault, 2020). In turn, these “first order drivers” impact components of the hydrological cycle, such as soil moisture (Manning et al., 2018), groundwater (Apuv et al., 2017), streamflow (Tallaksen & van Lanen, 2004), ecosystems (Crausbay et al., 2017) and human systems (Kuwayama et al., 2019). This leads to the identification of different types of drought (e.g., meteorological, agricultural, hydrological, socioeconomic, and ecological), which reflect the various sectors impacted by, and processes that determine, water shortages. These drought types are essentially different stages and consequences of the same natural and recurring process over various timescales that lead to cumulative impacts.

Monitoring the different aspects of the hydrologic cycle often requires a variety of drought indicators, indices and timescales of reference. Existing drought indices focused on the meteorological drivers of drought (hereafter, meteorological drought indices) range from simple temperature and precipitation based indices (such as temperature and/or precipitation percentiles, the Standardized Precipitation Index [SPI, (McKee et al., 1993)]), to metrics that model components of the water balance (such as the Standardized Precipitation Evapotranspiration Index [SPEI, (Vicente-Serrano et al., 2010)] or the Evaporative Demand Drought Index [EDDI, (Hobbins et al., 2016)]). However, it is important to note that there are numerous other drought indices and indicators used in contemporary drought assessment frameworks (M. D. Svoboda & Fuchs, 2016). For any drought index to be useful, it is important that the depiction of conditions and the timescales considered align with impacts on the sector(s) of interest.

Assessing drought conditions typically requires aggregating recent data and evaluating conditions for that time period relative to the historical past. The timescale evaluated (also referred to as lags or aggregation periods) represent the period over which a drought index is calculated. For example, a 30-day timescale represents a 30-

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day aggregation period over which a variable of interest (e.g., precipitation) is summarized. The appropriate timescale for any particular drought index depends upon the sector, system or indicator of interest (demonstrated below). Common timescales in drought monitoring range from several days to multiple years. For example, previous studies suggest that shorter timescales (30 days to a few months) characterize a large portion of terrestrial vegetation response, especially in arid and humid biomes (Vicente-Serrano et al., 2013), and shallow soil moisture (Halwatura et al., 2017; H. Wang et al., 2015), while longer timescales (from 6 months to multiple years) characterize hydrological dynamics such as streamflow, lake and reservoir levels (McEvoy et al., 2012), lowland groundwater aquifers (Hellwig et al., 2020) and gross primary production in some systems (Sun et al., 2021). However, in practice, drought assessments typically evaluate a range of different timescales across multiple indices. This can be time consuming and subjective, and can hinder objective drought assessments when practitioners do not possess the knowledge of which timescales best reflect a process of interest.

In seasonally dry landscapes, subsurface soil moisture is a key indicator of drought conditions but is often not adequately monitored. Furthermore, ecological and agricultural stress is frequently a direct result of soil moisture [un]availability (Chatterjee et al., 2022; Liu et al., 2020; Madadgar & AghaKouchak, 2017). Soil moisture deficits are also an early indicator of different forms of drought, representing a component of drought's propagation from meteorological to hydrological deficits of water (W. Wang et al., 2016). For example, soil moisture anomalies often precede streamflow anomalies by determining rainfall-runoff dynamics as well as groundwater recharge (Entekhabi et al., 1992). Additionally, soil moisture is coupled to atmospheric demand-based indices (e.g., EDDI) due to the imbalance of latent and sensible heat exchange associated with dry soils. Therefore, soil moisture is not only an important indicator of short term ecological and agricultural droughts, but also an important early warning indicator of longer term hydrologic drought.

Information about soil moisture conditions has proliferated over the last two decades in the United States. State and federal governments have invested in monitoring soil moisture by adding to existing networks (e.g., SNOTEL, USCRN, SCAN- defined below) and establishing networks of new stations (e.g., state Mesonets). Furthermore, soil moisture models have become more sophisticated as computational limitations are overcome by technological advancements. This has led to the development of many regional, continental and global scale models that are updated regularly (many of which are cited below) with sufficient periods of record to compute percentiles and standardized anomalies (the core conceptual tool used for drought assessment, reviewed within (Quiring, 2009)). These models in turn provide information at sufficient spatial scales, and with minimal temporal latency, to benefit operational drought assessment. Many soil moisture models are now integrated into modern assessment frameworks, such as the U.S. Drought Monitor (M. Svoboda et al., 2002), demonstrating their ability to enhance early warning.

Accurate monitoring of soil moisture dynamics has the potential to provide early warning for water stress in natural ecosystems, hydrological systems, rangelands and agricultural settings. However, there remains uncertainty in what models and/or metrics are most appropriate for this important task. To address this knowledge gap, we compared a selection of commonly used meteorological drought indices to observed soil moisture data in order to determine which were most closely aligned with soil moisture changes over time. We then compared the efficacy of these meteorological drought indices to operational soil moisture models to evaluate which are most accurate across the United States. As a whole, this information will enable better detection of the beginning and end of soil moisture drought conditions (i.e., when soil moisture is anomalously low) using common methods employed across the United States. Throughout this paper we address the following three questions:

1. At what timescales are drought indices most representative of soil moisture conditions?
2. During what season(s) do drought indices most accurately reflect changes in soil moisture across the U.S.?
3. How do drought indices optimized for predicting standardized soil moisture anomalies compare to gridded soil moisture models for soil moisture drought assessment?

2. Methods

2.1. In Situ Soil Moisture Data

2.1.1. Networks, Stations and Observation Depths

We compiled a database of daily soil moisture time series across federal and state networks. These networks include SNOwpack TELemetry (SNOTEL), Soil Climate Analysis Network (SCAN), the U.S. Climate Reference

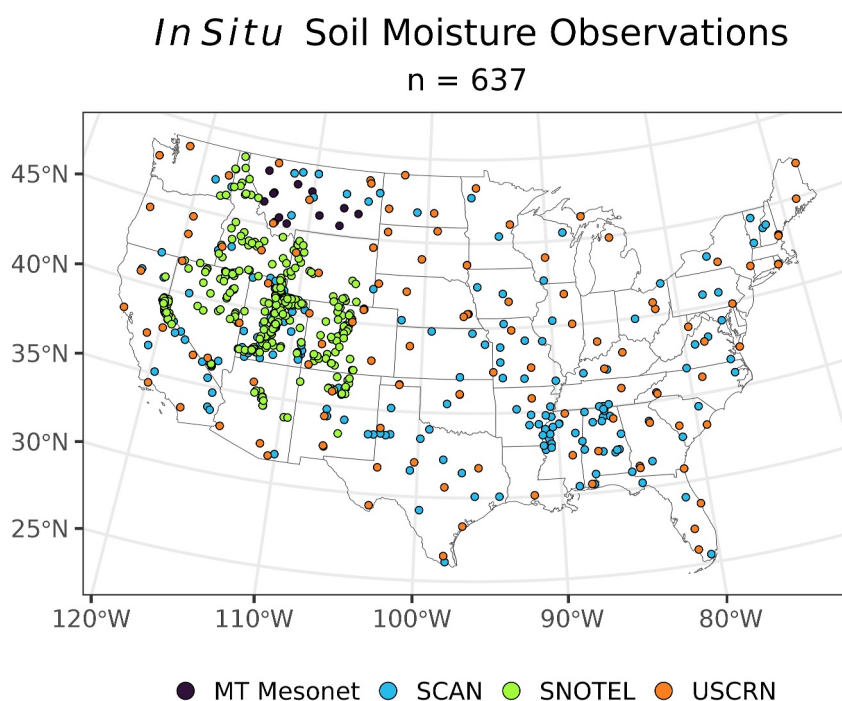


Figure 1. Site map showing the locations of in situ soil moisture data sets and their associated networks.

Network (USCRN) and the Montana Mesonet (Figure 1). In total, we evaluated 2,405 soil moisture time series from 637 locations, where each location reported volumetric soil moisture ($\text{m}^3 \text{m}^{-3}$) at 3–6 measurement depths. Soil moisture measurement depths ranged from 2 to 40 in below the ground surface. Time periods considered range from 1996–10–12 to 2022–12–19, but varied by site. All soil moisture time series were filtered for time periods when soil temperatures were above 1.1°C (34°F), ensuring the soil was not frozen and thereby removing potentially erroneous sensor readings. Soil moisture time series were then classified by depth into three classes, shallow (0–4 in), middle (8–20 in) and deep (>20 in). We also computed a depth averaged soil moisture time series for each site. To do so, we first computed the average soil moisture time series for each generalized depth (shallow, middle, deep) for each site. We then computed the depth averaged soil moisture time series for each location and day if (and only if) observations were present from each of the generalized depths. Therefore, depth averaged soil moisture reflects the average soil moisture for shallow, middle and deep soil moisture in every case.

2.1.2. Standardized Soil Moisture (In Situ)

We standardized each soil moisture time series using a parametric approach to account for non-Gaussian distributions within each site/depth specific time series. Here, we define the in situ, observed standardized soil moisture data set as the observed Soil Moisture Index (SMI_{obs}). This index leverages prior research focused on standardizing soil moisture data into relative measures (Cammalleri et al., 2016, 2024; Ravelo & Decker, 1979; Sheffield et al., 2004) by applying a beta distribution (described in greater detail below). Instead of only using the day of interest (e.g., June 1st) for each year to define the distribution, we used multiple observations centered about the day of interest to define the distribution. Specifically, we used a 31-day centered moving-window approach which required a minimum of 6 years of data (6 years $\times$ 31 days resulting in a minimum of 186 observations) to generate samples for the site/depth of interest. This approach is similar to (Ford et al., 2016) who used 31-day samples (one month) for each year to generate estimates of percentiles and concluded that 6 years of data is “sufficient in most conditions to create stable and robust percentiles” for soil moisture (Ford et al., 2016). Conceptually, this approach leverages naturally occurring cyclic and seasonal dynamics in soil moisture time series to bolster the probability distribution associated with any given day/location (e.g., conditions on May 31st are likely to be similar to, and/or provide probabilistic information about, June 1st).

