

Article

Development and Evaluation of the Forest Drought Response Index (ForDRI): An Integrated Tool for Monitoring Drought Stress Across Forest Ecosystems in the Contiguous United States

Tsegaye Tadesse ^{1,*} , Stephanie Connolly ² , Brian Wardlow ³ , Mark Svoboda ¹ , Beichen Zhang ^{1,4} , Brian A. Fuchs ¹ , Hasnat Aslam ¹, Christopher Asaro ⁵ , Frank H. Koch ⁶ , Tonya Bernadt ¹, Calvin Poulsen ¹, Jeff Wisner ¹, Jeffrey Nothwehr ¹, Ian Ratcliffe ^{1,3}, Kelsey Varisco ¹, Lindsay Johnson ¹ and Curtis Riganti ¹

¹ National Drought Mitigation Center, School of Natural Resources, University of Nebraska-Lincoln, Lincoln, NE 68583-0749, USA; msvoboda2@unl.edu (M.S.); bzhang5@lbl.gov (B.Z.); bfuchs2@unl.edu (B.A.F.); haslam2@unl.edu (H.A.); tbernadt5@unl.edu (T.B.); cpoulsen2@unl.edu (C.P.); jeffwisner@att.net (J.W.); jnothwehr2@unl.edu (J.N.); iratcliffe2@unl.edu (I.R.); kvarisco2@unl.edu (K.V.); ljohnson161@unl.edu (L.J.); criganti2@unl.edu (C.R.)

² USDA Forest Service, Northern Research Station, Monongahela National Forest, Elkins, WV 26241, USA; stephanie.connolly@usda.gov

³ Center for Advanced Land Management Information Technologies, School of Natural Resources, University of Nebraska-Lincoln, Lincoln, NE 68583-0749, USA; bwardlow2@unl.edu

⁴ Earth and Environmental Sciences Area, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA

⁵ USDA Forest Service, State and Private Forestry, Forest Health Protection, Atlanta, GA 30309, USA; christopher.asaro@usda.gov

⁶ USDA Forest Service, Southern Research Station, Research Triangle Park, Durham, NC 27713, USA; frank.h.koch@usda.gov

* Correspondence: ttadesse2@unl.edu; Tel.: +1-402-472-3383

Abstract

Forest drought monitoring tools are crucial for managing tree water stress and enhancing ecosystem resilience. The Forest Drought Response Index (ForDRI) was developed to monitor drought conditions in forested areas across the contiguous United States (CONUS), integrating vegetation health, climate data, groundwater, and soil moisture content. This study evaluated ForDRI using Pearson correlations with the Bowen Ratio (BR) at 24 Ameri-Flux sites and Spearman correlations with the Tree-Ring Growth Index (TRSGI) at 135 sites, along with feedback from 58 stakeholders. CONUS was divided into four forest subgroups: (1) the West/Pacific Northwest, (2) Rocky Mountains/Southwest, (3) East/Northeast, and (4) South/Central/Southeast Forest regions. Strong positive ForDRI-TRSGI correlations ($\rho > 0.7$, $p < 0.05$) were observed in the western regions, where drought significantly impacts growth, while moderate alignment with BR ($R = 0.35\text{--}0.65$, $p < 0.05$) was noted. In contrast, correlations in Eastern and Southern forests were weak to moderate ($\rho = 0.4\text{--}0.6$ for TRSGI and $R = 0.1\text{--}0.3$ for BR). Stakeholders' feedback indicated that ForDRI realistically maps historical drought years and recent trends, though suggestions for improvements, including trend maps and enhanced visualizations, were made. ForDRI is a valuable complementary tool for monitoring forest droughts and informing management decisions.

Keywords: forest drought; forest health; climate indices and indicators; satellite-based drought indices; tree water stress; tree-ring; Bowen Ratio



Academic Editor: Franco Biondi

Received: 9 June 2025

Revised: 11 July 2025

Accepted: 16 July 2025

Published: 18 July 2025

Citation: Tadesse, T.; Connolly, S.; Wardlow, B.; Svoboda, M.; Zhang, B.; Fuchs, B.A.; Aslam, H.; Asaro, C.; Koch, F.H.; Bernadt, T.; et al. Development and Evaluation of the Forest Drought Response Index (ForDRI): An Integrated Tool for Monitoring Drought Stress Across Forest Ecosystems in the Contiguous United States. *Forests* **2025**, *16*, 1187. <https://doi.org/10.3390/f16071187>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Forests are a vital part of the Earth's ecosystems and are crucial in maintaining the delicate balance of many natural environmental processes [1,2]. Ongoing climate and

biodiversity crises significantly impact forest ecosystems, which account for 80%–90% of global plant biomass and contain much of the Earth’s terrestrial biodiversity [3]. Drought is a common, recurring climate extreme that occurs globally and can have both positive and negative impacts on forest health, depending on the spatial location and timing of precipitation [4,5]. Forest health is defined by the conditions that meet human needs, alongside the resilience, recurrence, persistence, and biophysical processes that result in sustainable ecological conditions [6].

