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RESEARCH ARTICLE

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Key Points:

- Low-cost, custom-built soil moisture sensors allow high-resolution monitoring of surficial moisture dynamics across large, topographically complex regions
- Patterns of volumetric soil moisture content (VMC) across an 80± site sensor network in Great Smoky Mountains National Park (NC, TN, USA) indicate a fivefold increase in surficial (0–15 cm depth) VMC from low (250 m) to high (2,025 m) elevation, mediated by slope angle
- Low cost, low power requirements, and practicable accuracy (<5% vol vol⁻¹ root mean square error) indicate field-based soil moisture networks are feasible and may complement more precise, coarse-grained regional monitoring of ecosystem processes

Supporting Information:

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

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Topographic Drivers of Soil Moisture Across a Large Sensor Network in the Southern Appalachian Mountains (USA)

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Abstract Understanding the distribution of soil moisture is notoriously difficult in topographically complex regions that are subject to both large-scale climate gradients and fine-scale effects of terrain, vegetation, and soil structure. Remote sensing approaches capture large-scale moisture patterns but are limited in spatial and temporal resolution, while commercial field sensors remain too expensive to deploy intensively over large spatial extents. Here, we demonstrate the use of low-cost (<20 USD) custom sensors to create a large monitoring network of surficial (0–15 cm depth) volumetric soil moisture content (VMC) across Great Smoky Mountains National Park (GSMNP) (NC, TN, USA). In laboratory tests, temperature-calibrated VMC values approached the accuracy of commercial probes. We deployed over 80 sensors across multiple watersheds, topographic positions, and a 1,800-m elevation gradient, and created hierarchical models to understand associations of VMC with spatial (30-m resolution) and temporal (daily) variables related to water supply and demand. Elevation had the strongest association with VMC, with a fivefold increase across the gradient reflecting 1.5-fold changes in both (increased) precipitation and (decreased) evapotranspiration; slope angle was a strong mediating factor. Common proxies for moisture including topographic convergence index were not associated with VMC, likely due to limited contributions of surface drainage to local water balance. Our model predicted daily VMC of a set of validation sensors with a root mean square error of 4.8%, which may be improved by site-specific field calibration. Our study indicates that spatially extensive, field-based soil moisture networks are practical, accurate, and an important component of regional environmental monitoring.

Plain Language Summary Measuring hourly soil moisture across many locations simultaneously is expensive but required if we are to understand how local wetness is influenced by plants and soils rather than just weather. We built and tested low-cost moisture sensors in the laboratory, and put them in over 80 locations across Great Smoky Mountains National Park in the southern Appalachians of Tennessee and North Carolina, USA. Surprisingly, we found that soil moisture responded to weather—and in particular how weather changes from low to high elevation—but did not vary substantially by landscape position (e.g., near streams vs. adjacent ridges). Our study suggests that increases in regional temperature are likely to reduce soil moisture in this unusually wet region.

1. Introduction

Microclimate describes the temperature and water regimes experienced by organisms, most of which live and reproduce within a few meters of the Earth's surface and are thus subject to the influences of dominant vegetation and local topography (Geiger et al., 2003; Maclean & Klings, 2021; Potter et al., 2013). Although the roles of such fine-scale landscape factors are widely appreciated in global change studies (Bramer et al., 2018), microclimate research remains focused on temperature rather than water (Maclean et al., 2012; Robinson et al., 2008; Vereecken et al., 2014), which limits our ability to forecast global change impacts on species distributions (Engelbrecht et al., 2007) and ecosystem processes (Curiel Yuste et al., 2018; Green et al., 2019). Soil moisture dynamics of the uppermost soil horizons are particularly important to local biota, because water-dependent nutrient mineralization processes that support food webs are concentrated around fine roots and organic matter (Achat et al., 2012; Jackson et al., 1996). Remote sensing products from satellites or aircraft provide estimates of surficial moisture across large spatial extents, but remain of limited temporal and spatial resolution (Babaeian et al., 2019). Further, continued advances in remote sensing of soil moisture will require field validation data that to date have been rarely available (Gruber et al., 2020; Mohanty et al., 2017).

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Several logistical challenges must be overcome to monitor and model soil moisture at high spatial and temporal resolution across large landscapes (Vereecken et al., 2014). First, unlike advances in temperature sensors (Hubbart et al., 2005), commercial soil moisture sensors remain expensive and difficult to maintain in remote locations, limiting their use across large spatial extents (Bramer et al., 2018). For this reason, field-based soil moisture studies have often focused on temporal dynamics in one or few catchment basins, an extent appropriate for development of hydrologic models (e.g., Tyystjärvi et al., 2022; Vivoni et al., 2010; Wu et al., 2010) but less suited to advancing the understanding of soil moisture drivers across regions that vary significantly in macroclimate, vegetation, and soil structure (Lin et al., 2006; Petropoulos et al., 2015). Second, in contrast to meteorological variables like air temperature, soil properties such as moisture display high fine-scale variation as a result of structural heterogeneity; the proximity of sensors to rocks, roots, animal activity, or soil disturbances increases sample noise that can be difficult to distinguish from spatial pattern without a large number of sensors and appropriate modeling structures (Lookingbill & Urban, 2004; Robinson et al., 2008). Third, local soil water budgets display substantial temporal variation in response to complex patterns of supply (rain, throughfall, surface flow) and demand (drainage, evapotranspiration (ET)), creating temporal lag effects (Pan, 2012; Williams et al., 2009) and interactions between spatial and temporal moisture drivers that are difficult to quantify unless sites are monitored at the same time across a range of weather conditions (Osenga et al., 2019). Although interpolation-based methods like spatial kriging can overcome some of the statistical challenges in creating high resolution soil moisture maps (Chaney et al., 2015; Coopersmith et al., 2015; Kang et al., 2017; Stillman et al., 2014), such methods are typically site-specific with limited application to other regions and time periods.

In the absence of extensive soil moisture data, researchers have often relied on topographic proxy variables that reflect the influence of landscape factors on local water supply and demand (Dyer, 2009; Hoylman et al., 2019). On the scale of hillslopes to watersheds, a common metric for site potential wetness is topographic convergence index (TCI, $\ln(\text{upslope contributing area}/\tan(\text{slope}))$; Beven & Kirkby, 1979). Sites of high TCI values should be wetter because they collect more water from upslope areas and lose less water to surface drainage. However, the strength of the relationship between TCI and empirical moisture values depends on overall landscape wetness, soil depth, seasonality, and other variables (Burt & Butcher, 1985; Tromp-van Meerveld & McDonnell, 2006; Western et al., 1999). Other topographic indices, such as slope orientation or proxies of radiation intensity, may be related to soil moisture through differences in demand from ET (Beers et al., 1966; Lookingbill & Urban, 2004; Pierce et al., 2005). At fine spatial scales, site slope or local topographic position (TPI, the difference between the elevation of a raster cell and the mean of its surrounding cells; Wilson et al., 2007) also reflect site moisture balance through drainage and water retention, and plant density and canopy cover can affect soil moisture in complex ways. Increased transpiration and canopy interception can reduce soil moisture availability (Breshears et al., 1997; Peck et al., 2012; Scharenbroch & Bockheim, 2007), but the cooling and shading effects of canopy cover also reduce evaporation and thus can increase soil moisture (Walsh et al., 2017). Other studies focusing on fine-scale soil moisture variation have found that variation in moisture is linked to slope position and microclimate temperature (Tromp-van Meerveld & McDonnell, 2006; Walsh et al., 2017), but these results have not been generalized across landscapes. Validating the use of topographic and other proxies to describe soil moisture dynamics is a priority for microclimate-related global change research.

