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Does deadwood moisture vary jointly with surface soil water content?

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Abstract

Deadwood moisture plays a major role in regulating deadwood decomposition rates and may also affect forest microclimate. Despite this, the temporal variability of deadwood moisture at 15-min time scales remains relatively unknown because techniques for using high-frequency sensors for tracking moisture at appropriate spatial and temporal intensities have been lacking. We installed a high-density sensor array in and around a downed log to gain a detailed assessment regarding the temporal variation of volumetric water content at multiple locations within one downed dead log, the source snag, and the surrounding soil. We also measured micrometeorological variables near the log in order to predict variability of the deadwood moisture. We found that the deadwood varied in similar fashion as the soil moisture, and that this similarity allowed us to make accurate predictions of deadwood moisture using micrometeorological data and soil moisture. The primary driver of deadwood moisture was rainfall; however, diurnal cycles of subcanopy humidity and temperature seemed to cause variation in the deadwood moisture between rain events. Our findings highlight the need for applying similar techniques to a variety of forest types, deadwood types, and different forest management strategies to gain a broader understanding of high-frequency deadwood moisture dynamics and their feedbacks with ecosystem processes, like decomposition and forest fire hazards.

1 | INTRODUCTION

Deadwood in forested ecosystems influences numerous ecosystem processes, including biodiversity maintenance (Stokland et al., 2012), nutrient cycling (Laiho & Prescott, 1999), tree regeneration (Orman et al., 2016), and carbon storage (Woodall et al., 2015). Interest in deadwood has grown dramatically in recent decades, as evidenced by the increasing number of scientific publications on this topic over this period (Russell et al., 2015). Interest will likely continue, as climate change is expected to increase tree mortality (i.e., increased dead wood biomass inputs) across the world's forests (McDowell & Allen, 2015; McDowell et al., 2020; Seidl et al., 2011). In addition, given that deadwood represents a substantial forest carbon pool—often representing ~20% of the total aboveground biomass (Bradford et al., 2009)—a deeper understanding of deadwood pools and fluxes is critical for improving current forest carbon-cycle models (Harmon et al., 2020; Kurz et al., 2009; Russell et al., 2014).

Deadwood moisture content strongly influences a variety of ecological attributes and processes. For example, moisture content of decaying logs, as well as their physical structure,

Abbreviations: TDR, time domain reflectometry.

determine their use by Plethodontid salamanders for foraging and oviposition (Heatwole, 1962). Detailed work from Japan has demonstrated that tree seedling establishment on decaying wood substrates (i.e., nurse logs) is enhanced because this substrate has higher moisture compared with soil and forest floor litter (Takahashi et al., 2000). In addition, the water-holding capacity of downed deadwood can influence nearby microclimatic conditions, which has been shown to mediate soil moisture stress, thereby enhancing tree regeneration (Goldin & Hutchinson, 2014; Harrington et al., 2013). Deadwood moisture content also regulates wood decay rates (Bond-Lamberty et al., 2002; Forrester et al., 2015; Herrmann & Bauhus, 2013), as fungal activity is reduced under both excessive (Progar et al., 2000) and insufficient moisture conditions (Panshin & de Zeeuh, 1980).

Despite the influence of deadwood moisture on these ecological processes, we currently have a poor understanding of how deadwood responds to precipitation events and how deadwood and adjacent soils interact regarding moisture. This is because the typical moisture measurement techniques involve collecting wood samples and measuring the water loss from drying. Golden and Hutchinson (2014) demonstrated how responsive deadwood may be over short time steps (minutes) to precipitation events, but wider exploration in terms of sensor technology and across varying forest ecosystems has yet to be undertaken. This lack of wider investigations of subdiurnal-scale deadwood moisture dynamics results in part from constraints in efficient moisture-sensing and related technologies, which have only recently been overcome (Woodall et al., 2020). Filling this knowledge gap is timely because climate change will likely produce more episodic precipitation and storm weather (Janowiak et al., 2018), with the potential to increase forest disturbance with concomitant live tree mortality and deadwood inputs. A refined understanding of the relationship between deadwood moisture dynamics and various ecological processes should also improve carbon cycle models and associated land-surface components of earth system models.