Next, we fit a beta distribution to each day/location/depth specific sample using maximum likelihood for parameter estimation. The beta distribution accounts for non-Gaussian data that is bound at 0 and 1; these

constraints fit the theoretical constraints of volumetric soil moisture data sets (measured as $\text{m}^3 \text{m}^{-3}$). As such beta distributions have been used extensively to model soil moisture (e.g., Cammalleri et al., 2016; Cammalleri et al., 2024; Ravelo & Decker, 1979; Sadri et al., 2020; Sheffield et al., 2004). Using these parametrically derived probability distributions, we computed the associated parametric cumulative distribution function (CDF) associated with the observations. The CDF values were then evaluated within an inverse Gaussian function with a mean of zero and a standard deviation of one to obtain the final SMI_{obs} value. The “normalization” of the data centers CDF values of 0.5 about an SMI value of zero, and simply projects the CDF values in to a scale common in drought assessment (a standard normal distribution, i.e. standardized anomalies). However, it is important to note that this step does not distort the probabilistic CDF values (i.e., this transformation can be performed in both directions without information loss). This approach is functionally similar to methods used to compute other standardized drought indices, such as the Standardized Precipitation Index (SPI, [(McKee et al., 1993)]), described in greater depth below. For this analysis, SMI_{obs} values were truncated at 2 and -2 . This is consistent with common drought assessment practices, where values that exceed -2 and 2 are considered extreme and treated equal to -2 or 2 (representing roughly the 2nd and 98th percentiles) (M. Svoboda et al., 2002).

2.2. Meteorological Drought Index Calculation

Three meteorological drought indices were calculated across the conterminous U.S., the Standardized Precipitation Index (SPI), the Standardized Precipitation Evapotranspiration Index (SPEI) and the Evaporative Demand Drought Index (EDDI). We used daily time series of precipitation (P) and potential evapotranspiration (PET; defined here as grass reference evapotranspiration) from the gridMET data set (Abatzoglou, 2013) to compute these drought indices (described in greater detail below). Following the contemporary, non-shifting reference period used to compute the SMI_{obs} , we used the most recent 30 years of meteorological data from gridMET to compute these drought indices in order to reflect contemporary climate conditions (Hoylman et al., 2022). We calculated an array of drought timescales for each drought index, ranging from 10 to 730 days using 10 days increments, to reflect the common timescales employed in drought analysis (e.g., 30, 60, 90 days). Therefore, for each site and drought index we computed 73 time series representing very short to multi-annual drought timescales. Similar to the treatment of extreme values for the SMI (described above), all drought index values were truncated at 2 and -2 .

The SPI (McKee et al., 1993) was designed to standardize precipitation time series across an observational record in order to compute standardized precipitation anomalies in both time and space. To calculate the SPI we first aggregated (summed) the time series of precipitation based on the timescale of interest (10, 20 ... 730 days) for each day of the year. For example, we summed the precipitation from July 1st through July 10th for each year as input data to compute a 10 days SPI for July 10th. Each aggregate time series of precipitation for each day of year was then fit to a Gamma probability distribution based on the L-moments of the data (for more information on the linear combination of order statistics, also known as L-moments, see Hosking, 1990). Similar to the SMI_{obs} described above, we computed the cumulative distribution function (CDF) associated with the observations using the parameters from the Gamma distribution. The CDF values were then evaluated within an inverse Gaussian function with a mean of zero and a standard deviation of one to obtain the final SPI value. This method of standardization is abstracted to many drought indices, some of which are described below.

We calculated the SPEI in a similar fashion to the SPI (following methods in Beguería et al. (2014)), although the precipitation time series was replaced by the difference between daily precipitation and PET. Therefore, the SPEI incorporates both precipitation and atmospheric demand for moisture representing the supply and demand on soil moisture storage (Vicente-Serrano et al., 2010). Similar to before, this P–PET data set was aggregated over various timescales, ranging from 10 to 730 days, which was then fit to a generalized logistic distribution based on the L-moments of the data. The associated CDF was then evaluated within an inverse Gaussian function to compute the final SPEI value (Beguería et al., 2014).

EDDI was calculated following (Hobbins et al., 2016) using non-parametric methods and a daily PET time series aggregated (similar to above) over various timescales. This method differs from the metrics described above in that it is based on empirically estimated probabilities instead of those derived parametrically (such as the Gamma based parametric approach for SPI). To compute the empirical probabilities, EDDI uses a Tukey plotting position approximation (Wilks, 2011) which is then evaluated within an inverse normal approximation following

(Vicente-Serrano et al., 2010). Importantly, scales for these indices vary with larger values of SPI and SPEI representing wetter conditions, and larger values of EDDI representing drier conditions.

2.3. Modeled Soil Moisture Data

2.3.1. Models Considered

We extracted modeled soil moisture data from nine different soil moisture data sets to compare against observed soil moisture time series (Table 1). These models were selected because they are 1. operational (updated regularly) with less than a week latency in data availability, and 2. are used in current drought assessments at the state or national level. The models considered here (and described in greater detail within Table 1) are: 1. Land Surface Monitoring and Prediction, Climate Prediction Center (CPC) Leaky Bucket Model, 2. Gravity Recovery and Climate Experiment (GRACE) based rootzone soil moisture, 3. North American Land Data Assimilation System (NLDAS-2) Variable Infiltration Capacity (VIC) 0–100 cm, 4. NLDAS-2 Mosaic 0–100 cm, 5. NLDAS-2 Noah 0–100 cm, 6. NLDAS-2 Ensemble (averaged from NLDAS-2 VIC, NLDAS-2 Mosaic and NLDAS-2 Noah) 0–100 cm, 7. Soil Moisture Active Passive L4 (SMAP L4) rootzone soil moisture, 8. Short-term Prediction Research and Transition Center (SPoRT) rootzone (0–100 cm) mean soil moisture, and 9. Topofire rootzone soil moisture.

2.3.2. Standardized Soil Moisture (Modeled)

Similar to methods described in Section 3.1.2, we computed standardized soil moisture anomalies, the modeled Soil Moisture Index (SMI_{mod}), for each of the soil moisture products. When pre-computed soil moisture percentiles were available, we used these values as estimates of the distribution CDF ($CDF = \text{percentile}/100$) which were then evaluated within an inverse Gaussian function with a mean of zero and a standard deviation of one. This was done to most faithfully represent data used in contemporary drought assessment (applicable to CPC, GRACE, and SMAP L4). Where pre-computed percentiles were not available (e.g., NLDAS-2, SPoRT, and Topofire), we followed the same procedure outlined in Section 3.1.2 above (31-day moving window with at least 6 years of data). We modeled (and subsequently standardized) these data using either a gamma or beta distribution depending on the model units. Specifically we fit a gamma distribution for the NLDAS-2 models (kg m^{-2}) and Topofire (mm), and a beta distribution for the SPoRT model (%). Similar to the treatment of extreme values for the SMI_{obs} and drought index values, all SMI_{mod} values were truncated at 2 and -2 .

2.4. Statistical Analysis

2.4.1. Correlation Between Drought Indices and Observed Soil Moisture

We used correlation analysis to assess the relationship between the observed Soil Moisture Index (SMI_{obs}) and specific drought indices across a range of drought timescales (from 10 to 730 days, e.g. two years, at 10 days intervals). We computed the Pearson's correlation coefficient (r) to describe the strength of association between each drought index/timescale and each SMI_{obs} time series (for each station and each observation depth). We conducted this analysis for each month individually across the entire year, as well as for the May 1st through October 31st time period representing the “warm season.” We used this seasonal analysis to assess the optimal timescales for various drought indices to predict observed standardized soil moisture anomalies, SMI_{obs} , for various soil depths (described below). Correlation results were then aggregated by depth into three categories; shallow (correlations from depths 0–4 in.), middle (8–20 in.) and deep (depth >20 in.). Aggregation by depth allowed us to combine correlation results for non-standardized measurement depths across networks.

2.4.2. Kernel Density Estimation of Optimal Timescales

We used kernel density estimation (KDE) to evaluate the distribution of optimal timescales for each depth and drought index across space (sites). This method estimates nonparametric probability distributions (Silverman, 1986) which characterize the distribution of timescales (spatial variability) and allow for identification of the distribution's global maxima (generalized optimal timescale). We computed KDEs using the depth aggregated (shallow, middle and deep) correlation data sets for the “warm season” (Figures 2a, 3a, and 4a). To do so, we extracted the timescale associated with the highest correlation (or lowest for EDDI) at each site and depth and computed the KDE using the normal reference rule, “Scott's Rule,” for bandwidth selection (Odell-Scott, 1992). Throughout the remainder of the manuscript, the term “generalized optimal timescale” refers to the drought index