Here, we describe the development of low-cost (<20 USD), low-power field sensors designed for extensive, long-term monitoring of hourly volumetric soil moisture content (VMC) across large regions. We demonstrate sensor accuracy from laboratory tests, and describe application of the sensors to modeling surficial (0–15 cm depth) VMC using over 80 locations across the complex forested landscape of Great Smoky Mountains National Park (GSMNP) in the Southern Appalachian Mountains (North Carolina, Tennessee, USA). Although gradients of soil moisture in GSMNP have long been proposed as a key driver of ecological processes, extensive field measurements to date have been unavailable, and it remains unclear how predicted changes in regional climate (precipitation, ET, seasonality) will influence local water budgets. In addition to demonstrating the accuracy and feasibility of low-cost soil moisture sensors, we aimed to describe major spatial patterns of soil moisture in GSMNP, including relationships of VMC to major topographic factors (elevation, site exposure) and commonly used topographic proxies such as TCI and TPI. Finally, we present a hierarchical model of soil moisture that predicts daily variation of VMC across the spatial extent of GSMNP, assess model accuracy with a set of validation sensors, and describe opportunities for further development of empirically based soil moisture models.

Table 1
Calibration Coefficients for Soil Volumetric Moisture Content

Parameter	Value
Intercept	0.334876
Resistance	3.56×10^{-5}
Resistance ²	-3.24×10^{-9}
Resistance ³	5.64×10^{-14}
Soil temperature	-0.00327
Resistance * Soil temperature	5.18×10^{-8}

Note. See supplement for details of laboratory calibration.

2. Materials and Methods

2.1. Study Region

GSMNP (2,090 km²) is a predominantly forested landscape in the Southern Appalachian Mountains of North Carolina and Tennessee, USA, ranging in elevation from 256 to 2,024 m a.s.l. Elevation is associated with a temperature lapse rate of 3.5°C per 1,000 m (Fridley, 2009), corresponding to a mean annual temperature gradient of ca. 13 to 7°C from low-elevation piedmont hardwood forests to high-elevation spruce-fir forests (Lesser & Fridley, 2016). Total annual precipitation averages from 1,200 mm at low elevations to 1,800 mm at the highest, although rainfall in high elevation forests in some years has exceeded 2,500 mm (Lesser & Fridley, 2016; Shanks, 1954). In comparison, annual ET ranges from about 900 to 500 mm from low to high elevation with consistent seasonal water surplus, making

forests in GSMNP among the wettest in Eastern North America, and what Shanks (1954) categorized as rainforest. Seasonality of precipitation is relatively low, although September and October often have the lowest rainfall totals and fewest days of precipitation (Busing et al., 2005). The study period (2019–2021) was relatively wet; annual precipitation over this period in Gatlinburg, TN (443 m a.s.l.) in the north-central region of GSMNP averaged 1,670 mm, about one standard deviation (270 mm) above its long-term average of 1,430 mm (Lesser & Fridley, 2016). Soils are dominated by inceptisols and ultisols derived from Precambrian meta-sandstone, characterized by steep (>30° slope), clay-dominated colluvium at mid- and lower elevations, high organic content at high elevations, and rocky alluvial material along streams (USDA, NRCS, 2009). Although some slates, limestone, and mafic bedrock occur in small regions of the GSMNP, spatial variation in soil structure and organic matter content is more determined by elevation, slope, exposure, and vegetation type than bedrock composition (Southworth et al., 2005; USDA, NRCS, 2009).

2.2. Sensor Design and Calibration

We adopted the microcontroller design of Mickley et al. (2019), with modifications to improve durability and memory storage. For a full construction protocol, microcontroller code, and bill of materials see https://github.com/jordanstark/Soil_temp_moisture_EMU. Major components of the system included: (a) an Arduino-like microcontroller to run a sensing program and store data in on-board flash memory; (b) a real-time clock to activate the system once per hr and prevent battery drainage when not taking readings; (c) two solder-plated resistance-based volumetric moisture sensors (5 cm sensor length) and an analog-to-digital converter to read sensor outputs; (d) a digital soil temperature probe; (e) a battery holder and 4 alkaline AAA batteries; (f) a custom-printed circuit board; and (g) a PVC sensor housing.

Soil resistance probes were calibrated to VMC (vol water vol⁻¹ soil) using mass balance and comparison with commercial probes (Decagon EC-5, Pullman, WA, USA); see Text S1 in Supporting Information S1 for full calibration details. A previous calibration for these probes (Mickley et al., 2019) did not account for effects of temperature on resistance; such correction is commonly recommended for VMC probes, including the Decagon EC-5 (Saito et al., 2013). Based on Mickley et al. (2019) and initial testing at different temperatures, we fit a maximal model of VMC as a cubic function of resistance plus a cubic function of temperature and an interaction of resistance and temperature. The model also included a random intercept for each trial to account for potential differences in soil contact. For this procedure we used the “lmer” function in the “lme4” package in R (Bates et al., 2015; R Core Team, 2021); AIC was then compared with all nested models using the “dredge” function in the “MuMIn” package (Barton, 2020). Only models that included lower power terms for all variables with interactions or higher power terms were accepted; the most parsimonious model was used in cases of model delta AIC < 2 (see Table S1 in Supporting Information S1). When applied back to the data without random intercepts, the best model (Table 1; Figure S1 in Supporting Information S1) had a RMSE of 0.039 VMC, and a RMSE-based accuracy of 0.028 VMC when predicting weighed soil moisture content in the laboratory ($R^2 = 0.92$). All residuals were less than 0.102 VMC, although there was some evidence of bias in the driest values, with the calibration underpredicting moisture at values below 0.2 VMC (Figure S2 in Supporting Information S1). The full calibration model presented here had comparable accuracy to commercial probes (reported accuracy of Decagon EC-5 probes ± 0.03 VMC) and was accurate across soils ranging from fine sand to those

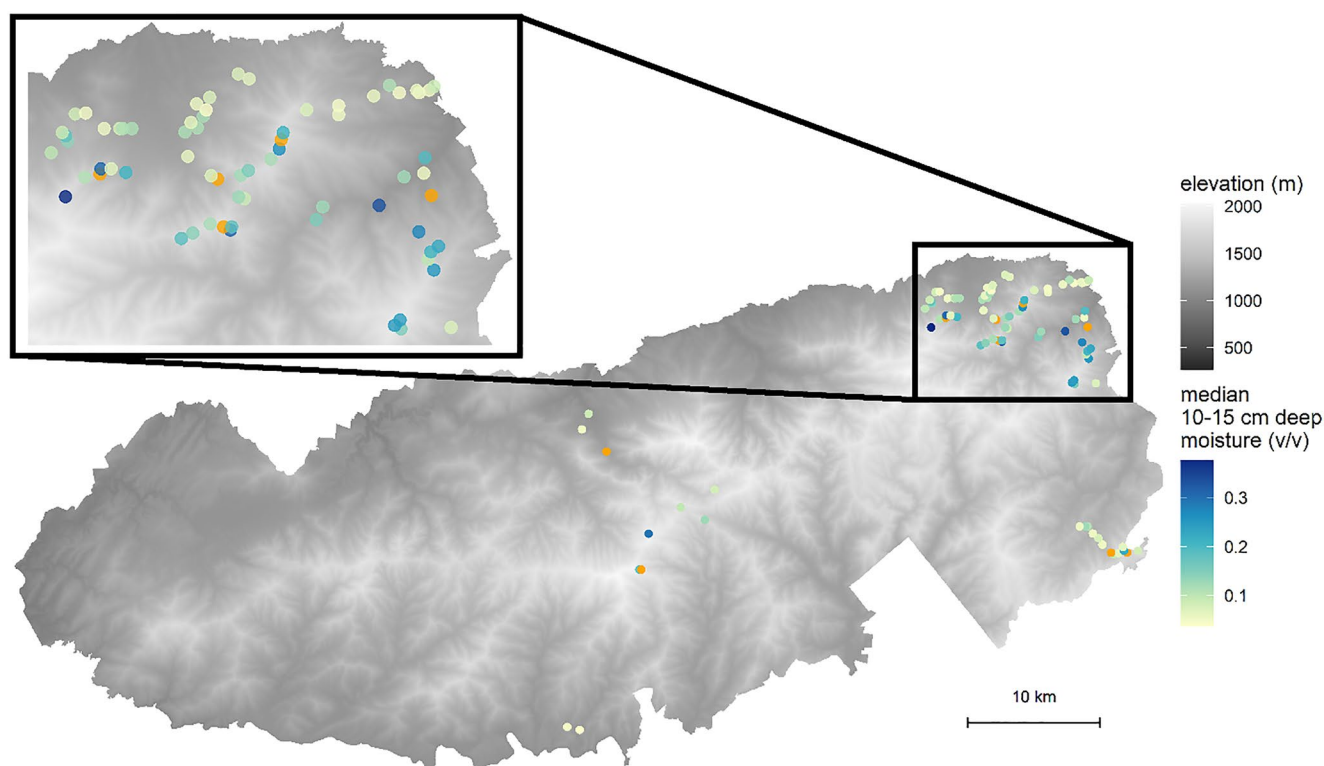


Figure 1. Map of sensor locations in Great Smoky Mountains National Park, TN, NC (USA). Orange points do not have any recorded 10–15 cm deep VMC values due to sensor damage. All other points are colored based on their median deep soil moisture content. The inset map includes Big Creek and Cosby watersheds where stratified random sampling was used to choose sensor locations for topographic modeling.

of high organic matter content (results not shown). We did not attempt field-based calibration of our sensors due to management restrictions on destructive soil sampling and the high failure rate of commercial dataloggers from black bear (*Ursus americanus*) activity.