The objectives of our study were (a) to document high-frequency deadwood moisture to understand the response to rain events and micrometeorology during rain-free periods; and (b) to evaluate the ability to predict deadwood moisture using soil moisture. The implementation of emerging field-based sensor technology shows promise for characterizing high-temporal-resolution deadwood moisture (Woodall et al., 2020). The results from the sensing in this study allowed us to address both objectives and opened new lines of inquiry for future deadwood moisture studies.

Core Ideas

- High-frequency deadwood moisture variation can be monitored with TDR sensors.
- Deadwood wets and dries in a similar fashion as shallow soil moisture.
- Diurnal evaporation and condensation variation causes deadwood moisture variation.
- Temporal variation of deadwood moisture can be well predicted with machine learning models.

2 | MATERIALS AND METHODS

2.1 | Site and instrumented log

This study was conducted within Watershed 3 at the Hubbard Brook Experimental Forest, New Hampshire, USA (Supplemental Figure S1) The watershed has an average annual precipitation of 1,373 mm and an average annual temperature of 5.7˚C. Watershed 3 supports a mature, mixed hardwood forest composed of primarily sugar maple (*Acer saccharum* Marshall), yellow birch (*Betula alleghaniensis* Britton), and American beech (*Fagus grandifolia* Ehrh.) (Siccama et al., 2007). After reconnaissance of the watershed, we selected a sugar maple log for instrumentation, primarily because of its relatively large size, orientation perpendicular to the slope, and partial contact with the forest floor. The instrumented log was located at elevation 600 m asl on a southeast-facing, 16˚ slope. The soil underneath and adjacent to the log was a Spodosol of sandy loam texture, formed from ablation till source material (Bailey et al., 2014, 2019). The log had a large end diameter of 37 cm, length of 10.4 m, and was in direct contact with the forest floor for ∼50% of its length. It was classified as decay class 3, based on the Sollins (1982) five-class system. This species and decay class was considered representative of most deadwood in this forest. We also instrumented the adjacent snag (standing dead tree) from which the log originated; the snag was 8.2 m tall and had a diameter at breast height (1.37 m) of 51.7 cm.

2.2 | Field measurements

The log and its surrounding soil was instrumented with time domain reflectometry (TDR) sensors (Acclima 315L, Acclima), with readings beginning on 6 June 2018 and ending on 15 Octo. 2018. Twelve TDR sensors were installed along the log's length and inserted into 150-mm predrilled pilot holes in the log (the full length of the TDR tynes), six sensors on the upslope side and six on the downslope side (Woodall et al., 2020). Five sensors were installed into the log at the onset of the study, and another seven were installed on 20 July. The snag from which the downed log originated was instrumented with five TDR sensors, installed using the same method as the log and installed on 8 August. Snag sensor heights ranged from 0 to 1.5 m above the forest floor. The TDR sensors were installed in the soil at 10- and 20-cm depth below the organic soil layer at 25 locations, every 1 m along five transects perpendicular to the log. The sensors record volumetric water content (hereafter moisture), permittivity, and temperature. Air temperature and relative humidity were monitored using a sensor in a nonaspirated Gill radiation shield (Meter Atmos 14, Meter Group) deployed at 1.5-m height adjacent to the log. Wind direction was monitored using an analog wind vane. Precipitation was measured with a NOAH IV rain gauge that is part of the Hubbard Brook Experimental Forest long-term monitoring in a clearing 240 m from the log (Green et al., 2018). All data except precipitation were logged with the Arduino-based logger (Mayfly, Stroud Water Research Center) on a 15-min basis. The precipitation data were measured with an NOAH IV automated weighing precipitation gauge every 15 min (NOAH IV, ETI Instrument Systems).

2.3 | Data analysis

All data analyses were performed using R version 3.4.4 (R Core Team, 2018).

The TDR data were aggregated into log, snag, 10-cm soil, and 20-cm soil data by averaging across each 15-min measurement within each group. This was done to simplify the comparison of the moisture dynamics across groups. The group of five log sensors installed for the duration of the whole study were aggregated into a long log moisture time series by averaging their 15-min values, and a shorter time series was generated by averaging all 12 sensors.