Table 1

Description of the Soil Moisture Models Considered

Model	Shorthand name	Description	Spatiotemporal resolution and latency	Percentile/standardized anomaly reference period	Pre-computed percentiles/standardized anomalies?	Data access	Reference(s)
Climate Prediction Center, Leaky Bucket Model 0–160 cm	CPC	The CPC Leaky Bucket soil moisture product is a one-layer bucket water balance model. Model parameters are tuned spatially and constant to reproduce runoff of several small river basins in eastern Oklahoma.	Daily data, 1-day data latency, 1-degree resolution (resampled from 0.5° by CPC)	1895–2022	Yes	Climate Prediction Center (n.d.), <i>Climate Prediction Center, Leaky Bucket Model</i> . Retrieved 1 August 2023, from ftp://ftp.cpc.ncep.noaa.gov/GIS/USDM_Products/soil/percentile/daily/	Fan and van den Dool (2004)
Gravity Recovery and Climate Experiment Rootzone Soil Moisture (variable depth)	GRACE	The GRACE rootzone soil moisture model leverages a numerical model of land surface water and energy processes along with observations of terrestrial water storage (derived from gravity) from the GRACE-FO satellite to estimate moisture.	Weekly data, <1 week data latency, 0.125° resolution	1948–2012	Yes	National Aeronautics and Space Administration, National Drought Mitigation Center (n.d.). <i>Groundwater and Soil Moisture Conditions from GRACE-FO Data Assimilation for the Contiguous U.S. And Global Land</i> . Retrieved 1 August 2023, from https://nasagrace.unl.edu/data/	Houborg et al. (2012)
North American Land Data Assimilation System (NLDAS-2) Variable Infiltration Capacity (VIC) 0–100 cm	NLDAS-2 VIC	The NLDAS-2 VIC land surface model uses three soil layers, with thicknesses that vary spatially and a two-layer energy balance snow model forced by the hourly NLDAS-2 forcing data.	Hourly data (first hour of each day used here), <1 week data latency, 0.125° resolution	1991–2022	No	NLDAS project (2022), NLDAS VIC Land Surface Model L4 Monthly 0.125 × 0.125° V2.0, Edited by David M. Mocko, NASA/GSFC/HSL, Greenbelt, Maryland, USA, Goddard Earth Sciences Data and Information Services Center (GES DISC), Accessed: [8-1/2023], https://doi.org/10.5067/NL7ITZY02RVK	Liang et al., 1994; Wood et al., 1997
North American Land Data Assimilation System (NLDAS-2) Mosaic 0–100 cm	NLDAS-2 Mosaic	The NLDAS-2 MOSAIC land surface model uses three soil layers with thicknesses of 10, 30 and 160 cm and accounts for the sub-grid heterogeneity of	Hourly data (first hour of each day used here), <1 week data latency, 0.125° resolution	1991–2022	No	NLDAS project (2021), NLDAS Mosaic Land Surface Model L4 Hourly 0.125 × 0.125° V2.0, Edited by David M. Mocko, NASA/GSFC/HSL, Greenbelt,	Koster and Suarez (1994, 1992)

Table 1
Continued

Model	Shorthand name	Description	Spatiotemporal resolution and latency	Percentile/standardized anomaly reference period	Pre-computed percentiles/standardized anomalies?	Data access	Reference(s)
North American Land Data Assimilation System (NLDAS-2) Noah 0–100 cm	NLDAS-2 NOAH	vegetation and soil moisture with a tiling approach. The model is forced by the hourly NLDAS-2 forcing data.	Hourly data (first hour of each day used here), <1 week data latency, 0.125° resolution	1991–2022	No	Maryland, USA, Goddard Earth Sciences Data and Information Services Center (GES DISC), Accessed: [8/1/2023], https://doi.org/10.5067/T5S8ZCZJW75	Chen et al. (1996) and Ek et al. (2003)
North American Land Data Assimilation System (NLDAS-2) 0–100 cm Ensemble	NLDAS-2 Ensemble	The NLDAS-2 NOAH land surface model uses four soil layers, with spatially invariant thicknesses of 10, 30, 60 and 100 cm and simulates the soil freeze-thaw process and its impact on soil heating/cooling and transpiration. The model is forced by the hourly NLDAS-2 forcing data.	Hourly data (first hour of each day used here), <1 week data latency, 0.125° resolution	1991–2022	No	NLDAS project (2021), NLDAS Noah Land Surface Model L4 Hourly 0.125 × 0.125° V2.0, Edited by David M. Mocko, NASA/GSFC/HSL, Greenbelt, Maryland, USA, Goddard Earth Sciences Data and Information Services Center (GES DISC), Accessed: [8/1/2023], https://doi.org/10.5067/T4OW83T8EXDO	N/A
Soil Moisture Active Passive L4 (SMAP L4) rootzone (0–100 cm) soil moisture	SMAP L4	Time and site specific mean (ensemble) soil moisture from the NLDAS-2 VIC, NLDAS-2 MOSAIC and NLDAS-2 NOAH models.	Three hourly data (first hour of each day used here), <1 week data latency, 11 km resolution	2001–2021	Yes	Reichle, R.H., G. De Lannoy, R.D. Koster, W.T. Crow, J.S. Kimball, Q. Liu, and M. Bechtold. 2022. <i>SMAP L4 Global 3-hourly 9 km EASE-Grid Surface and Root Zone Soil Moisture Analysis Update, Version 7</i> . Root zone soil moisture (0–100 cm; percentile units). Boulder, Colorado USA. NASA National Snow and Ice Data Center Distributed Active Archive Center. https://	R. Reichle et al. (2022)

Table 1
Continued

Model	Shorthand name	Description	Spatiotemporal resolution and latency	Percentile/standardized anomaly reference period	Pre-computed percentiles/standardized anomalies?	Data access	Reference(s)
Short-term Prediction Research and Transition Center (SPoRT) rootzone (0–100 cm) mean soil moisture	SPoRT	The SPoRT soil moisture model estimates soil moisture using the NASA Land Information System (LIS) and a long-term run of the NLDAS-2 NOAA model. SPoRT integrates information from the Visible Infrared Imaging Radiometer Suite (NOAA/NESDIS VIIRS) instrument into the model, estimating near real time green vegetation fraction.	Three hourly data (first hour of each day used here), 1-day data latency, 3 km resolution	2005–2022	No	doi.org/10.5067/LWJ6TF5SZRG3 Historical Data Accessed Directly via NASA, current data can be found at https://geo.ndc.nasa.gov/SPoRT/modeling/lis/conus3km/	Case and White (2014)
Topofire rootzone soil moisture (variable depth)	Topofire	Topofire soil moisture is a single layer soil water balance model that assumes uniform vegetation and with soil water holding capacity defined by gridded soil water holding capacity from SSURGO.	Daily data, 3-day data latency, 250 m resolution	1991–2022	No	Topofire (2019). Topofire Daily Data. Retrieved 1 August 2023, from https://topofire.dbs.unt.edu/public_data/topofire_weather/daily_grids/	Holden et al. (2019)

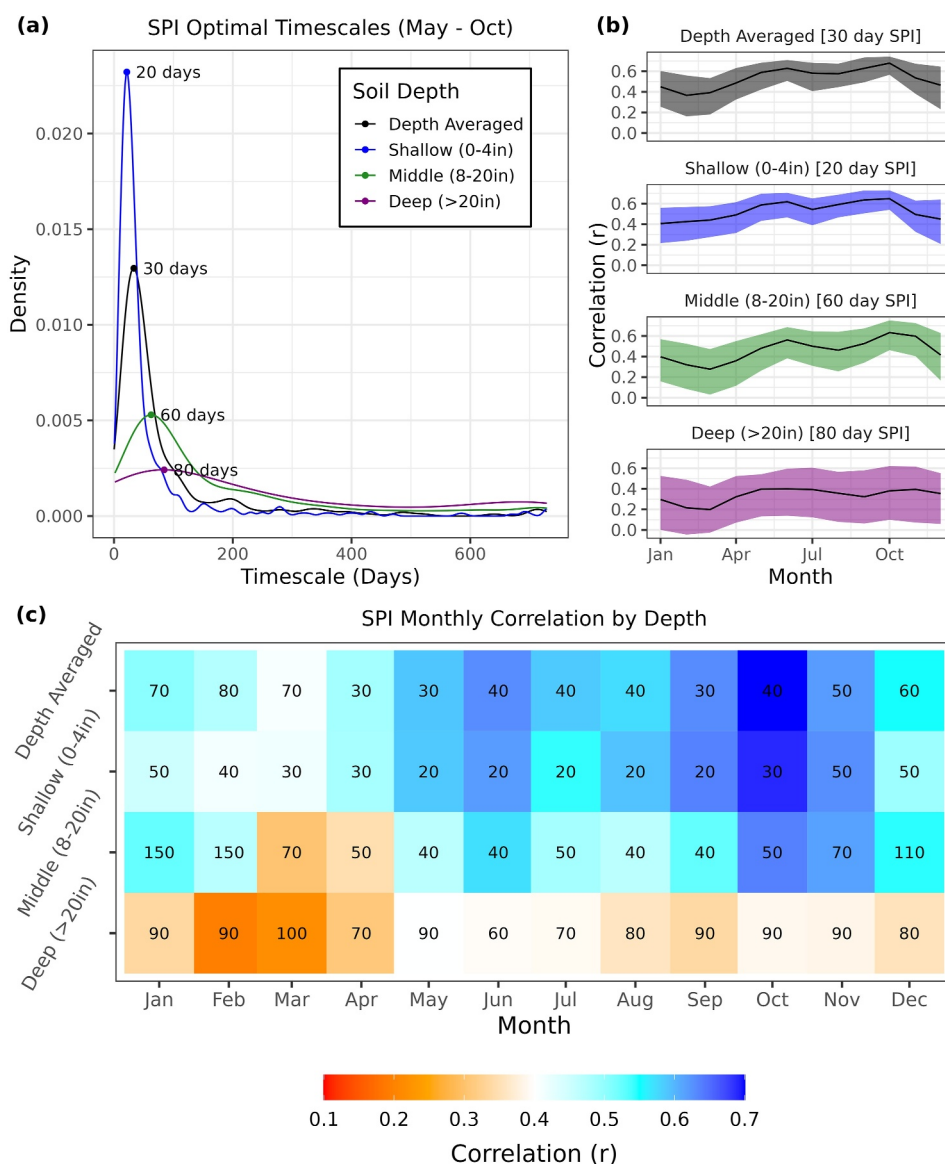


Figure 2. Correlation analysis between the Standardized Precipitation Index (SPI) and observed standardized soil moisture anomalies across the conterminous United States (U.S.); (a) Kernel Density Estimation (KDE) showing generalized optimal SPI timescale by depth for all sites in the analysis between May 1st and October 31st, (b) annal correlation timeseries for all sites using the generalized optimal drought timescale from the global KDE analysis. Black line represents the median correlation coefficient across all sites while the ribbon denotes the inter-quartile range (IQR) of the correlation coefficients across sites, and (c) monthly optimal timescales using monthly specific KDEs separated by depth. Color scaling represents the average (median) month and depth specific correlation coefficient when using the month and depth specific optimal timescale. Soil moisture observations have been transformed into standardized anomalies, the Soil Moisture Index (SMI).

timescale that is most commonly associated with the highest correlation with observed standardized soil moisture anomalies (SMI_{obs}) for a given drought index and soil depth (Figures 2a, 3a, and 4a). This is in distinction to site-specific or month-specific optimal timescales, which exhibit spatial (site) and temporal (month) variability across the U.S.