2.3. Sensor Deployment and Data Retrieval

We deployed 114 sensors across 101 sites from October 2019 to July 2021 (Figure 1). Sensors were deployed in three stages, with the majority installed in June 2020, and some were replaced or removed after failure in March 2020 and June 2020. All were removed in July 2021. A deployment record of each sensor is shown in Figure S3 in Supporting Information S1. The largest batch of sensors was installed at 64 sites between March and July 2020 using a stratified random sampling approach according to the distribution of three factors in GSMNP: elevation, log-transformed TCI, and annual potential relative radiation (Pierce et al., 2005) (Figure 2). To determine locations of each stratum, we sampled a raster layer of each environmental variable across a 250×250 m grid throughout GSMNP, and boundaries were determined that split points into 27 equal groups (low, middle, and high values for each of the three factors). We randomly selected three locations in each stratum in each of two watersheds from a 100×100 m sampling grid, masked to only include areas within 5 km of parking areas and between 25 and 150 m of established trails. For logistical reasons, locations chosen for model building were restricted to the eastern side of GSMNP (Cosby and Big Creek watersheds; see inset, Figure 1), while otherwise including the above stratum-based sampling along the full extent of each gradient. After each point was selected, the nearest 25 points were checked and removed if they were from the same stratum to reduce spatial autocorrelation. Stratification and site selection were conducted in R using the “sf” (Pebesma, 2018) and “raster” packages (Hijmans, 2021); TCI was calculated using the “topmodel” package (Buytaert, 2018) and log-transformed to reduce substantial right skew; potential relative radiation was calculated using the “hillshade” function in the “raster” package and the “solartime” package (Wutzler, 2021). Twenty-four additional sensors were deployed in October 2019 or October 2020 along low-, mid-, and high-elevation trails in other watersheds without stratified random sampling. A set of 13 sites with sensors deployed in July 2020 across the full elevation gradient of the

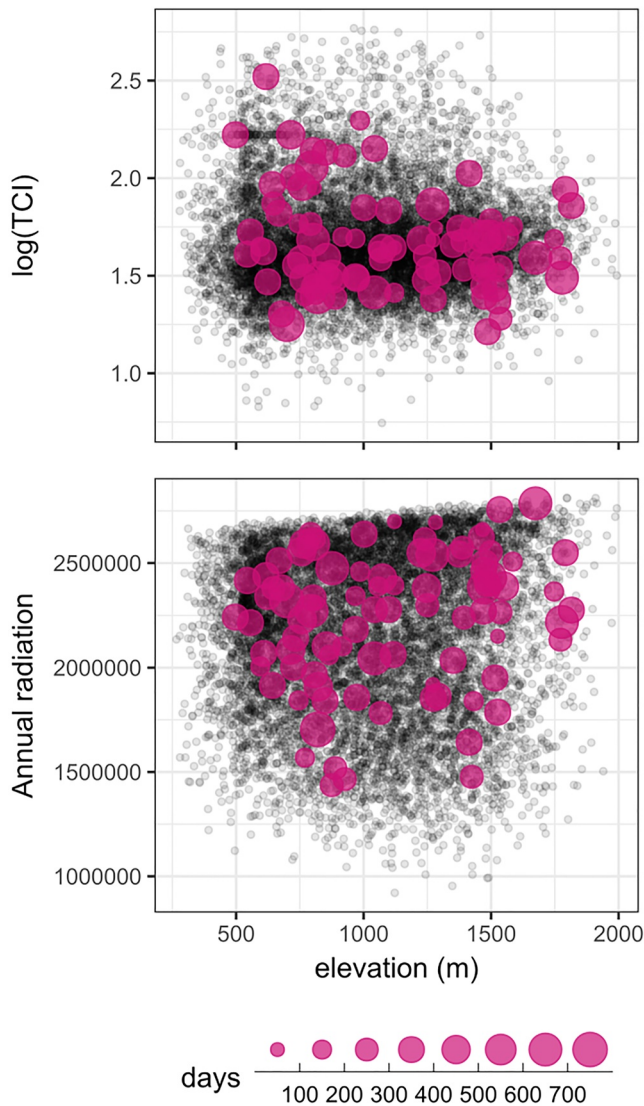


Figure 2. Distribution of sensors across environmental gradients in Great Smoky Mountains National Park (GSMNP). In each panel, black points are 10,000 points evenly spaced across GSMNP; purple points are sensor locations. Point size indicates the length of soil moisture sensor records. TCI = topographic convergence index (large values indicate high relative wetness). Annual radiation = potential relative radiation (units are a relative index; Pierce et al., 2005).

central region of GSMNP was used for model validation (Figure 1). All sites were forested with canopy cover at or near 100%.

At each site, we installed a soil temperature sensor and one VMC sensor just below the soil surface (0–5 cm depth), and an additional VMC sensor at 10–15 cm depth. Sensors that were damaged when examined in March or June 2020 were replaced at the same locations. All other sensors were collected in July and August 2021. Upon retrieval, we converted raw resistance and temperature values to VMC based on the laboratory calibration, and omitted those VMC values associated with negative (frozen) soil temperature values. We also excluded from analysis times of apparent sensor disturbance (e.g., a sudden change in VMC followed by near stability of readings, or sudden increase in daily soil temperature range), or those cases where, due to the need for temperature calibration, sensor resistance was recorded but soil temperature was not.

2.4. Soil Moisture Models

Modeling strategy. We created three types of models to meet our analytical objectives. The objective of the first model was to understand spatial differences in VMC across sites, and how such relationships change seasonally. In a second set of models, we tested hypotheses related to whether certain topographic or weather-related variables are significantly associated with surficial soil moisture across a large montane region. For this purpose we used weather data at both the daily scale and data summarized over an 8-day period to conform to available ET estimates (Running & Mu, 2015) to enable hypothesis tests specific to ET. We then used a third model to make daily VMC predictions across all of GSMNP. For this final model, to prevent overfitting we removed those variables that had no explanatory power in hypothesis tests, and we used only a set of 82 non-validation sensors to construct the model; predictions were then evaluated with a set of 11 validation sensors. We used a mixed effects structure for all models reflecting the nested data structure of time nested within site, using the R packages “lme4” and “lmerTest” (Bates et al., 2015; Kuznetsova et al., 2017). To allow comparison of effect sizes, predictors were standardized to a mean of zero and standard deviation of one before model fitting. Conditional (fixed effects) and marginal (full model) R^2 values were calculated following Nakagawa et al. (2017). Collinearity was checked using variance inflation factors (VIF) with the function “vif” from the R package “car” (Fox & Weisberg, 2019). No VIF values were above 2.5 in any model, nor were there significant linear correlations between any predictor variables, except for temperature and elevation (Table S2 in Supporting Information S1).