Micrometeorological variables were calculated from the air temperature and relative humidity measurements. Vapor pressure deficit was calculated using equations from Bolton (1980):

$$\mathrm{VP_{sat}} = 0.1\left\{6.112e^{[(17.67T_a)/(T_a+243.5)]}\right\}$$

$$\mathrm{VP} = \mathrm{VP_{sat}} \times \mathrm{RH}$$

$$\mathrm{VPD} = \mathrm{VP_{sat}} - \mathrm{VP}$$

where T_a is air temperature (˚C), RH is relative humidity (dimensionless), $\mathrm{VP_{sat}}$ is saturated vapor pressure (kPa), VP is vapor pressure (kPa), and VPD is vapor pressure deficit (kPa). Air dewpoint temperature (T_d in ˚C) was used to indicate the evaporation/condensation gradient to aid interpretation of moisture variation during nonrainfall periods. The T_d was calculated using the two-step calculation where B is a coefficient:

$$B = \left\{\log(\mathrm{RH}) + \left[(17.27T_a)/(237.3+T_a)\right]\right\}/17.27$$

$$T_d = (237.3B)/(1-B)$$

To compare the moisture data from the log, snag, 10-cm soil, and 20-cm soil, each variable was scaled by converting to Z scores. Only simultaneous measurements of all four components were used for the moisture comparison. The distribution of each variable was assessed by calculating the kernel density using the *density()* function in R. The spatial variability of soil and log moisture was compared by calculating the median from the 19 d when all sensors were operating simultaneously. This was due to challenges in keeping all sensors powered with batteries.

Diurnal variation of the meteorological drivers, wood moisture, and soil moisture was analyzed using the data collected in August. We chose this period of the record because it is when the forest is driest due to high atmospheric demand and high transpiration rates and would thus accentuate any moisture dynamics that were not due to rainfall. The median diurnal curve was calculated, and the uncertainty in the hourly median values was calculated using bootstrap resampling (n = 1,000) and reporting of the interquartile range. The median was used instead of the mean to minimize the influence of high moisture after precipitation events on the diurnal curves. To further reduce the effect of precipitation, only moisture measurements when there was no measured precipitation were used to build the diurnal curves.

We assessed the ability to monitor deadwood moisture without direct measurement by exploring the correlation with soil moisture and by modeling with a machine learning algorithm. The relationship between soil and deadwood moisture was quantified with a Spearman rank correlation (ρ). Moisture in the snag, log, 10-cm soil, and 20-cm soil was modeled with the random forest algorithm (Breiman, 2001; Liaw & Wiener, 2002). Independent variables were T_a, VPD, and precipitation, and the antecedent conditions for each of these three variables (2-d and 7-d sums). Random forest models for the snag and log were also built using the previously mentioned variables plus soil moisture to test whether predicted deadwood moisture improved when soil moisture was included. The dataset was split into two equal sets, with the first half used for model training and the second half for model testing. This emulated the process of using the early record to build a model and then using that model to make predictions going forward. Model fit was assessed using the Nash–Sutcliffe efficiency (Nash & Sutcliffe, 1970).

3 | RESULTS

3.1 | Temporal variation of moisture

There was considerable differences in the magnitude and temporal variation of moisture at each of the soil and deadwood moisture sensor locations (Supplemental Figure S2), resulting in spatial differences in soil and deadwood moisture that did not clearly vary with any characteristics that we measured in this study (Supplemental Figure S3). Estimates of log and snag moisture followed similar temporal patterns as the soil, wetting with rainfall and receding during drying events (Figure 1). There were clear differences in the moisture magnitude between the ecosystem components: the log had the highest moisture, the snag had the lowest moisture, and the soil was intermediate. Across the growing season, there was an overall pattern of increasing snag and log moisture from their initial early summer measurements to their last measurements in October. The late July multiday rainfall, which produced 183 mm from 22 to 28 July, caused the log moisture to drastically increase and remain elevated throughout the monitoring period. A similar pattern of log moisture was produced whether the original five sensors or all 12 were used to calculate the composite log moisture (Figure 1). Soil moisture at 10-cm and 20-cm depths exhibited similar magnitude and temporal variation. The overall soil moisture trend was decreasing in August and September, followed by increasing moisture in October. The variability of all moisture values, when scaled to a common magnitude, showed similar distributions (Supplemental Figure S4).