2.4.3. Monthly Analysis Using Optimal Timescales

We used the generalized optimal timescales estimated by the KDE (global maxima) to evaluate seasonal correlations for each depth category and drought index (Figures 2b, 3b, and 4b) assuming the use of the generalized optimal timescale. To do so we computed the median, 25th and 75th percentiles (line and ribbon in Figures 2b, 3b,

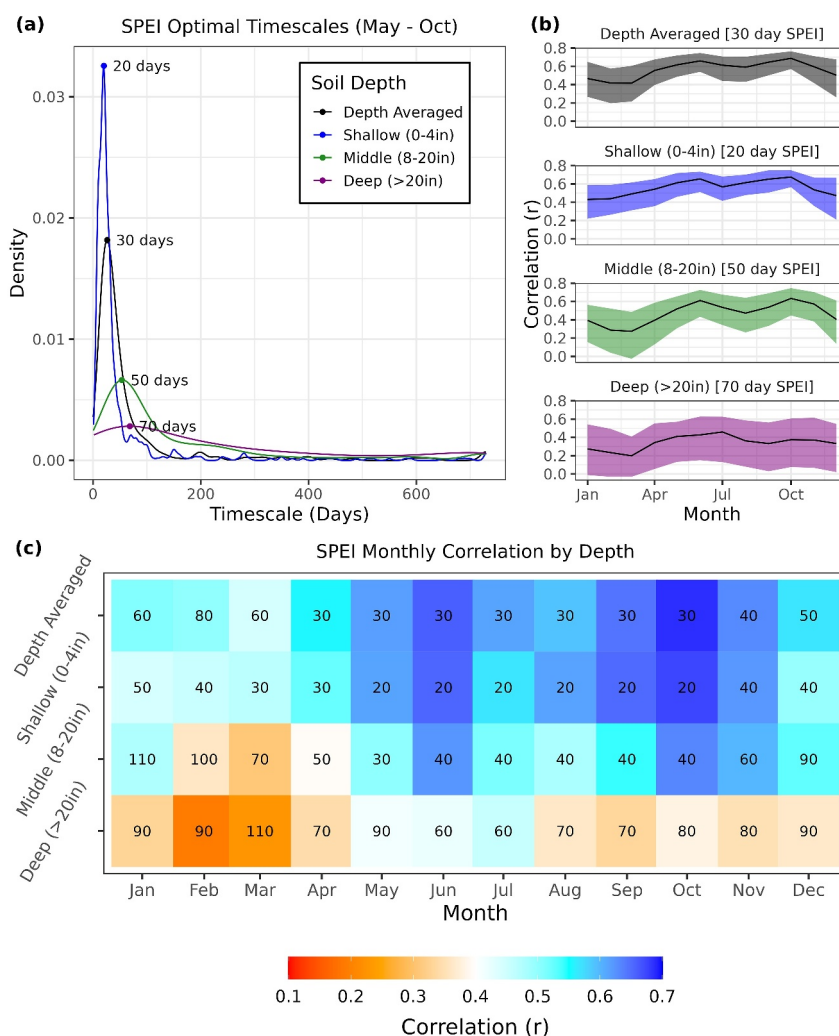


Figure 3. Correlation analysis between the Standardized Precipitation Evapotranspiration Index (SPEI) and observed standardized soil moisture anomalies across the conterminous United States (U.S.); (a) Kernel Density Estimation (KDE) showing generalized optimal SPEI timescale by depth for all sites in the analysis between May 1st and October 31st, (b) annal correlation timeseries for all sites using the generalized optimal drought timescale from the global KDE analysis. Black line represents the median correlation coefficient across all sites while the ribbon denotes the inter-quartile range (IQR) of the correlation coefficients across sites, and (c) monthly optimal timescales using monthly specific KDEs separated by depth. Color scaling represents the average (median) month and depth specific correlation coefficient when using the month and depth specific optimal timescale. Soil moisture observations have been transformed into standardized anomalies, the Soil Moisture Index (SMI).

and 4b) of the correlation distributions for each depth and month. As an example, using the generalized optimal timescale for the shallow depth for SPI (Figure 2b, blue line, 20 days), we extracted the correlations associated with the 20 days timescale for each month/site and computed the median, 25th and 75th percentiles of the correlation distributions. This analysis is meant to summarize observed correlations when using generalized optimal timescales across space (sites) and time (season) to analyze how well a meteorological drought index performs across the conterminous U.S.

2.4.4. Month and Depth Specific Optimal Timescales

To evaluate if optimal timescales vary over time, and to assess the month/depth specific median correlation for each drought index, we repeated the analysis described in Sections 2.4.2 and 2.4.3 for each month and depth independently (Figures 2c, 3c, and 4c). Here the month/depth specific optimal timescale is reported as a numeric

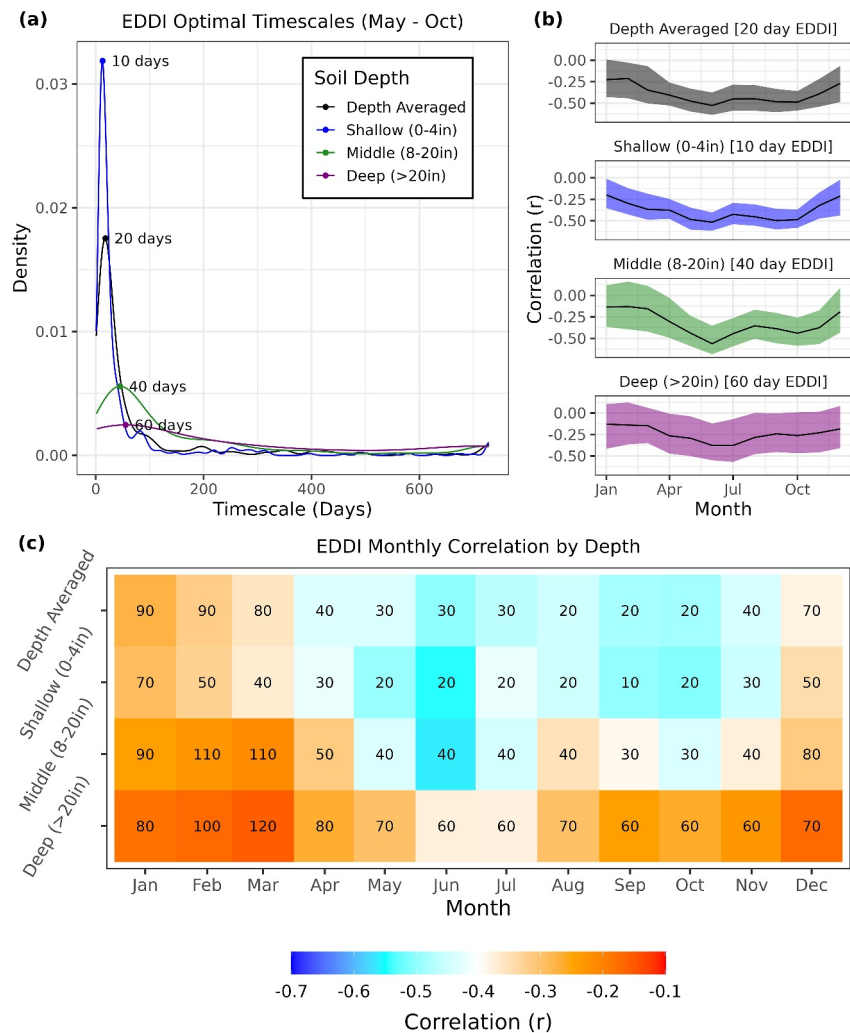


Figure 4. Correlation analysis between the Evaporative Demand Drought Index (EDDI) and observed standardized soil moisture anomalies across the conterminous United States (U.S.); (a) Kernel Density Estimation (KDE) showing generalized optimal EDDI timescale by depth for all sites in the analysis between May 1st and October 31st, (b) annal correlation timeseries for all sites using the generalized optimal drought timescale from the global KDE analysis. Black line represents the median correlation coefficient across all sites while the ribbon denotes the inter-quartile range (IQR) of the correlation coefficients across sites, and (c) monthly optimal timescales using monthly specific KDEs separated by depth. Color scaling represents the average (median) month and depth specific correlation coefficient when using the month and depth specific optimal timescale. Soil moisture observations have been transformed into standardized anomalies, the Soil Moisture Index (SMI).

value in the graphic, while the color scaling represents the median Pearson's r correlation coefficient for that month/depth specific distribution.

2.4.5. Comparing Optimal Timescales to Soil Moisture Models

We compare the performance of the timescale optimized drought indices and the nine soil moisture models for predicting SMI_{obs} , by computing both the Pearson's correlation coefficient (r) and the root mean square error (RMSE) for each model and depth (Figure 5, Figure S1 in Supporting Information S1, Table 2). While similar, these two measures differ on whether the expected relationship implicitly follows a “one-to-one” relationship; RMSE implicitly expects one-to-one while r does not. Here we present the raw data as a two dimensional KDE with an axis-aligned bivariate normal kernel (Venables & Ripley, 2002) in Figure 5, Figures S1, S7, and S8 in Supporting Information S1. For this analysis, EDDI values were inverted (multiplied by -1) in order to be consistent with the positive relationship between SMI_{mod} and SMI_{obs} for all other metrics and models considered.