Model 1: VMC spatial patterns across seasons. We regressed VMC against elevation, a local topographic factor found to significantly moderate elevation effects (slope angle), and a “season” effect that was estimated as a continuous

sine-cosine transformation of day-of-year (DOY) with a period of 365 days (Fridley, 2009). We included interactions of elevation and slope with the sine-cosine seasonal effect. VMC was logit-transformed to conform to residual normality assumptions. We evaluated 0–5 cm and 10–15 cm depth VMC values in separate models. Model 1 took the form:

$$\text{logit}(\text{VMC}) = \text{intercept} + (\text{elevation} + \text{slope}) * (\cos(\text{DOY} * 0.0172) + \sin(\text{DOY} * 0.0172)) \quad (1)$$

Model 2: Hypothesis testing. In a second set of models we used a model structure appropriate for hypothesis testing of whether certain topographic and weather-related variables significantly predict VMC, considering VMC variation over time within sites (with temporal predictors at the daily and 8-day scale), in addition to variation across sites (with static spatial predictors; Table 2). For ease of interpretation, we excluded from the model values of VMC obtained outside the period of canopy leaf display, given strong relationships of all microclimate

Table 2
Predictor Variables in VMC Models

Variable	Resolution (m)	Source	Description
Elevation	30	Fridley (2009)	Elevation in meters above sea level
Slope	30	terrain() from “raster”	Slope of each cell in elevation raster
Radiation	30	Fridley (2009)	Modeled daily above-canopy direct solar radiation from “r.sun” in GRASS GIS
TPI	30	terrain() from “raster”	Topographic position index; difference between cell elevation and mean elevation of eight surrounding cells
TCI	30	Fridley (2009)	Topographic convergence index; $\ln(\text{upslope area} / \tan(\text{slope}))$; “r.topidx” in GRASS GIS
Temperature	30	Fridley (2009)	Mean daily below-canopy temperature, calculated from Fridley (2009) model
Precipitation	4,000	PRISM Climate Group (2021)	Daily rainfall interpolated from weather stations
API	4,000	PRISM Climate Group (2021)	Antecedent Precipitation Index, based on fitted duration ($i = 14$ days) and decay constants ($k = 0.673, 0.786$ for surficial and deep soils, resp.)
Max EVI	500	MODIS MCD12Q2v6	Maximum annual enhanced vegetation index; 10-year mean derived from minimum EVI and EVI amplitude
Maturity	500	MODIS MCD12Q2v6	Day of year when EVI first crosses 90% of maximum EVI; 10-year mean
Senescence	500	MODIS MCD12Q2v6	Day of year when EVI last crosses 90% of maximum EVI; 10-year mean
ET	500	MODIS MOD16A3	Actual evapotranspiration derived from MODIS leaf area index using the Penman-Monteith equation, available at 8-day resolution

variables to canopy cover. This “growing season” window was determined separately for each pixel of GSMNP using MODIS yearly land cover dynamics (MCD12Q2) product version 6 at 500 m resolution (Friedl et al., 2019). We obtained estimates of leaf maturity and senescence (first and last cross of 90% of annual maximum enhanced vegetation index, EVI) for the years 2010–2019, the most recent available decade. After removing all pixels that were designated as less than “best” quality for the given variable by Friedl et al. (2019), we calculated the decadal mean maturity and senescence times for each raster cell. These dates were used to limit the duration of the growing season values for each pixel.

Once the duration was set for each site, we created data sets of two different temporal resolutions to enable hypothesis testing involving (a) weather variables that are commonly available at daily resolution (precipitation, temperature, radiation), and (b) empirical estimates of ET derived from MODIS (Running & Mu, 2015), available at 500 m spatial resolution but only for 8-day segments. The daily resolution model for sites s and days t took the form:

$$\text{logit}(\text{VMC}_{s,t}) = \beta_0 + \beta_1 \text{elevation}_s + \beta_2 \log(\text{TCI}_s) + \beta_3 \text{slope}_s + \beta_4 \text{TPI}_s + \beta_5 \text{precipitation}_{s,t} + \beta_6 \text{API}_{s,t} + \beta_7 \text{radiation}_{s,t} + \beta_8 \text{temperature}_{s,t} + N(0, \sigma_{\text{site}}^2) + N(0, \sigma_{\text{residual}}^2) \quad (2a)$$

where the last two terms indicate a random intercept for between-site variation and within-site residual variation, respectively. In this model, elevation, TCI, slope, and TPI were static spatial variables, and precipitation, Antecedent Precipitation Index (API), radiation, and temperature varied daily within and across sites. Daily precipitation values per site were retrieved from PRISM at a 4 km scale (PRISM Climate Group, 2021). Daly et al. (2017) reported that PRISM-based estimates of precipitation in the Southern Appalachians are accurate to within 5% of rain gauges. API captures the influence of past rainfall and storage (Ali et al., 2010), and is calculated as: $\text{API} = \sum_{t=-1}^{-i} P_t k^{-t}$ where P is daily precipitation of antecedent day t , k is the decay constant ($[0,1]$), and i is the number of antecedent days of rainfall. To determine k and i parameters, we considered them constant across sites and

took those values that maximized the nonparametric (Spearman's rho) correlation between API and VMC values, fit separately for 0–5 cm and 10–15 cm soil depths. We considered 5, 10, and 14 days of antecedent precipitation (i), and varied k between 0.5 and 1. The correlation of API was always maximized at $i = 14$, and best-fit k values included $k = 0.673$ for 0–5 cm depth VMC and $k = 0.786$ for 10–15 cm VMC, consistent with previous studies (Ali et al., 2010). Although we could have allowed k and i to vary with site characteristics, interactions of API with radiation and temperature captured effects of variation in soil water storage with landscape position in computationally efficient way. We estimated temperature as the daily below-canopy mean air temperature (1 m height) using the microclimate model developed in Fridley (2009), which uses topographic variables to modify minimum and maximum site temperature estimates from daily weather station-based lapse rates. Daily above-canopy radiation was calculated using the “r.sun” algorithm of GRASS GIS (Neteler & Mitasova, 2004) as described in Fridley (2009). We used estimated incident radiation rather than transformed topographic aspect (e.g., Beers et al., 1966) because the former captures both solar angle and topographic shading effects. Topographic convergence index was calculated using the ‘r.topidx’ function in GRASS GIS (Fridley, 2009). We fit separate daily scale models for 0–5 cm and 10–15 cm depth VMC values.

We also used an 8-day temporal resolution model to enable estimates of the effect size of ET on VMC. In GSMNP, ET is available as a modeled product from MODIS-estimated leaf area index using the Penman-Monteith equation at a spatial scale of 500 m at 8-day intervals (Running & Mu, 2015). Each ET value is the sum of ET values of the previous 8 days. Because ET is correlated with temperature and radiation, we removed these predictors from the 8-day model. We also used the sum of the previous 8 days of rainfall as a precipitation predictor rather than API, so that ET and precipitation would be compared at the same temporal resolution. Topographic predictors remained the same as in the daily model, and we summarized VMC as the median value over each 8-day period. The model otherwise had the same mixed effects form as the daily resolution model:

$$\text{logit}(\text{VMC}_{s,t}) = \beta_0 + \beta_1 \text{elevation}_s + \beta_2 \log(\text{TCI}_s) + \beta_3 \text{slope}_s + \beta_4 \text{TPI}_s + \beta_5 \text{precipitation}_{s,t} + \beta_6 \text{evapotranspiration}_{s,t} + N(0, \sigma_{\text{site}}^2) + N(0, \sigma_{\text{residual}}^2) \quad (2b)$$

Model 3: Spatial predictions of VMC across GSMNP. We created a third model for the purpose of prediction, using the subset of 82 non-validation sensors. Our main objective in predictive modeling was to evaluate the potential for accurate, high resolution (30 m) VMC mapping over large spatial scales, using commonly available GIS and weather predictors. For simplicity we restricted our predictive modeling to 10–15 cm soil depth and daily weather data, and only considered VMC values during canopy leaf out. Because this third model was for prediction only, we eliminated TCI, which explained little variance in VMC in the second model, and to limit the potential for overfitting we considered only two-way interactions between daily weather variables and spatial predictors (elevation, slope, TPI). The full predictive model took the form (note β coefficients omitted for clarity):

$$\text{logit}(\text{VMC}_{s,t}) = \beta_0 + (\text{elevation}_s + \text{slope}_s + \text{TPI}_s) * (\text{precipitation}_{s,t} + \text{radiation}_{s,t} + \text{temperature}_{s,t} + \text{API}_{s,t}) + N(0, \sigma_{\text{site}}^2) + N(0, \sigma_{\text{residual}}^2)$$

Predictions of the model were validated using a separate set of 11 sensors from the central region of GSMNP (Figure 1), and evaluated statistically as the RMSE of predicted versus observed daily VMC values.