We highlight two events that demonstrate the wetting–drying dynamics in response to varying rainfall (Figure 2). A 40.3-mm rainfall event on 22 August caused moisture in soil and deadwood to increase in a similar fashion with rapid wetting and receding moisture after rainfall ceased (Figure 2a). A 3.7-mm rainfall event on 29 August caused only deadwood moisture to respond but at a much lower magnitude than the 22 August event (Figure 2b). The snag exhibited a higher peak moisture than the log. With both events, the moisture remained elevated for days after the rainfall, if the component wetted.

The diurnal variation of micrometeorology illustrated how nonrainfall periods affect deadwood moisture. The median wind direction shifted diurnally, consistent with anabatic wind moving upslope in the late morning and katabatic wind moving downslope as the sun sets (Supplemental Figure S5a). Vapor pressure deficit showed clear diurnal variation with the daily low of 0.1 kPa around 0600 h and a daily peak near 0.7 kPa at 1500 h (Supplemental Figure S5b). Air temperature showed an almost 6˚C diurnal range, dewpoint showed a 2˚C diurnal range, and soil temperature showed almost no diurnal variation (Supplemental Figure S5c). Air temperature peaked at 1500 h, showing similar diurnal variation as VPD. Dewpoint temperature ramped up linearly from 0600 to 1800 h and then rapidly decreased. The 10-cm soil temperature was cooler than the T_d during the daytime hours, creating the potential for a net condensation gradient. The deadwood indicated diurnal variation in moisture, with the highest values occurring in the morning, then a decrease in the late afternoon (Supplemental Figure S5d,e). Curiously, the log exhibited a secondary increase in moisture during the evening. The diurnal variation of soil moisture was less clear relative to the bootstrapped interquartile range for each hour

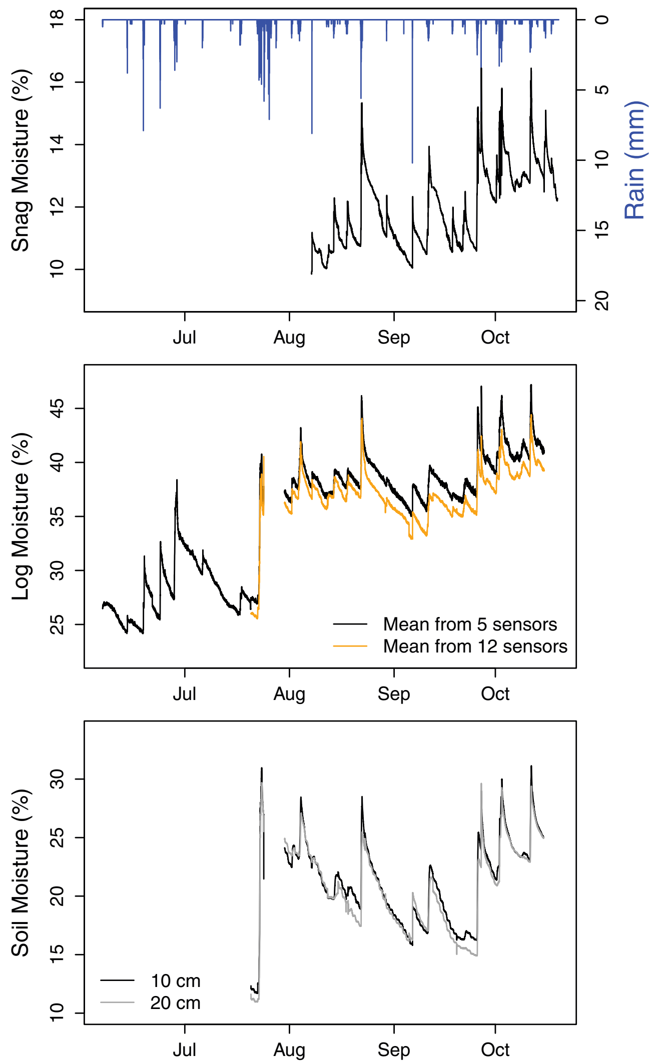

FIGURE 1 Time series of average snag, log, and soil moisture (at depths 10 and 20 cm). Fifteen-minute accumulated rain is also shown for reference. Note that moisture axes are on different scales. Only five sensors were installed into the log initially, and another seven were installed in late July. The mean from both the five sensors over the full time series and the mean from all 12 is shown for the log moisture