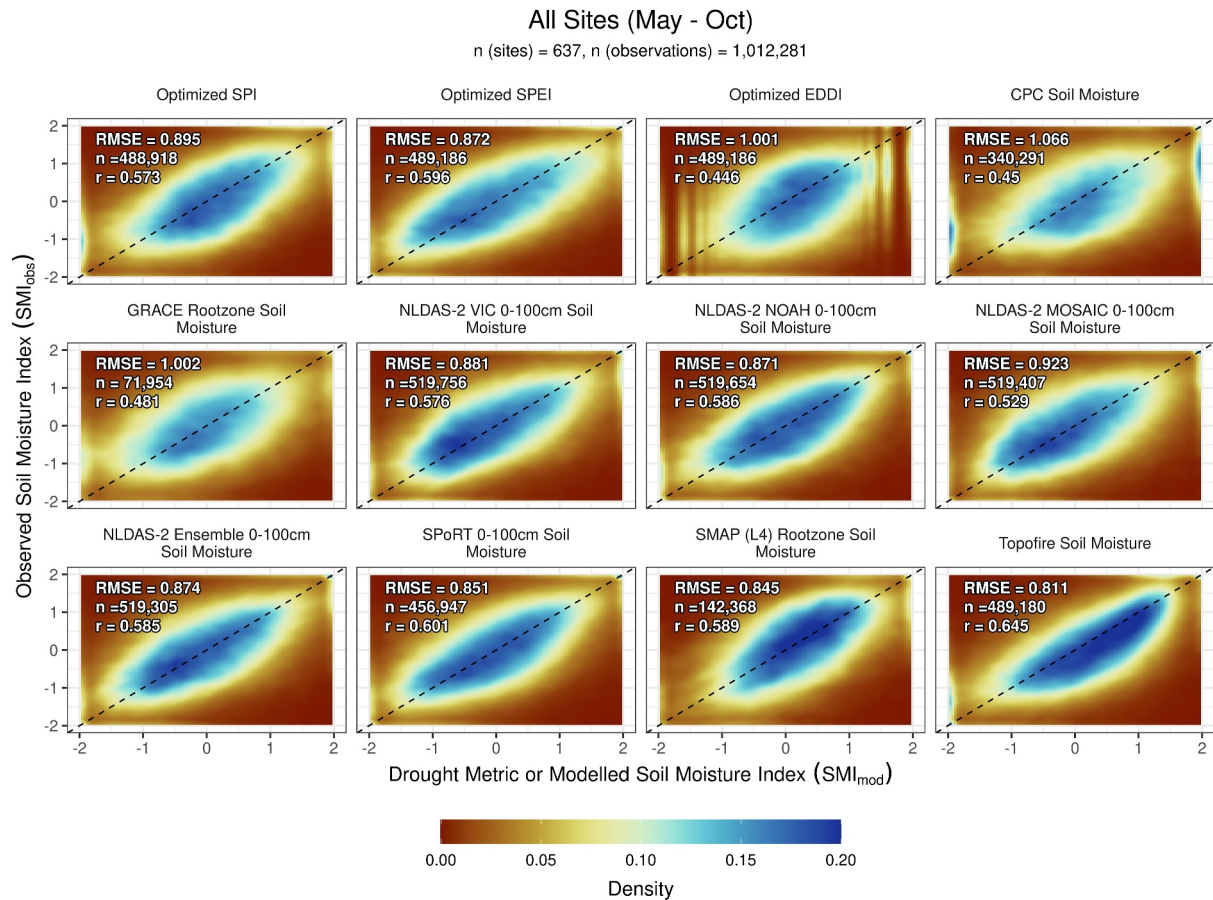


Figure 5. Comparison of timescale optimized meteorological drought indices (optimized by depth, shown in Figures 2–4) and soil moisture models to observed soil moisture dynamics for the depth averaged soil moisture timeseries. Soil moisture models and observations have been transformed into standardized anomalies, the Soil Moisture Index (SMI).

2.4.6. Comparing Drought Indices and Soil Moisture Model Performance Across Drought and Wetness States

In order to compare the performance of the optimized drought indices and soil moisture models across gradients in soil water conditions, we performed an ordinal error analysis (Table 3 and Table S2 in Supporting Information S1). To do so we adopted the drought classification scheme of the U.S. Drought Monitor for standardized variables like SPI and SPEI (U.S. Drought Monitor, 2024), ranging from exceptional drought (D4) to abnormally dry (D0), and expanded this classification to include neutral conditions and abnormal wetness. Target classes (considered “truth,” or “theoretical drought class” henceforth) were defined using the observed soil moisture index values: D4 Exceptional Drought ($SMI_{obs} < -2$), D3 Extreme Drought ($-2 < SMI_{obs} < -1.6$), D2 Severe Drought ($-1.6 < SMI_{obs} < -1.3$), D1 Moderate Drought ($-1.3 < SMI_{obs} < -0.8$), D0 Abnormally Dry ($-0.8 < SMI_{obs} < -0.5$), Neutral ($-0.5 < SMI_{obs} < 0.5$), W0 Abnormally Wet ($0.8 > SMI_{obs} > 0.5$), W1 Moderately Wet ($1.3 > SMI_{obs} > 0.8$), W2 Severely Wet ($1.6 > SMI_{obs} > 1.3$), W3 Extremely Wet ($2 > SMI_{obs} > 1.6$), W4 Exceptionally Wet ($SMI_{obs} > 2$). We then applied this classification scheme to the optimized drought indices and soil moisture models. Using this ordinal structure and assuming a 1-class difference between each category, we computed the drought/wetness class mean square error (MSE; Gaudette & Japkowicz, 2009) for each index/model aggregated across target classes (defined using the observed soil moisture index). As an example, assuming the target drought class defined by SMI_{obs} is D3 Extreme Drought, a prediction of D1 (Moderate Drought) would be assigned a 2 class error whereas a D2 (Severe Drought) prediction would be assigned a 1 class error, and so forth. We also computed the mean absolute error (MAE) to aid in error interpretation.

Table 2

Table Summarizing the Comparison of Timescale Optimized Drought Indices (Optimized by Depth, Shown in Figures 2–4) and Soil Moisture Models to Observed Soil Moisture Dynamics for all Depths

Model	Depth	Pearson's r	p -value	RMSE	n
Optimized SPI	Depth averaged	0.573	<0.01	0.895	488,918
Optimized SPEI	Depth averaged	0.596	<0.01	0.872	489,186
Optimized EDDI	Depth averaged	0.446	<0.01	1.001	489,186
CPC Soil Moisture	Depth averaged	0.45	<0.01	1.066	340,291
GRACE Rootzone Soil Moisture	Depth averaged	0.481	<0.01	1.002	71,954
NLDAS-2 VIC 0–100 cm Soil Moisture	Depth averaged	0.576	<0.01	0.881	519,756
NLDAS-2 NOAH 0–100 cm Soil Moisture	Depth averaged	0.586	<0.01	0.871	519,654
NLDAS-2 MOSAIC 0–100 cm Soil Moisture	Depth averaged	0.529	<0.01	0.923	519,407
NLDAS-2 Ensemble 0–100 cm Soil Moisture	Depth averaged	0.585	<0.01	0.874	519,305
SPoRT 0–100 cm Soil Moisture	Depth averaged	0.601	<0.01	0.851	456,947
SMAP (L4) Rootzone Soil Moisture	Depth averaged	0.589	<0.01	0.845	142,368
Topofire Soil Moisture	Depth averaged	0.645	<0.01	0.811	489,180
Optimized SPI	Shallow (0–4in)	0.559	<0.01	0.912	665,191
Optimized SPEI	Shallow (0–4in)	0.581	<0.01	0.886	666,262
Optimized EDDI	Shallow (0–4in)	0.421	<0.01	1.024	666,262
CPC Soil Moisture	Shallow (0–4in)	0.384	<0.01	1.135	460,695
GRACE Rootzone Soil Moisture	Shallow (0–4in)	0.452	<0.01	1.028	98,340
NLDAS-2 VIC 0–100 cm Soil Moisture	Shallow (0–4in)	0.52	<0.01	0.936	707,793
NLDAS-2 NOAH 0–100 cm Soil Moisture	Shallow (0–4in)	0.539	<0.01	0.917	707,661
NLDAS-2 MOSAIC 0–100 cm Soil Moisture	Shallow (0–4in)	0.473	<0.01	0.974	707,311
NLDAS-2 Ensemble 0–100 cm Soil Moisture	Shallow (0–4in)	0.527	<0.01	0.929	707,179
SPoRT 0–100 cm Soil Moisture	Shallow (0–4in)	0.569	<0.01	0.884	618,109
SMAP (L4) Rootzone Soil Moisture	Shallow (0–4in)	0.534	<0.01	0.903	184,146
Topofire Soil Moisture	Shallow (0–4in)	0.601	<0.01	0.858	664,874
Optimized SPI	Middle (8–20in)	0.482	<0.01	0.962	2,338,776
Optimized SPEI	Middle (8–20in)	0.502	<0.01	0.947	2,338,906
Optimized EDDI	Middle (8–20in)	0.389	<0.01	1.02	2,338,906
CPC Soil Moisture	Middle (8–20in)	0.378	<0.01	1.145	1,569,257
GRACE Rootzone Soil Moisture	Middle (8–20in)	0.347	<0.01	1.184	350,243
NLDAS-2 VIC 0–100 cm Soil Moisture	Middle (8–20in)	0.439	<0.01	0.998	2,488,768
NLDAS-2 NOAH 0–100 cm Soil Moisture	Middle (8–20in)	0.441	<0.01	0.992	2,488,489
NLDAS-2 MOSAIC 0–100 cm Soil Moisture	Middle (8–20in)	0.392	<0.01	1.027	2,486,808
NLDAS-2 Ensemble 0–100 cm Soil Moisture	Middle (8–20in)	0.449	<0.01	0.989	2,486,529
SPoRT 0–100 cm Soil Moisture	Middle (8–20in)	0.468	<0.01	0.958	2,238,266
SMAP (L4) Rootzone Soil Moisture	Middle (8–20in)	0.496	<0.01	0.93	424,717
Topofire Soil Moisture	Middle (8–20in)	0.548	<0.01	0.883	2,338,906
Optimized SPI	Deep (>20in)	0.341	<0.01	1.087	458,821
Optimized SPEI	Deep (>20in)	0.353	<0.01	1.088	458,821
Optimized EDDI	Deep (>20in)	0.263	<0.01	1.13	458,821
CPC Soil Moisture	Deep (>20in)	0.32	<0.01	1.175	316,994
GRACE Rootzone Soil Moisture	Deep (>20in)	0.278	<0.01	1.169	67,362
NLDAS-2 VIC 0–100 cm Soil Moisture	Deep (>20in)	0.366	<0.01	1.066	487,538