3. Results

3.1. Sensor Performance

Out of 114 sensor deployments, 56 sensors recorded for their entire deployment period, 12 sensors were not found, 2 sensors never recorded data, and 22 were sufficiently damaged by wildlife, humans, or frost heave to stop recording data before retrieval. This left 22 sensors which failed for unknown reasons; about half of these likely failed due to loss of clock battery power. Data were retrieved from all but four sensors (two badly damaged and corroded, two that did not record data); even sensors that had water infiltrate the sensor housing (following physical damage to the housing) did not have data loss. Three other sensors collected some data but were unusable due to very short collection periods or faulty sensors. For the sensors that recorded data and were collected, the majority had >90% of recorded soil moisture measurements over the duration of deployment (Figure 3). The exponential rate of decline for deep and shallow sensor data availability from Figure 3 across the final year of deployment (July 2020–July 2021) was -0.00167 , which corresponds to a monthly failure rate of 5% and an

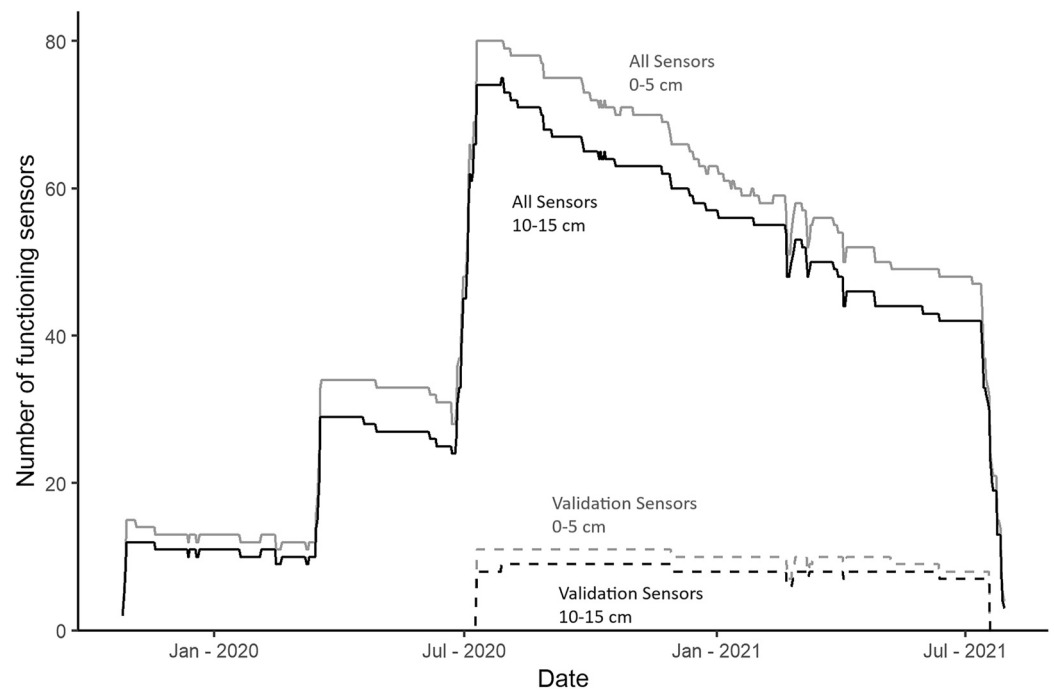


Figure 3. Number of functioning VMC sensors over time, by depth (light gray: data from 0 to 5 cm depth sensors; black: data from 10 to 15 cm sensors). The main period of deployment (including a set of 13 model validation locations (two dashed lines at bottom, colors indicate soil depth)) started in July 2020, after smaller installations in October 2019 and March 2020. An additional 12 sensors were not relocated and four sensors collected no useable data.

annual rate of 46%. There were no significant relationships between sample stratum factors (elevation, TCI and radiation) and the fraction of possible data recorded by a sensor (all $P > 0.5$). Of the 13 locations chosen for validation sensors, deep sensors for two sites were not collecting data for the period used for model validation, leaving a total of 11 validation sensors for evaluating predictive model performance.

3.2. Patterns of Median VMC Values Across sites

Across sites, temporal median VMC across the full duration of measurement ranged from 0.04 to 0.39 (vol vol⁻¹) at 0–5 cm depth, and 0.04 to 0.33 at 10–15 cm depth. The strongest spatial correlate of VMC was elevation; sites at the highest elevations (max. 2,025 m) in GSMNP had 4.7 times higher median VMC at 10–15 cm depth than sites at the lowest elevations (min. 267 m) ($P < 0.0001$, $R^2 = 0.301$) (Figure 4). To explore the elevation effect seasonally, we modeled daily VMC in response to a periodic function of day-of-year (DOY). After elevation, slope angle had the largest topographic influence on temporal median VMC values, so we included slope and its interaction with elevation in the seasonal model of VMC (Figure 5; Table 3). In general, VMC was more seasonally variable at low elevations, with maximum values in early spring and minimum values in autumn; high elevation VMC varied little over the year (Figure 5). Sites on steep slopes had lower median VMC values: a high elevation site with a 40° slope had the same median annual VMC as a flat site more than 700 m lower (Figure 4). In addition, slope had nearly twice the drying effect on VMC at high elevation than at low elevation (Figure 5). Seasonal effects and interactions with elevation and slope for VMC at 0–5 cm depth were of the same sign but generally lower in magnitude as a result of greater fine-scale temporal variation (Figure S4 and Table S3 in Supporting Information S1).

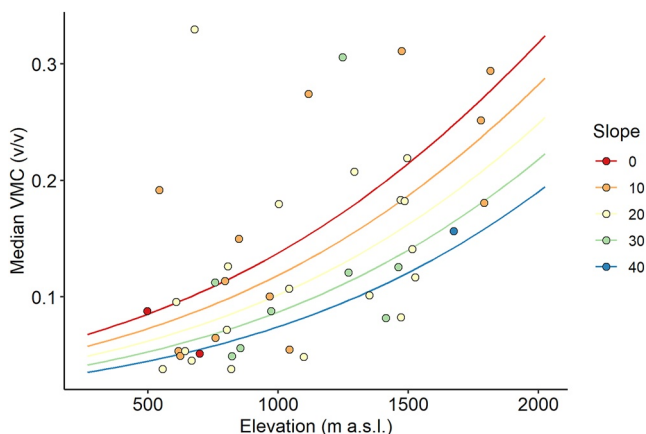


Figure 4. Effect of slope and elevation on median annual 10–15 cm deep VMC. Lines represent predictions of an additive model of elevation and slope; points are measured median soil moisture values (color of points is based on slope rounded to the nearest 10°). VMC was logit-transformed to improve normality and back-transformed for visualization.

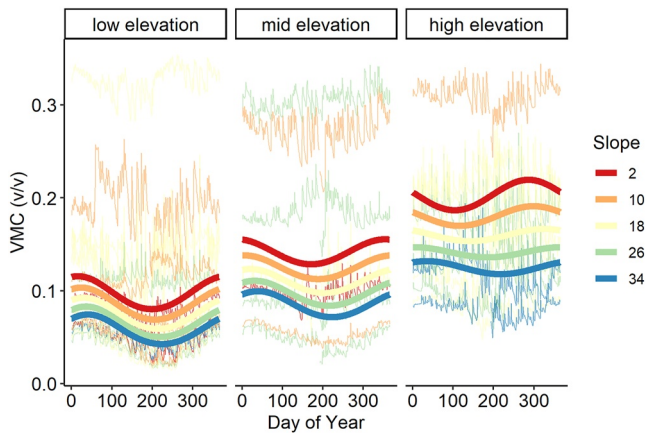


Figure 5. Annual variation of 10–15 cm deep VMC across sites grouped by slope and elevation. Panels represent low (mean–1 SD), middle (mean) and high (mean + 1 SD) elevations. Thin lines show data binned into nearest integer SD from the mean for elevation and slope. Thick lines represent predictions of VMC from a linear model with sine- and cosine-transformed day of year, slope, elevation, and interactions between the topographic variables and the seasonal variables. Soil moisture was logit-transformed to improve normality and back-transformed for visualization. Day of Year 1 is January 1.