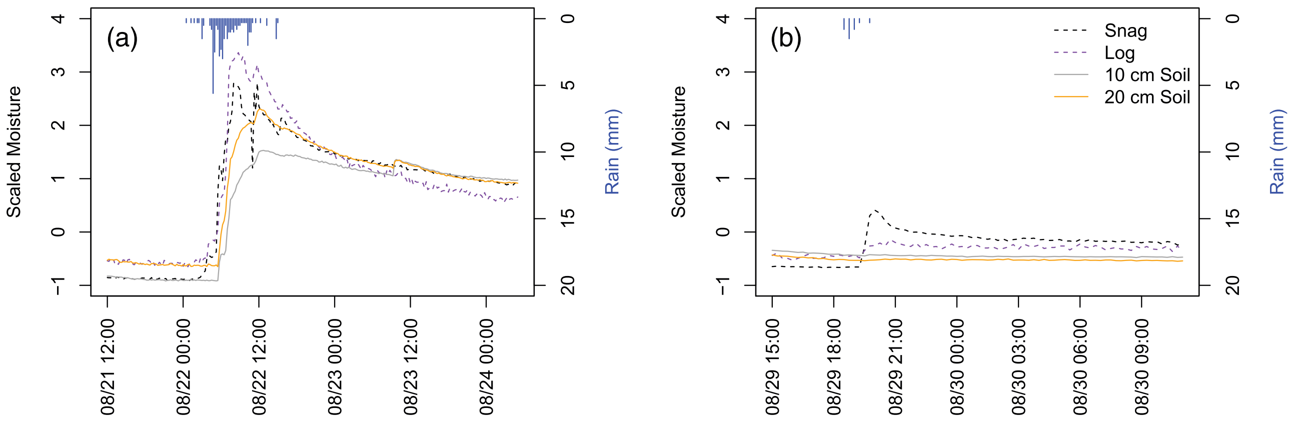

FIGURE 2 Two example rain events where the soil and deadwood responded similarly to (a) a 40.3-mm rain event and (b) a 3.7-mm rain event that showed a small response in the deadwood but not the soil

(Supplemental Figures S5f); however, the figures hint at diurnal variation with a daily high moisture at 0900 h and daily lows at 1600 and 1700 h.

3.2 | Predicting deadwood moisture

Moisture from individual soil sensors were generally correlated with individual log moisture sensors, with Spearman ρ values typically greater than .4; however, there were a few log–soil pairs that produced very low correlations (Supplemental Figure S6). The correlations did not clearly depend on variables that we measured for this study (e.g., ground contact of the log), thus they demonstrate the range of correlations that are possible with any soil–log moisture sensor pair. Both the snag and the log were most correlated with the 20-cm soils (ρ of .76 and .83, respectively). The correlation between shallow soil and snag moisture was $\rho = .71$, and the correlation between the 10-cm soil and log moisture was $\rho = .75$.

The trained random forest models all had Nash–Sutcliffe efficiencies (NS) greater than 0.99. When the models using only meteorological variables were used to predict the testing period data, they produced NS values of 0.60, 0.53, 0.50, and 0.52 for the predicted snag, log, 10-cm soil, and 20-cm soil moisture, respectively. When the 10-cm and 20-cm soil moisture was included in the model, the testing period NS values increased to 0.77 to 0.80 for the snag and log moisture, respectively. Generally, the models underpredicted the actual moisture during the testing period, especially peak moisture values (Figure 3).

4 | DISCUSSION

Our high-frequency sensor measurements demonstrated that deadwood moisture varies considerably across short time scales, primarily related to the magnitude of individual precipitation events. Previous empirical studies have demonstrated similar temporal variability in deadwood moisture content (see Boddy, 1983; Forrester et al., 2015; Harmon & Sexton, 1995; Pichler et al., 2012). Pichler et al. (2012) demonstrated that deadwood moisture closely follows shallow soil moisture through time; however, they did not record moisture frequently enough to detect storm-scale drying and wetting. Our study is novel in that it provides a picture of 15-min interval moisture patterns across many sensors, allowing us to simultaneously track moisture in both deadwood and soils as they respond to storm events. This dataset provides us with a first-of-its-kind lens by which to understand moisture dynamics within and around deadwood in a northern hardwood forest.