Table 2
Continued

Model	Depth	Pearson's r	p -value	RMSE	n
NLDAS-2 NOAH 0–100 cm Soil Moisture	Deep (>20in)	0.356	<0.01	1.073	487,434
NLDAS-2 MOSAIC 0–100 cm Soil Moisture	Deep (>20in)	0.336	<0.01	1.083	487,206
NLDAS-2 Ensemble 0–100 cm Soil Moisture	Deep (>20in)	0.372	<0.01	1.061	487,102
SPoRT 0–100 cm Soil Moisture	Deep (>20in)	0.348	<0.01	1.074	427,526
SMAP (L4) Rootzone Soil Moisture	Deep (>20in)	0.393	<0.01	1.019	133,423
Topofire Soil Moisture	Deep (>20in)	0.375	<0.01	1.057	458,821

Note. Soil moisture models and observations have been transformed into standardized anomalies, the Soil Moisture Index (SMI). Bold font represents the model with the lowest RMSE while blue font represents the model with the highest Pearson's r when separated by depth.

2.5. USCRN Comparison

The USCRN network is considered one of the highest quality long-term soil moisture networks in the conterminous U.S., boasting triplicate-configuration soil moisture observations (Bell et al., 2013; Diamond et al., 2013). While other networks may contain data sets with comparatively less rigorous quality control, inclusion of their observations is beneficial for this analysis to provide greater spatial coverage and to capture a greater degree of natural variability in soil moisture dynamics. Further, because this analysis is focused on standardized soil moisture anomalies, systematic bias in any network/location/probe would be accounted for in the parametric normalization. However, in light of this undeniable quality, we re-conducted all of the above analysis using only USCRN data (Figures S4–S7, Table S1 in Supporting Information S1) to allow for the comparison of results when considering only USCRN station data (112 sites) versus all of the stations considered in this analysis (641 sites).

3. Results

This analysis has revealed several key insights that stand to enhance soil moisture drought assessment using meteorological drought indices and soil moisture models. First, the generalized optimal drought index timescales for standardized soil moisture anomalies are relatively short (less than 90 days) and increase with increasing soil depth (from ~10 [shallow] to ~80 [deep] days). Incorporation of precipitation dynamics into meteorological drought indices is critical to capture standardized soil moisture anomalies, however inclusion of atmospheric demand improves predictions slightly (Figures 2–4). Atmospheric demand alone is a comparatively poor predictor of standardized soil moisture anomalies (Figure 4). However, modern soil moisture models outperform timescale optimized drought indices for soil moisture anomaly prediction across the U.S. without the use of timescales (e.g., 30-, 60-, or 90-days SPI); Topofire, SMAP L4, and SPoRT soil moisture models generally performed best (Figure 5, Table 2).

3.1. Meteorological Drought Index Generalized Optimal Timescales

Generalized optimal timescales never exceeded 80 days (Figures 2a, 3a, and 4a) indicating that shorter timescales are representative of subsurface soil moisture dynamics, even at depth. These results are reflective of the “warm season,” which is when optimal timescales are most consistent (Figures 2c, 3c, and 4c) allowing for a robust estimation of generalized optimal timescales. However, it is important to note that all months are considered in this analysis (Figures 2c, 3c, and 4c), but discussed separately in Section 4.2. Results were generally consistent when considering all sites (Figures 2–4) or USCRN sites only (Figures S4–S6 in Supporting Information S1), though there is slight variation in the optimal timescales selected and correlations observed for each drought index and soil depth.

3.1.1. Variation by Depth

Generalized optimal timescales for each metric varied strongly by depth (Figures 2a, 3a, and 4a). In all cases, the generalized optimal timescale increased at greater depths (with the exception of EDDI, where mid- and deep soils exhibited the same generalized optimal timescale; Figure 4a). Generalized optimal timescales for depth averaged

soil moisture were between 20 (EDDI) and 30 (SPEI and SPI) days. The generalized optimal timescale for shallow soil depths (0–4 in.) varied from 10 to 20 days, depending on the drought index (10 and 20 days for EDDI and SPI/SPEI respectively). KDE analysis shows that the generalized optimal timescale for shallow soils is comparatively very consistent across sites (large density values for blue lines in Figures 2a, 3a, and 4a). The generalized optimal timescale for middle soil depths (8–20 in.) varied from 40 to 60 days, depending on the drought index (40-, 50-, and 60-days for EDDI, SPEI and SPI respectively). Here, density estimates show that there is more variance across sites compared to shallow soil depths (green lines in Figures 2a, 3a, and 4a). Finally, the longest generalized optimal timescales were observed at deep soil depths (>20 in.), which varied from 60 to 80 days, depending on the drought index (60-, 70-, and 80 days for EDDI, SPEI and SPI respectively). In all cases, KDE estimates of density show that there is the greatest variation across sites of optimal timescales for deep soils (purple lines in Figures 2a, 3a, and 4a).

3.1.2. Variation by Drought Index

Generalized optimal timescales also varied by drought index, though SPI and SPEI had the same generalized optimal timescales at shallow depths and for depth averaged conditions. In all cases EDDI reflected the shortest optimal timescales ranging from 10 to 60 days for shallow and deep soil moisture measurements respectively. Alternatively, SPI reported the longest optimal timescales for deep soil moisture dynamics. However, overall generalized optimal timescales were relatively consistent (Figures 2a, 3a, and 4a).

3.1.3. Seasonal Correlation

We evaluated how correlation (or anticorrelation for EDDI) of a specific drought index and SMI_{obs} varied over the season at each depth using the generalized optimal timescales (Figures 2b, 3b, and 4b). Unsurprisingly, the highest correlations [anticorrelations] occurred during the “warm season” over which the generalized optimal timescale was computed. The highest average correlations [anticorrelations] were generally observed for depth averaged soil moisture (gray lines in Figures 2b, 3b, and 4b), followed by shallow soil depths (blue lines), middle soil depths (green lines) and deep depths (purple lines). For depth averaged, shallow and middle soil depths, correlations to SPI and SPEI tended to increase across the season (from May to October), with October reporting the highest average correlation. Alternatively, June was the month with the highest anticorrelation (best) for EDDI, with a general decrease in anticorrelation earlier or later in the season. Correlations [anticorrelations] decreased significantly during the winter months (November–March) likely associated with an increase in the monthly specific optimal timescale (described below in Section 4.2).

3.2. Monthly Optimal Timescales and Correlation

In order to evaluate changes in optimal timescales over time, we replicated methods to determine optimal timescales for each month independently (numeric values in Figures 2c, 3c, and 4c represent month specific optimal timescales). Results indicate that longer timescales are more optimal for the cold winter months, while shorter timescales are better in the warm, spring, summer and fall months. For SPI, September, October and November were typically the months with the highest correlations. Similar patterns were observed for SPEI, however comparatively strong correlations were also observed in May and June. EDDI also performed best in the early summer (May and June) and the late summer/early fall (September and October). In all cases, correlations [anticorrelations] declined and timescales increased with increasing depth. Overall, EDDI was comparatively much less predictive of soil moisture dynamics (SMI_{obs}) with respect to SPI and SPEI, while SPEI was the most predictive drought index tested in this study.

3.3. Comparison of Timescale Optimized Drought Indices and Soil Moisture Models

We compared the performance of nine soil moisture models (CPC, GRACE, NLDAS-2 VIC, NLDAS-2 Mosaic, NLDAS-2 Noah, NLDAS-2 Ensemble, SMAP L4, SPoRT, and Topofire, Table 1) and the three optimized drought indices (SPI, SPEI, and EDDI) using the depth specific generalized optimal timescales to evaluate which model provided the greatest predictive power for standardized soil moisture anomalies across the conterminous U.S. (Figure 5, Figures S1, S7, and S8 in Supporting Information S1, Table 2 and Table S1 in Supporting Information S1). This analysis represents more than eight million ($n = 8,175,329$) distinct, daily soil moisture observation pairs from 2,405 individual time series (various depths) at 637 sites (Figures 1 and 5, Figure S1 in

Supporting Information S1). Results indicate that Topofire standardized soil moisture anomalies (SMI_{mod}) were the most predictive of observed standardized soil moisture anomalies (SMI_{obs}) for depth averaged, shallow and middle soil depths (when all soil moisture conditions were considered) regardless of if RMSE or Pearson's r is used to determine performance (RMSE = 0.811, 0.858, and 0.883 [standardized units], r = 0.645, 0.601, and 0.548 for depth averaged, shallow and middle soil depths respectively; Figure 5, Figure S1 in Supporting Information S1, Table 2). Additionally, these conclusions generally hold regardless of if one is evaluating all stations in this study (e.g., MT Mesonet, SCAN, SNOTEL and USCRN, n = 637), or just USCRN sites (n = 112), however SPoRT was identified as having the lowest RMSE (best model) for shallow depths at USCRN sites (Figures S7, S8, and Table S1 in Supporting Information S1). SMAP L4 Rootzone soil moisture anomalies were the most predictive of deep soil moisture conditions regardless of performance metric (RMSE = 1.019, r = 0.393) when all sites were considered, though correlations were much lower and error was much higher than those observed for shallow and middle soil depths. When evaluating only USCRN sites, SMAP L4 soil moisture was still the best model based on RMSE (RMSE = 0.968), however Topofire soil moisture had the highest Pearson's r (r = 0.479).