3.3. Topographic Drivers of Daily and 8-Day VMC

In a mixed model of the effects of all topographic and weather drivers on logit-transformed VMC over the growing season, elevation remained the strongest predictor ($P < 0.001$) (Table 4 and Table S4 in Supporting Information S1). Several daily weather-related variables had significant relationships with 5–10 cm depth VMC as expected ($P < 0.001$ in all cases): VMC increased with precipitation, with a much stronger signal of antecedent precipitation (API) compared to same-day precipitation, and decreased with radiation and below canopy temperature (Figure 6). VMC was also marginally related to slope, with decreased moisture at steeper sites ($P = 0.076$; Table 4). Moisture was not significantly related to TCI or TPI. The marginal (fixed effects) R^2 of the full model for 5–10 cm depth VMC was 0.31 and the conditional (including random site effects) R^2 was 0.95. Variance inflation factors for all variables were less than 1.72, indicating no collinearity. The same model fit to 0–5 cm depth VMC included the same significant drivers but with generally lower effect sizes (Table S4 in Supporting Information S1), and its marginal (fixed effects) R^2 was substantially smaller (0.12), suggesting a noisier signal of surface soil VMC.

In the 8-day resolution mixed model that included ET, ET was the best temporal predictor of 10–15 cm depth VMC, with an effect size more than twice that of 8-day summed precipitation (Table 5). In part this reflects the larger seasonal signal of ET (from temperature) than precipitation at an 8-day temporal resolution. Elevation was the only significant spatial predictor of VMC at the 8-day scale. Evaporation and precipitation had similar effect

sizes for 0–5 cm depth VMC (Table S5 in Supporting Information S1), and the surficial VMC model had significantly lower marginal R^2 than that of 10–15 cm depth (0.11 vs. 0.29).

3.4. VMC Predictions Across GSMNP

A model of daily VMC using a subset of 82 sensors from the eastern side of GSMNP was able to predict daily VMC values of sensors located in the central portion of GSMNP (Figure 1) with an accuracy of 0.048 (i.e., 4.8% VMC) RMSE. Nearly all (96.5%) differences of observed and predicted values were less than 0.1 VMC. This model included significant interactions of daily predictors (precipitation, temperature, radiation, API)

and interactions of spatial and temporal variables (Table S6 in Supporting Information S1), with a marginal (fixed effects) R^2 of 0.26 and a fitted value (non-validation) RMSE of 0.018. A map of predicted annual median VMC is shown in Figure 7.

Table 3
Effects of Slope, Elevation, Day of Year, and Their Interactions on 10–15 cm Deep VMC

Parameter	Standardized estimate	<i>t</i> value	<i>P</i> value
Intercept	−2.09	−22.0	<0.001
cosine(doy*0.0172)	0.12	63.0	<0.001
sine(doy*0.0172)	0.05	23.3	<0.001
Elevation	0.43	4.5	<0.001
Slope	−0.14	−1.5	0.141
cosine(doy*0.0172)*Elevation	−0.09	−43.3	<0.001
sine(doy*0.0172)*Elevation	−0.08	−38.7	<0.001
cosine(doy*0.0172)*Slope	0.01	3.9	<0.001
sine(doy*0.0172)*Slope	0.03	17.1	<0.001

Note. Slope and elevation were standardized to a mean of zero and standard deviation of one. VMC was logit transformed. Model results for 0–5 cm deep VMC are presented in Table S3 in Supporting Information S1.

4. Discussion

4.1. The Feasibility of Large, Field-Based Soil Moisture Networks

Our study demonstrates the feasibility of creating a large soil moisture monitoring network in rugged, remote terrain, given inevitable tradeoffs between sensor accuracy and robustness versus the resources required to build and maintain a large sensor network. Although our approach has several advantages over existing commercial sensors, these advantages apply most directly to researchers interested in regionally extensive soil moisture mapping and validation, with potential costs in failure rate and accuracy, depending on the extent of calibration efforts. The total cost of our units is an order of magnitude less than other sensor-logger combinations at 20 USD per unit, including sensors, housing, batteries, and data storage. Low power requirements support hourly readings for over 1 year on 4 AAA batteries and one watch battery, allowing deployment of a large number of sensors in remote

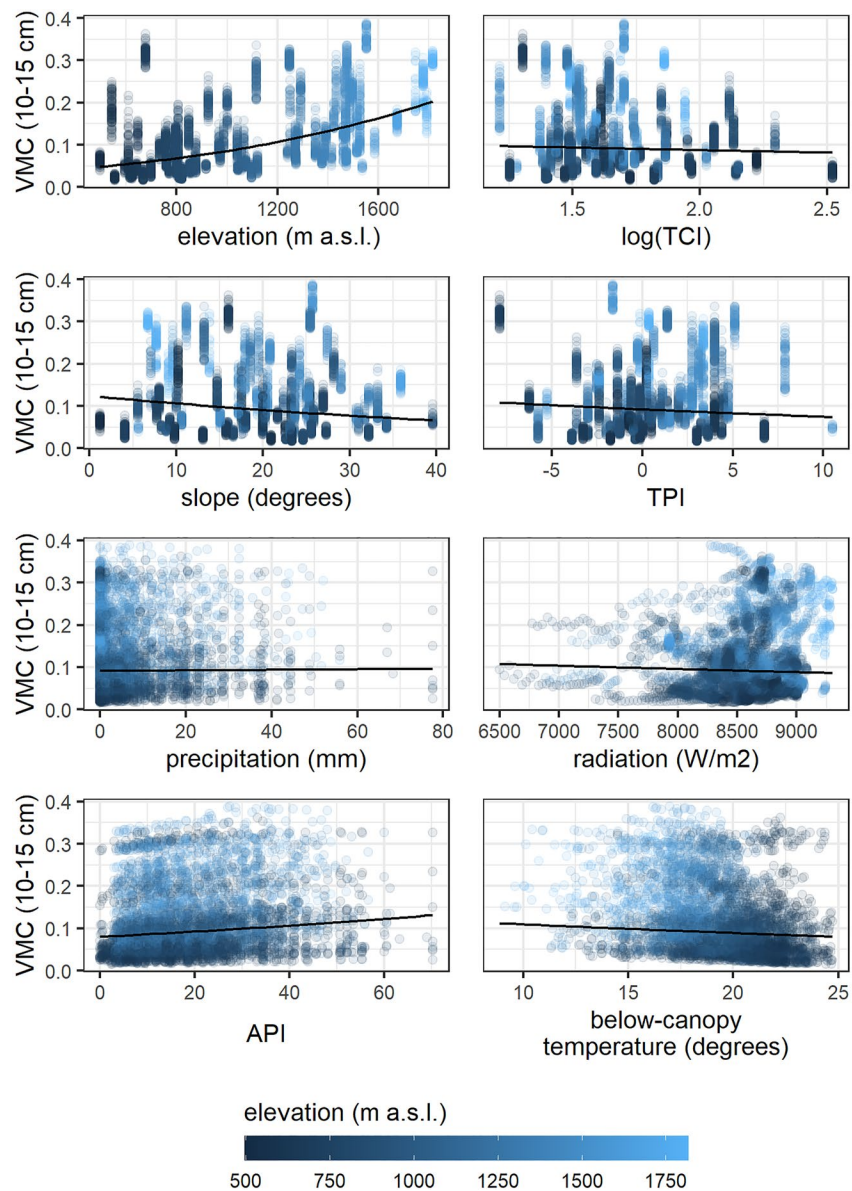


Figure 6. Effects of topographic and daily weather predictors on soil moisture across all measured sites. Lines show partial slopes from a linear mixed model of the effect of all predictors and random site intercepts on logit-transformed VMC (Table 4). Points show VMC values used in the model; only values when canopies were between maturity and senescence dates were used.

locations. The logger is robust enough to retain stored data through waterlogging and freezing, and burial of the unit minimizes damage from humans and wildlife. In places like GSMNP where wildlife (bear) disturbances pose the largest failure threat to environmental sensors, the low cost and small size for burial makes long-term soil moisture monitoring viable.