Our results demonstrate that deadwood responded to rainfall events similarly to soil moisture over our 3-mo study, with slightly greater sensitivity to small precipitation events than soil. The wood experienced rapid wetting followed by a slower drying process after cessation of rainfall, in a similar fashion as soil. The overall trend of increasing wood moisture from June to October was a bit more pronounced than the soil, which showed less wetting from June to September. These seasonal moisture dynamics can be attributed to soil water uptake for transpiration, whereas the deadwood was only subject to evaporation, which is minimal from subcanopy soils at Hubbard Brook (Green et al., 2015). The deadwood wetted more easily than soil in response to small rain events, which was likely due to the wood having no overlying porous media to dampen the wetting process by storing and redistributing moisture (Klamerus-Iwan et al., 2020). As deployed, the soil sensors were overlain by the forest floor and 10 cm of mineral soil; if they were deployed just beneath the forest floor surface, they would likely have shown a response to the smaller rain events. The log and snag had a sharper peak moisture with rapid recession compared with the

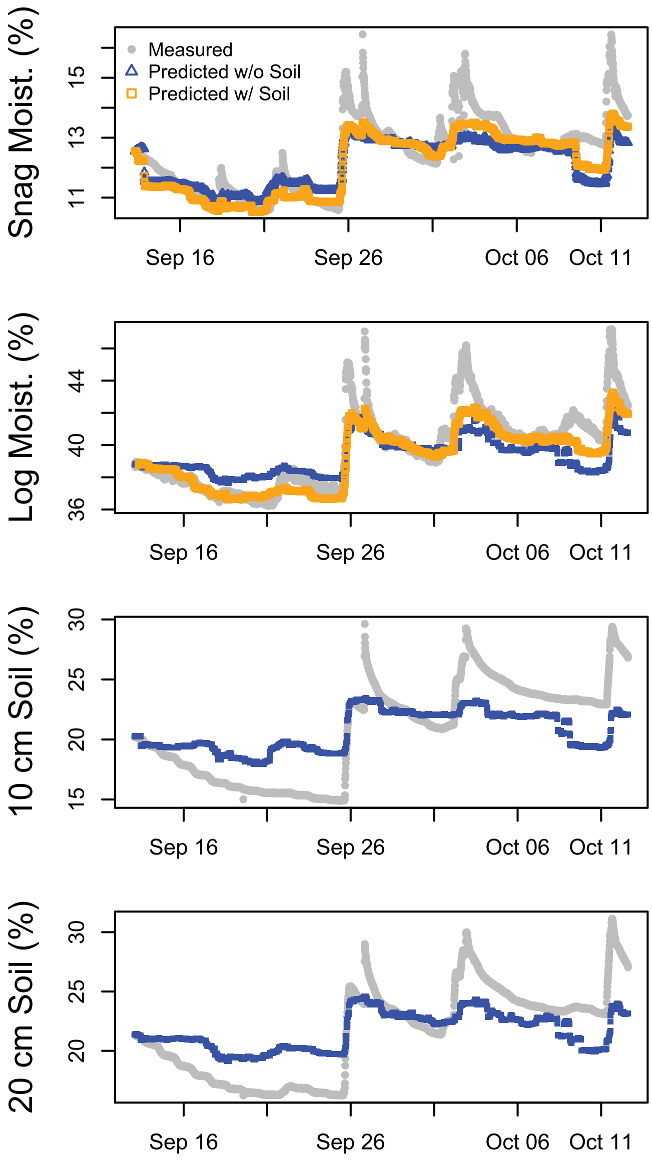

FIGURE 3 Predicted compared with measured 30-min volumetric water content based on the random forest model. Only predictions for the model testing period are shown. The snag and log include two predictions: one using only meteorological data, and another using meteorological data and soil moisture data. Moist., moisture

soil, which may have also been due to the more direct exposure of the deadwood to precipitation when compared with soil.

The somewhat similar behavior of soil and deadwood moisture highlights that deadwood in this moderate stage of decay behaves hydrologically as porous media, similar to soil. This finding may not hold for less decayed pieces, as porosity is known to increase as decay advances (Boddy, 1983; Yoneda, 1975), with a corresponding increase in water holding capacity (Bütler et al., 2007; Pouska et al., 2016). In fact, the mass moisture content in well decayed logs can exceed 250% (Harmon & Sexton, 1995; Savely, 1939; Sollins et al., 1987), and moisture in such logs typically exceeds that of adjacent soil (Pichler et al., 2012; this study).