The second most predictive model for depth averaged soil moisture dynamics for all sites was either SPoRT (which had the second highest r of 0.601) or SMAP L4 (which had the second lowest RMSE of 0.845). When only USCRN sites were included, the second best model was SPoRT soil moisture (RMSE = 0.753, r = 0.691). The second most predictive model(s) for shallow soil dynamics were SPoRT soil moisture (based on RMSE of 0.884) and the timescale optimized SPEI (based on r of 0.581) when considering all sites. For mid-depth soils, the second most predictive model was SMAP L4 soil moisture (based on an RMSE of 0.930) or the timescale optimized SPEI (based on an r of 0.502) when all sites were considered. However, SPoRT was the second most predictive model (RMSE = 0.843, r = 0.609) when only USCRN sites were considered. For deep standardized soil moisture anomalies, Topofire was the second best model irrespective of performance metric when all sites were considered with an RMSE of 1.057 and Pearson's r of 0.375.

CPC soil moisture performed the worst for depth averaged conditions based on RMSE regardless of which sites included (RMSE = 1.066 and 1.037 for all sites and USCRN respectively) while EDDI performed the worst based on Pearson's r regardless of which sites included (r = 0.446 and 0.489 for all sites and USCRN respectively). CPC soil moisture performed worst for shallow soil depths, irrespective of performance metric or sites included; all sites (RMSE = 1.135, r = 0.384), USCRN sites (RMSE = 1.103, r = 0.434). When all sites were considered, GRACE soil moisture performed worst at mid soil depths irrespective of performance metric (RMSE = 1.184, r = 0.347). At mid depths for USCRN sites only, CPC performed the worst based on RMSE (1.103) and EDDI performed worst based on Pearson's r (0.403). At deep soil depths, CPC soil moisture performed worst based on RMSE when all sites (1.175) or just USCRN sites (1.140) were analyzed. At deep soil depths, EDDI performed worst based on Pearson's r when all sites (0.263) or just USCRN sites (0.336) were analyzed.

When considering all soil moisture conditions (e.g., drought to abnormal wetness), Topofire standardized soil moisture anomalies were most predictive of observed standardized soil moisture anomalies for depth averaged conditions, followed by SPoRT and SMAP L4 when all sites were included. When taken as a whole, this analysis indicates that the Topofire, SPoRT and SMAP L4 soil moisture models are all good predictors of soil moisture dynamics, though their performance varies by depth and locations considered. Further, this analysis shows that these soil moisture models routinely outperform traditional drought indices without the use of timescales, even when generalized optimal timescales are applied to drought indices. While this comparison of RMSE and r is useful in a relative sense (e.g., relative ranking of performance), a more interpretable performance metric, the mean absolute drought classification error, is explored below. Spatial patterns of site specific error can be observed in Figure S2 (RMSE) and Figure S3 (r) in Supporting Information S1.

3.4. Comparing Drought Indices and Soil Moisture Model Performance Across Drought and Wetness States

Results from the ordinal error analysis (i.e., the ability for models to correctly determine drought/wetness classes) demonstrate that the SPoRT soil moisture model was the most accurate model for predicting observed drought classes (defined using depth averaged soil moisture conditions) when all sites were considered, with the exception of D2 (Severe Drought), where the NLDAS-2 VIC model performed best (Table 3). Average drought class mean absolute error (MAE) for the SPoRT model ranged from 0.620 to 0.881 D0 and D4 conditions respectively,

Table 3
Table Summarizing the Ordinal Error Analysis

Best model	Depth	Theoretical drought class	MSE	MAE	<i>n</i>
SPoRT 0–100 cm Soil Moisture	Depth averaged	D4 (Exceptional Drought)	1.296	0.881	6,395
SPoRT 0–100 cm Soil Moisture	Depth averaged	D3 (Extreme Drought)	1.045	0.777	13,016
NLDAS-2 VIC 0–100 cm Soil Moisture	Depth averaged	D2 (Severe Drought)	0.769	0.68	22,648
SPoRT 0–100 cm Soil Moisture	Depth averaged	D1 (Moderate Drought)	0.673	0.641	61,260
SPoRT 0–100 cm Soil Moisture	Depth averaged	D0 (Abnormally Dry)	0.611	0.62	49,195
Topofire Soil Moisture	Depth averaged	Neutral	0.582	0.609	179,056
Topofire Soil Moisture	Depth averaged	W0 (Abnormally Wet)	0.507	0.544	47,179
Topofire Soil Moisture	Depth averaged	W1 (Moderately Wet)	0.511	0.523	61,240
Topofire Soil Moisture	Depth averaged	W2 (Severely Wet)	0.614	0.567	22,074
Topofire Soil Moisture	Depth averaged	W3 (Extremely Wet)	0.796	0.674	14,772
Topofire Soil Moisture	Depth averaged	W4 (Exceptionally Wet)	0.952	0.716	9,903

Note. The best model (lowest MSE) is shown for each theoretical drought/wetness class defined by the depth averaged soil moisture index (SMI_{obs}). The mean square error (MSE), mean absolute error (MAE) and number of observations (*n*) for the best model are also reported within.

demonstrating the models ability to predict the theoretical drought class with less than a 1 class averager error. Topofire performed best when neutral or abnormally wet conditions were observed and all sites were considered. Results were generally consistent when only USCRN sites were considered (Table S2 in Supporting Information S1). However, notable differences include Topofire performing best during D4 (Exceptional Drought) conditions and SMAP L4 performing best in W4 (Exceptionally Wet) conditions.

4. Discussion

Well constructed soil moisture models better predict standardized anomalies in soil moisture when compared to timescale optimized drought indices. This finding is intuitive, and suggests that a transition away from commonly used drought indices toward well performing soil moisture models may improve agricultural and ecological drought assessment accuracy across the continental U.S. While soil moisture is only one component of the hydrologic cycle, soil moisture anomalies have a cascading impact on many parts of the hydrologic system (Entekhabi et al., 1992), drive important climate-atmosphere feedbacks (Koster et al., 2004), impact fire activity via fuel moisture (Jensen et al., 2018; Krueger et al., 2017) and can have a disproportionate socio-economic impact on communities reliant on agriculture (Madadgar & AghaKouchak, 2017; Mishra & Singh, 2010). While we ultimately suggest usage of soil moisture models (as opposed to meteorological drought indices) in soil moisture focused drought assessments (discussed in Section 4.2), we will begin this section by discussing the optimal use of meteorological drought indices given their broad application and historical significance.

4.1. At What Timescale and Season Are Drought Indices Most Representative of Soil Moisture Dynamics?

Traditional meteorological drought indices, including SPI, SPEI and EDDI, are commonly used for drought assessment across the U.S. and the globe. This broad application of drought indices represents decades of capacity building (Haile et al., 2020) that has resulted in widespread usage for operational assessment (M. D. Svoboda & Fuchs, 2016). Enhancing the application and accuracy of meteorological drought indices by utilizing the optimal timescales identified in this study will improve the spatial representation of drought where soil moisture is a critical resource. Furthermore, this methodological advancement is broadly applicable to drought assessment practitioners worldwide who leverage existing drought informatics infrastructure. However, it is important to note that information captured by drought indices at other timescales may represent important drought dynamics not characterized by soil moisture and therefore should also be considered.

A key result from this analysis is that standardized soil moisture anomalies respond to relatively short meteorological anomalies (meteorological drought index timescales), even at depth and during the winter (longest

month specific optimal timescale was 150 days for SPI in January for middle soil depths; Figure 2). Generally speaking, drought timescales shorter than 100 days are most widely associated with standardized soil moisture anomalies across the conterminous U.S. when applied to SPI, SPEI, and EDDI, with ~30 days being optimal for depth averaged soil moisture. These findings support previous research which has documented that short timescales (<90 days) generally reflect shallow subsurface processes such as soil moisture (H. Wang et al., 2015) and in some cases, hydrological drought (e.g., streamflow dynamics; (Peña-Gallardo et al., 2019)), whereas longer timescales (many months to multiple years) are more representative of deep hydrological processes such as groundwater recharge (Hellwig et al., 2020). Our results expand upon previous work and demonstrate that depth specific optimal timescales are relatively consistent across time (i.e., across seasons; Figures 2c, 3c, and 4c), but do contain seasonal patterns.

Our analysis highlights that optimal timescales tend to increase with increasing depth (Barnard et al., 2021). This reflects soil's role as a "low pass filter" for meteorology, dampening and integrating precipitation and evaporative demand signals temporally (Wu et al., 2002). In addition to an overall shorter optimal timescale, shallow and mid-depth soil moisture is much more correlated to meteorology than deep soil moisture. This reflects the stronger coupling of surface and shallow subsurface processes to the atmosphere (Entekhabi et al., 1992). Overall, this analysis can help guide the appropriate choice of timescales to consider when soil moisture dynamics at multiple depths are of interest.

Optimal drought timescales are typically longer during the cooler months (November–April), and shorter during the warmer months (May–October) when considering all sites (high and low elevation) across the conterminous U.S. One potential explanation for this response is the relatively higher proportion of precipitation falling as snow during the winter months, especially at high elevations or high latitudes due to cooler air temperatures (Ding et al., 2014). This transition from rain to snow impacts drought indices such as SPI and SPEI because they are forced with instantaneous measures of precipitation that do not account for a non-instantaneous release of moisture into the soil column (i.e., a lag between snowfall and melt; (Staudinger et al., 2014)). Therefore, soil moisture anomalies in snow impacted regions during the winter are most strongly related to precipitation dynamics from the previous fall and late summer (when precipitation is falling primarily as rain) until the melt season is realized. Further, snow can buffer the underlying soil from variations in temperature (Grundstein & Todhunter, 2005) and atmospheric demand, impacting the relationship between potential evapotranspiration in the atmosphere and release of moisture from the soil. Results from USCRN sites, typically located at lower elevations and evenly distributed across latitudes, show a similar seasonal pattern (Figures S4, S5, and S6 in Supporting Information S1).