Our approach has several disadvantages compared to commercial units. These include build time (about 2 hr per unit), the need for some programming and soldering expertise, and parts ordering that can be time consuming and prone to shipping delays. We also caution that, although we found lab-calibrated sensor accuracy to rival that of less expensive commercial sensors ($<5\%$ vol vol⁻¹ RMSE), calibration takes time and careful consideration of covarying factors that influence resistance values. Although regulatory and wildlife constraints in GSMNP prevented us from attempting field calibrations, field tests are likely to increase sensor accuracy over lab tests due to inevitable differences in soil structure (disturbed vs. undisturbed soil profiles) between field and potted soil.

Table 4
Effects of Topographic and Meteorological Drivers on 10–15 cm Depth VMC Across All Sensors During the Growing Season

Parameter	Standardized estimate	<i>t</i> value	<i>P</i> value
Intercept	−2.30	−31.3	<0.001
Elevation	0.42	5.7	<0.001
log(TCI)	−0.03	−0.4	0.665
Slope	−0.15	−1.8	0.076
TPI	−0.07	−0.8	0.419
Precipitation	0.07	2.15	0.032
API	0.09	27.8	<0.001
Radiation	−0.07	−4.9	<0.001
Below-canopy temperature	−0.08	−14.9	<0.001

Note. Predictors were standardized to a mean of zero and standard deviation of one to allow comparison of effect sizes. VMC was logit transformed. Model parameters for 0–5 cm depth VMC values are shown in Table S4 in Supporting Information S1.

for further development of low-cost environmental sensing are vast (Mickley et al., 2019), and, along with remote sensing (Mohanty et al., 2017), promise to reveal physical properties of landscapes that to date have been beyond the capabilities of most researchers.

4.2. Spatial Soil Moisture Variation in Complex Terrain

Studies that monitor surficial soil moisture at fine spatial and temporal scales across large, topographically complex regions are uncommon, and ours yielded several surprising results. First, VMC at 10–15 cm soil depth was largely associated with elevation, with a nearly fivefold increase from 0.06 median VMC at 250 m to 0.30 at 2,025 m (Figure 4). This increase in VMC from low to high elevation is associated with a decrease in annual ET from ca. 900 to 500 mm, a gradient that mirrors the increase in annual rainfall (ca. 1,200–1,800 mm; Lesser &

Fridley, 2016). Soil moisture supply rates are also driven by canopy interception that vary from 4% to 20% in Southern Appalachian forests, depending on stand age (Brantley et al., 2019). Although most forest stands in GSMNP are mature secondary and primary forests of relatively high canopy interception, changes in forest composition and structure from low to high elevation may also contribute to the patterns we report here (Bolstad et al., 2001; Whittaker, 1966). The large effect of ET is associated with the direct influence of temperature lapse rate (3.5°C per 1,000 m on average), impacts of high elevation cloud cover on radiation (Wang et al., 2022), and, indirectly, shifts in vegetation composition and behavior that influence transpiration (Ford et al., 2011). We also note that a significant portion of precipitation in GSMNP is represented by fog and fine water particles (Prat & Barros, 2010), which are not captured by weather stations and may influence soil moisture by reducing transpiration, as occurs with fog immersion of high elevation trees (Carter Berry & Smith, 2014). In addition, as our sensors are limited to surface soils (0–15 cm), the dominance of elevation as a predictor of soil moisture may not reflect spatial patterns of moisture deeper in the soil profile. However, the dominant roles of precipitation and ET in driving VMC

Table 5
Effects of Topographic Drivers, Precipitation, and Evapotranspiration on 10–15 cm Depth VMC Across All Sensors During the Growing Season, Summarized as 8-Day Increments

Parameter	Standardized estimate	<i>t</i> value	<i>P</i> value
Intercept	−2.13	−32.6	<0.001
Elevation	0.37	5.5	<0.001
log(TCI)	−0.02	−0.3	0.778
Slope	−0.01	−1.4	0.146
TPI	−0.05	−0.7	0.497
Precipitation (8-day)	0.04	11.3	<0.001
Evapotranspiration (8-day)	−0.09	−26.6	<0.001

Note. Predictors were standardized to a mean of zero and standard deviation of one to allow comparison of effect sizes. VMC was logit transformed. Model parameters for 0–5 cm depth VMC values are shown in Table S5 in Supporting Information S1. Marginal (fixed effects) $R^2 = 0.29$.

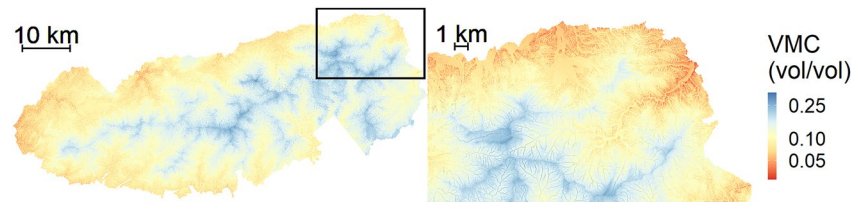


Figure 7. Spatial predictions of 10–15 cm depth VMC across Great Smoky Mountains National Park (left) and for a subregion (inset) of the Cosby and Big Creek watersheds (right) at 30 m resolution. Values are predicted median VMC (vol vol⁻¹) across the growing season, from relatively dry (red) to wet (blue).

in our study, both of which were estimated from coarser-scale, remotely sensed data (4,000 and 500 m resolution, respectively), suggest high-resolution soil moisture modeling using publicly available geospatial predictors calibrated with sensor network data is widely accessible.

Second, we found that topographic variables often used as proxies for soil moisture in montane regions played at best a minor role in spatial variation of VMC. The most important topographic variable was slope angle: differences of 40° corresponded with a 0.05 VMC difference at low elevations and more than 0.10 at high elevations (Figure 4). Our interpretation is that local drainage—high magnitude, short-duration decreases in VMC that occur within 24 hr of rain events—is more pronounced on steep slopes of relatively coarse soil texture, allowing rapid water penetration deeper into the soil profile. In contrast, surficial soils of flatter sites contain higher clay content (USDA, NRCS, 2009) and thus retain more moisture between rain events, increasing median VMC over the growing season. This hypothesis could be tested with high resolution soil texture data, but such data remain too coarse in GSMNP (USDA, NRCS, 2009). The lack of mapped soil texture data also influences our interpretation of the VMC pattern across the elevation gradient. Although Golden (1981) found low- and mid-elevation sites in the central portion of GSMNP to have higher B horizon clay content than those of high elevations, organic matter of A horizon soils generally increases with elevation (USDA, NRCS, 2009), and there is evidence that moisture retention increases with organic matter content in coarse textured soils (Rawls et al., 2003).

We found little association of soil moisture with the common topographic proxies topographic position index (TPI) and topographic convergence index (TCI). TCI in particular is a common substitute for soil moisture in montane regions due to its integration of potential supply (upslope contributing area) and loss through drainage (Beven & Kirkby, 1979), but its observed relationship with soil moisture has varied widely across studies (Dyer, 2009; Western et al., 1999). In the Southern Appalachians, local topography has long been assumed to drive spatial variation in soil moisture but empirical studies have been rare. Helvey et al. (1972) reported surprisingly little difference in soil moisture content of cove forest locations and adjacent ridges, whereas Yeakley et al. (1998) found a decrease in soil moisture in 80-m upslope transects from streams that was significantly associated with TCI. However, the study of Yeakley et al. (1998) was performed from October to February, a period where moisture demand from transpiration is low; those authors also showed that topographic control of moisture was greatest during drought conditions and relatively weak after precipitation events, presumably due to effects of saturation and soil texture that are poorly reflected in TCI. Our interpretation is that topographic moisture indices like TCI are generally poor proxies of soil moisture in the Southern Appalachians because (a) demand from transpiration during the growing season overwhelms relatively small effects of local topography, (b) at the daily scale, soil texture and vegetation structure mediate VMC more than local topography, particularly during periods of high rainfall, and (c) when applied across whole watersheds of large variation in elevation and exposure, TCI signals are too weak in comparison to climatological drivers of local water balance to be supported in regression models (Lookingbill & Urban, 2004). We note, however, that TCI and other topographic moisture indices may have larger effects on moisture deeper in the soil profile; it is also possible that more explicit seasonal modeling of VMC in GSMNP may identify particular weather conditions where TCI is a significant predictor of VMC.