Although the snag and log exhibited similar temporal variability, the snag was consistently drier. Lower moisture in snags is well reported (Boulanger & Sirois, 2006) and is generally attributed to lack of contact with damp soil (van Geffen et al., 2010), which would also make it subject to the drier subcanopy air. The snag moisture after storms generally peaked at higher levels than the downed dead wood, likely related to the pore size distribution of the wood; however, further study is needed to document a reason. The dry snag wood has implications for decomposition and hence carbon dynamics, as the wood may become too dry to support fungal activity, thereby slowing decomposition (Boulanger & Sirois, 2006; Yatskov et al., 2003).

The diurnal variability of deadwood and soil moisture was less apparent than the response to rainfall, yet it provides insight into the micrometeorological controls over moisture during nonrainy periods. The wood showed clearer diurnal moisture variation than the soil. This moisture variation was likely due to occult precipitation associated with fog and condensation onto the wood, with the wettest conditions in the deadwood typically occurring in the morning when the wood surface temperature was closest to the dew point. Occult precipitation is an important—but often overlooked—source of water to many forest ecosystems (Weathers et al., 2020). At Hubbard Brook Experimental Forest, soil water showed evidence of net condensation, suggesting a strong presence of occult precipitation in this forest (Green et al., 2015). Our monitoring suggests that the deadwood is a recipient of occult precipitation, which likely contributes to the characteristically moist conditions associated with decaying wood (as above), which in turn provide ideal conditions for seedling establishment and survival (Takahashi et al., 2000; Weaver et al., 2009) and facilitates fungal decomposition (Pouska et al., 2016).

The random forest model results suggest that machine learning algorithms can improve deadwood moisture predictions. The predictions generated from this model and dataset do not identify peak moisture values; however, the baseline magnitudes are generally captured accurately. This result is especially encouraging because the training dataset used in model construction was collected closer to the peak growing season when the summer canopy was at its fullest and transpiration rates were highest, resulting in different micrometeorological conditions than the autumn period when the model was tested. This suggests that the model captures a more basic relationship between meteorological drivers of deadwood moisture. The stronger performance when soil moisture was included and the correlations between soil moisture and deadwood moisture suggests that soil moisture monitoring data could be useful in predictions of deadwood moisture. Similarly, Gough et al. (2007) used soil moisture to successfully model deadwood moisture throughout one calendar year. Further data across multiple annual cycles and using a larger number and greater diversity of deadwood pieces could improve the performance of our models. The broadest applicability of these machine learning models will be achieved once they can be trained under diverse conditions and predict locations not included in the training. Despite the limitations of our relatively small study, these modeling results show promise that deadwood moisture can be effectively predicted with machine learning algorithms, provided sufficient training data are available. Given the challenges in monitoring deadwood moisture dynamics instrumentally across wide areas, this outcome could facilitate more effective monitoring and modeling estimates in forest systems.

Overall, our study demonstrates that dead wood moisture exhibits similar temporal variability as soil, provides evidence of how meteorological variables influence temporal variability of moisture, and presents an empirical method for predicting the temporal variability of deadwood moisture. Further study of the temporal variability of deadwood moisture is needed to characterize the different seasonal and storm-scale wetting–drying dynamics experienced in diverse forests under various management regimes. That is, future in situ monitoring of dead wood moisture could be used more broadly to aid the understanding of how forest management practices influence habitat conditions, carbon storage, and fire risk resulting from dead wood moisture variability.

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AUTHOR CONTRIBUTIONS

Mark B. Green: Conceptualization; Data curation; Formal analysis; Writing – original draft. Anthony W. D'Amato: Conceptualization; Writing – review & editing. Shawn Fraver: Conceptualization; Writing – original draft. David A. Lutz: Conceptualization; Methodology; Writing – original draft. Christopher W. Woodall: Conceptualization; Writing – original draft. Daniel M. Evans: Data curation; Investigation; Writing – review & editing.

DATA AVAILABILITY STATEMENT

The data used in this study are available through the Hubbard Brook Ecosystem Study data catalog (https://hubbardbrook.org/d/hubbard-brook-data-catalog).

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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