Understanding when to use drought indices is also a key consideration for accurate drought monitoring. Our results show that drought indices are most applicable for predicting standardized soil moisture anomalies during the comparatively warm spring, summer and fall months, with the greatest predictive power occurring in early summer (June) and fall (October; Figures 2c, 3c, and 4c). This result supports conclusions from previous work (Vicente-Serrano et al., 2012), though here we extend these findings by applying time and depth dependent optimal timescales. This pattern was consistent across all meteorological drought indices when all sites were considered, for shallow and middle soil depths. This conclusion was also consistent when only USCRN sites were evaluated, though correlations were higher, especially at shallow depths (Figures S4c, S5c, and S6c in Supporting Information S1). Conversely, meteorological drought indices struggled to describe soil moisture in the winter months at mid- and deep soil depths, even when longer optimal timescales were applied.

SPI and SPEI outperformed EDDI in predicting soil moisture dynamics at every soil depth and at any time during the season. SPEI typically performed better than SPI, but the difference was subtle. EDDI exhibited comparatively low predictive power, and exhibited strong artifacts (vertical "ribbing"; Figure 5, Figures S1, S7, and S8 in Supporting Information S1, Table 2, and Table S1 in Supporting Information S1) due to the non-parametric formulation of EDDI (Hobbins et al., 2016). These results highlight the first order impact of precipitation, as opposed to atmospheric demand, for soil moisture anomaly prediction and provides more evidence that deficits in precipitation are the primary driver of most soil moisture droughts (Manning et al., 2018). However, our results also support the conclusion that accounting for evaporative demand in addition to precipitation can modestly enhance predictions of soil moisture anomalies and potential drought impacts (Vicente-Serrano et al., 2012). Previous research suggests that accounting for potential evapotranspiration in drought indices may be more important in wet (Teuling et al., 2013) versus dry (Luo et al., 2017) climates, especially during the warm months.

Furthermore, accounting for anomalies in atmospheric demand may be more important when monitoring rapidly occurring “flash droughts” (Christian et al., 2021; Noguera et al., 2022). Our study did not consider these intricacies as we are focused on drought assessment associated with soil moisture across the U.S. as a whole. However, future research could address these differences, potentially highlighting locations across the U.S. where soil moisture anomalies are more sensitive to evaporative demand.

4.2. How do Drought Indices Optimized for Soil Moisture Compare to Gridded Soil Moisture Models?

Perhaps one of the most important findings of this analysis is the ability of soil moisture models to outperform timescale optimized meteorological drought indices for soil moisture anomaly prediction (Figure 5, Figures S1, S7, and S8 in Supporting Information S1, Tables 2 and 3, Table S1 in Supporting Information S1). This is important because drought indices are commonly used proxies for soil moisture (Halwatura et al., 2017), and represent a baseline performance generally accepted for operational drought assessment. Not only do soil moisture models exceed this “threshold” of utility, they do so without the use of timescales, which greatly simplifies the usage of these models in the practical drought assessment context. The reason for this enhanced performance is likely associated with their representation of physical surface and subsurface conditions and processes, albeit a representation that is often highly simplified (Western et al., 2003). Furthermore, proper standardization of model output has been shown to effectively converge inter-model depictions of soil moisture anomalies, despite model specific intricacies (Koster et al., 2009). Our analysis of NLDAS-2 model configurations is a good example of this conclusion. Simple “bucket” style accounting of hydrologic fluxes—input (i.e., rainfall and snowmelt), output (i.e., evapotranspiration, vertical “leakage” of moisture to deeper groundwater systems, etc), surplus (i.e., input excess leading to overland flow, or evaporative demand excess not met by supply, etc) and storage (i.e., snowpack, antecedent moisture conditions)—appears to be an effective means of capturing reasonable anomaly estimates in most cases (Figure 5, Figures S1, S7, and S8 in Supporting Information S1, Table 2, Table S1 in Supporting Information S1). A distinct advantage of soil moisture models when compared to meteorological drought indices is their ability to leverage existing estimates of soil properties (e.g., (Xu et al., 2023)) to determine spatially heterogeneous distributions of water holding capacity.

Of the nine soil moisture models tested, the Topofire, SPoRT, and SMAP L4 soil moisture models performed particularly well. When considering all moisture states, the Topofire soil moisture model performed best for depth averaged, shallow and mid-soil depths, while the SMAP L4 soil moisture performed best for deep soil moisture. The SPoRT model also performed very well, particularly at USCRN sites (Figures S7 and S8, Table S1 in Supporting Information S1), but exhibited slightly higher RMSEs than Topofire at all depths. However, SPoRT was the most accurate model for predicting observed soil moisture drought severity during periods of drought (with less than a 1 class drought class MAE), whereas Topofire was the most accurate model during periods of water surplus (Table 3). This key result suggests that these models may be leveraged differently for drought and hydrological risk assessment; SPoRT should be favored to identify the occurrence of soil moisture drought, while Topofire should be favored for assessing potential drought amelioration and general patterns of water surplus.

The Topofire soil moisture model is unique to these other soil moisture models due to its very high spatial resolution of model output (~250 m) and its hydrological process resolution of terrain-mediated variations in local soil moisture (Holden et al., 2019). For example, terrain geometries have significant influence over spatial distribution of energy inputs (e.g., radiation and temperature) that can result in a delay of as much as 4 weeks in the timing of snowmelt on north-facing slopes (Holden & Jolly, 2011); these processes are explicitly integrated into the Topofire model. SMAP L4 soil moisture is unique in that it assimilates remotely sensed information from the SMAP mission (L-band radiometer brightness temperature observations) into a land surface model to enhance soil moisture estimates at depth (R. H. Reichle et al., 2017). This assimilation process propagates the surface soil moisture and temperature information observed from SMAP into the deeper soil levels. Our results suggest that this method is effective and contributes to better predictions of soil moisture, particularly for deep standardized soil moisture anomalies. Finally, the SPoRT model also ingests real-time, remotely-sensed observations of Green Vegetation Fraction (GVF) via the land information system (LIS) process (Kumar et al., 2006), which provides information about vegetation health and status. This real-time assimilation of observed data in conjunction with the soil moisture model information from the long-term Noah–Multi-parameterization Land Surface Model (Noah-MP LSM) produces robust soil moisture predictions across the conterminous U.S. Future work should

consider applying this assimilation system to the observed soil moisture data used here in order to further improve the accuracy of these models for real time monitoring applications. In summary, all three of these models perform well, however the SPoRT model was the most accurate for determining the occurrence of drought (Table 3), Topofire was the most accurate for determining moisture surplus and SMAP L4 was most accurate for monitoring standardized soil moisture anomalies at depth.

The CPC and GRACE soil moisture models failed to predict standardized soil moisture anomalies with greater accuracy than the optimized SPI and SPEI. The CPC soil moisture model tended to overestimate extreme anomaly values (>2 or <-2) when observed standardized soil moisture anomalies were neutral to only moderately wet or dry for all soil depths. GRACE soil moisture also tended to overemphasize extreme drought conditions at mid-soil depths. This might reflect a propensity for these model's buckets to be completely empty (overemphasized extreme drought for CPC and GRACE) or full (overemphasized extreme wetness for CPC), when observed soil moisture conditions disagree. This problem has been recognized in previous research (Fowler et al., 2020) and should be considered when using these models. In the future, benchmarking soil moisture model performance against meteorological drought indices may be useful for evaluating their utility in drought assessment.

Spatial patterns of model performance (RMSE and Pearson's r) are presented in Figures S2 and S3 in Supporting Information S1. In general, there are no strongly apparent geographical patterns of error (or correlation) across the conterminous U.S., especially for the top three performing soil moisture models (Topofire, SPoRT and SMAP L4). However, it is possible that there are patterns of error unrelated to continental-scale geography. While a robust evaluation of these patterns is outside the scope of this study, future work should consider evaluating these patterns in greater detail, and in particular, potential bias associated with physiographic position (e.g., elevation, aspect, slope angle, topographic position, etc), long-term environmental conditions (e.g., meteorological climatologies) or local geographical patterns (such as proximity to weather stations used in input data sets).

The analysis presented here complements previous research evaluating the performance of various soil moisture models. For example, our results support a recent evaluation of SPoRT and SMAP L4 soil moisture model performance, concluding that both performed well across the conterminous U.S. (Tavakol et al., 2019). Other studies have also reported that SMAP L3 (Beck et al., 2021) and NLDAS-2 (the soil moisture model “backbone” of SPoRT) outperform other models in soil moisture prediction, for example, CPC soil moisture, when focused on drought dynamics (Ford & Quiring, 2019). Our analysis expands upon this legacy of research by evaluating a broad range of indices and models with a greatly expanded set of standardized observations that we evaluate across soil depths.

5. Conclusion

Soil moisture is a critical component of the hydrological cycle that directly impacts human activities including agriculture and livestock production. We examined three common meteorological drought indices and nine soil moisture models used for operational drought assessment to determine which meteorological drought index or soil moisture model most accurately predicts standardized soil moisture anomalies. Our results show that optimal drought index timescales are generally short (~ 30 days for depth averaged soil moisture, less than ~ 100 days for all depths) and that optimal timescales generally increase with increasing soil depth. These results will help practitioners to most effectively monitor soil moisture drought using traditional meteorological drought indices. However, well constructed soil moisture models (e.g., Topofire, SMAP L4, and SPoRT) outperform optimized meteorological drought indices for soil moisture anomaly prediction, specifically during periods of drought (particularly the SPoRT soil moisture model). We conclude by recommending a increased utilization of modern soil moisture models in drought assessment to improve accuracy and better reflect true soil moisture deficits.

Data Availability Statement

The authors would like to acknowledge the soil moisture monitoring networks and soil moisture model data providers who made these essential data open, findable and accessible to researchers. All code used for this analysis can be accessed in zhoylman (2023). All data can be accessed in Hoylman, Z. (2024).

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