We did not detect a qualitative difference in spatial or temporal patterns of VMC when measured at 0–5 cm versus 10–15 cm depths. However, the combined explanatory power of fixed effect predictors was over twice as high (R^2 0.31 vs. 0.12) using 10–15 cm depth values. We suspect this is due to several factors. First, temporal variation

of surficial moisture is significantly higher than that of the 10–15 cm zone, which introduces noise at the daily scale that may not be present at the hourly scale. Second, surficial probes are more subject to small soil surface variations (leaf cover, rocks, roots, small animal disturbance) that likely generate VMC artifacts related to sensor soil contact. Third, the inherent nonlinear temperature sensitivity of resistance-based probes, combined with soil surface temperature variability, may have introduced artifacts related to diurnal averaging of VMC values. For these reasons we recommend those interested in mapping soil moisture in topographically complex landscapes avoid sensors placed at soil surface when possible.

4.3. Forest Vegetation May Buffer Soil Moisture Variation

The predominance of late-successional forest communities may be an important moderating factor of soil moisture across topographic gradients in GSMNP, against the expectation that near-stream, protected locations should generally be wetter than more exposed ridge-top sites. On average, only about 75% of rainfall is able to penetrate mature forests canopies to reach the mineral soil surface in the Southern Appalachians (Brantley et al., 2019), and small rain events may often go undetected in VMC sensors, particularly in near-stream cove forests that are often characterized as highly mesic. In addition, although canopy cover reduces soil water loss from evaporation through shading and cooling effects, loss through transpiration is enhanced with leaf area index (Granier et al., 2000), and the reduced mid-day vapor pressure deficit of protected sites may lengthen the daily duration of leaf water loss from photosynthesis, contributing to soil drying (Ellsworth & Reich, 1992). On the other hand, more topographically exposed ridgetop sites in GSMNP may experience greater wind-based evaporation and understory transpiration as a result of a more developed shrub layer, which may negate greater throughfall in stands of sparser canopies. Thus, forest structure and composition are likely to play important roles in buffering microclimatic variation in relation to both temperature (Fridley, 2009; Von Arx et al., 2013) and soil moisture (Davis et al., 2019), which may partly explain the lack of large variation in VMC with stream distance and site exposure in our study.

The absence of a strong topographic signal in soil moisture related to site exposure prompts a reevaluation of the role of topography in the spatial organization of vegetation and other biota across the Southern Appalachians, a region where topographic complexity has long been thought to drive high biodiversity and endemism (Nekola & White, 1999; Whittaker, 1956). Whittaker (1956) was the among the first to suggest site exposure as a principal driver of vegetation composition, and he, along with many subsequent researchers (Boerner, 2006), presumed exposure effects to be driven largely by soil moisture. Our data are not consistent with this view; although we did find that soils of relatively flat terrain near valley-bottom streams are generally wetter than adjacent soils of steep, mid-slope locations, ridgetop soils are no drier than streamside soils of the same elevation (see also Helvey et al., 1972), and local topographic influences on VMC like TPI were generally minor in comparison to elevation. Indeed, Fridley (2009) found significantly greater variation in below-canopy temperature along stream-to-ridge gradients (as high as 4°C within 500 m, compared to 6°C from low to high elevation) than we document here for VMC. However, we caution that our data are specific to shallow soil depths (0–15 cm) and it may be that moisture dynamics at greater depths are more important to large plants such as canopy trees. Unfortunately, field sensor-based sampling of deeper soils in GSMNP is currently limited by the absence of accessible deep profiles in many areas, which may require proximal or remote sensing techniques (Babaeian et al., 2019).

4.4. Mapping Soil Moisture in Montane Regions

Our predictive model of VMC could accurately determine daily VMC of validation sensors located far from sites used to create the model, with an RMSE <5%. Such accuracy justifies the use of surficial spatial moisture maps across all of GSMNP for some purposes, but we advise caution in application. Our models explain only about a third of the total variance in VMC across sites, leaving the majority of surficial soil moisture dynamics unaccounted for by the spatial predictors of our model. This is compared to R^2 values of over 0.5 and 0.9 for GSMNP maximum and minimum daily temperatures, respectively, at the same spatial resolution (Fridley, 2009). Like other researchers (e.g., Lookingbill & Urban, 2004), we suggest there is a limit to the ability of small point sensors to capture fine-scale spatial moisture dynamics, due to large effects of soil heterogeneity (texture, effects of biota and disturbances) and the sensitivity of sensor readings to small differences

in placement (depth, soil contact). One approach is to average hourly values of many sensors at a single site, with necessary tradeoffs in network size. Another is to prioritize finer scale mapping of soil texture, as textural differences have been found to be important driving variables of VMC along hillslopes in the Southern Appalachians (Yeakley et al., 1998). Indeed, improved understanding of the influence and distribution of local factors like soil texture and vegetation properties may allow for a more explicit approach to high resolution soil moisture modeling based on supply and demand factors (Dyer, 2009; Stephenson, 1990), which could incorporate how, for example, different forest types moderate both supply (e.g., canopy interception) and demand (e.g., transpiration).

4.5. Potential Global Change Impacts on Soil Moisture

How will landscape patterns of soil moisture change in the future, and what are the implications for regional biodiversity and ecosystem functioning? Models that predict soil moisture in relation to daily weather variables and their interaction with site variables can, in theory, be used to forecast impacts of climate change on site moisture budgets (Davis et al., 2019). Such predictions are important, because soil moisture moderates effects of atmospheric warming on population dynamics (Töpper et al., 2018), range boundaries (Oldfather et al., 2020), and ecosystem processes such as carbon cycling (Winkler et al., 2016). In GSMNP, the strong association of VMC with ET suggests a gradual drying of soils as annual temperatures increase (Novick et al., 2016), and justify development of water balance approaches (e.g., Dyer, 2009) that take into account the influence of local site factors on future ET. However, GSMNP has experienced less warming over the past century than much of the rest of North America (Lesser & Fridley, 2016); in addition, GSMNP precipitation is on average 10% higher today than a century ago (Lesser & Fridley, 2016) and is predicted to increase further this century (Easterling et al., 2017). Thus, whether soil moisture patterns will change in the coming decades depends on relative changes in supply and demand, and we have observed only a fraction of the possible states of important drivers. For example, compared to the size of rainfall events, precipitation frequency shows little spatial variation across GSMNP, yet expected reductions in frequency from warming may amplify impacts of increasing ET (Easterling et al., 2017). Thus, rather than the correlative approach used here, we suggest forecasts of soil moisture dynamics take advantage of a more mechanistic modeling approach that decomposes local water budgets into supply and demand factors, and their sensitivity to climate change. Large monitoring networks like that described here will facilitate the development of such models, particularly as their application grows to include other global change factors such as forest disturbances (Fraterrigo et al., 2018).

5. Conclusion

Our study demonstrates that custom-built sensor arrays that monitor surficial soil moisture in large, remote landscapes at high spatial and temporal resolution are inexpensive, accurate, and an important component of climate downscaling in complex terrain. In GSMNP, predictive soil moisture modeling using climatic and topographic variables indicated a surprisingly weak association of moisture with terrain indices, with landscape moisture patterns dominated by elevation-related changes in rainfall and evapotranspiration. Improved understanding of spatial moisture gradients in this region will require more detailed mapping of fine-scale soil structure and vegetation properties that alter water storage, rainfall interception, and transpiration. Nonetheless, strong relationships of soil moisture with climate, particularly evapotranspiration, suggest forested ecosystems of this region may see overall reductions in moisture with continued warming.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Data sets and predictive maps used in this study are available in the U.S. National Park Service Data Store (irma.nps.gov/DataStore/). All statistical analysis scripts in R used in this study are available at https://github.com/jordanstark/GSMNP_moisture_drivers. Information on sensor design, construction, and use is available at https://github.com/jordanstark/Soil_temp_moisture_EMU.

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