As climate change progresses, droughts are expected to become more severe, frequent, and prolonged throughout much of the U.S. [7–11]. Drought can have a negative impact on tree growth, resulting in leaf loss and decreased canopy cover. This, in turn, diminishes nutrient cycling and alters the amount of sunlight that reaches the forest floor. [12–14]. Prolonged or severe drought significantly impacts forests [15,16], placing chronic stress on trees and forest ecosystem processes. While forests have some natural resistance to drought, the adverse effects of drought may take several years to appear and require additional time to recover [17,18]. For instance, California faced five consecutive years of drought from 2012 to 2016, contributing to the death of over 100 million trees. The development of this situation made millions of additional trees more vulnerable to insect infestations and disease outbreaks [19,20]. Similarly, New Mexico endured severe drought conditions in the early 2000s, resulting in widespread mortality of piñon pines (*Pinus edulis* Engelm, two-needle piñon), with estimates indicating a 90% loss in some areas, due to drought stress and subsequent bark beetle infestations [21].

Water supply significantly impacts forest health and gross primary productivity [4,5,22,23]. As drought conditions intensify, trees take measures to minimize water loss. Initially, they close their stomata to reduce short-term water loss. Over the long term, this can increase growth allocation to their root systems and reduce above-ground biomass [13,24]. However, under prolonged or severe drought conditions, trees may resort to extreme responses, such as shedding leaves. Severe drought can also cause cavitation in the tree’s water transport system, leading to rapid mortality [13]. With drought projected to become more prevalent across the U.S., more impacts are to be expected.

Forest ecosystems vary significantly across regions and are influenced by several factors, including tree species composition, disturbance regimes, and exposure to extreme climate conditions, such as drought [25]. Soil water availability is crucial for the health of these ecosystems, emphasizing the importance of understanding the hydrologic variables that impact forest sustainability. However, geographical patterns in soil moisture availability often precede species-specific responses to drought [26].

Improved near-real-time forest drought monitoring tools are essential for effective forest management and enhancing long-term drought resilience. A drought monitoring tool developed specifically for forests is vital for enhancing forest management practices [15,27,28]. Integrating drought monitoring indices and indicators could change static forest management into adaptive strategies using near-real-time data to enhance resilience and mitigate climate-related issues like wildfires and pest outbreaks [29]. The primary goal of a forest stress indicator is to assess when trees begin to experience significant drought stress that can trigger physiological responses by limiting water loss. This water loss can ultimately impact tree growth and increase their vulnerability to biotic threats (e.g., pests and diseases) and abiotic stressors (e.g., extreme temperatures and soil degradation).

Various methods have traditionally been used to monitor drought conditions in forested areas. Most conventional techniques rely primarily on climate data, particularly precipitation and temperature measurements, as well as drought indices derived from this data. Climatic variables are increasingly available as gridded geospatial datasets derived from observations made at weather stations. Approaches based on climatic data,

while helpful, tend to characterize forest drought indirectly [28]. Climate-based drought indices, such as the Keetch-Byram Drought Index (KBDI), the Palmer Drought Severity Index (PDSI), and the Root Zone Soil Moisture (RZSM), focus on quantifying moisture deficits. However, they do not directly measure the canopy stress response of forests caused by drought or the mortality rates among trees in forest stands. Instead of directly evaluating the physiological state of forests, these indicators primarily reflect the potential impacts of climatic variables, such as rainfall and temperature anomalies. This limitation indicates the need for more comprehensive drought monitoring tools that consider other types of environmental information in addition to more effectively characterizing forest drought conditions.

Remote sensing techniques are increasingly used to monitor forests, offering spatially continuous observations at higher resolutions than traditional climate indicators that rely on discrete station data [30,31]. However, these methods have limitations in establishing the impact of drought on forests, as multiple factors can affect reflectance values and, consequently, forest health. For example, traditional remote sensing tools like the Normalized Difference Vegetation Index measure canopy greenness but often struggle to distinguish drought stress from background noise in dense, multi-layered forests due to saturation effects. Therefore, remote sensing data alone cannot identify forest drought response [28]. Additionally, forests have various tree species, each exhibiting different levels of drought tolerance, further complicating drought monitoring in these ecosystems [24].

Hybrid indices like the Vegetation Drought Response Index (VegDRI) have been developed in the past decade to improve drought monitoring of specific ecosystems [32]. VegDRI integrates satellite-derived vegetation indices with climate and biophysical data. However, this tool primarily focuses on seasonal drought monitoring and does not address the long-term impacts of prolonged drought. While VegDRI is effective for monitoring drought in croplands and grasslands, it lacks parameters specifically tailored to address forest-specific drought responses, such as delayed tree mortality, species-specific vulnerability, and subsurface water deficits in trees. VegDRI also does not incorporate specific remote sensing indicators, such as soil moisture estimates and evapotranspiration data. Including these additional datasets can provide valuable insights into forest water availability and stress, therefore improving forest drought monitoring.

Because forest ecosystems are complex, existing tools have limitations for monitoring drought-related forest stress. Thus, a drought monitoring tool that combines climate and satellite data, like VegDRI, but is designed specifically for monitoring water stress in forests, is needed. When integrated with climate and other hydrologic model-based outputs, these datasets can enhance forest drought monitoring by developing forest-specific indicators.

This study develops and evaluates the Forest Drought Response Index (ForDRI) to monitor forest drought conditions across the contiguous United States (CONUS). It builds upon a proof-of-concept ForDRI initially created by Tadesse et al. [28] to assess drought conditions in eastern U.S. forests. The ForDRI is designed to identify drought signals specific to forests while considering historical climate data and other ecological factors, thereby addressing the complex nature of forest ecosystems. In this research, we enhance previous methods and broaden the dataset by integrating additional historical data from 2003 to 2022 to develop the model, while the evaluation includes unseen data from 2023 to 2025. Our goal is to develop the ForDRI model specifically for CONUS and assess its performance across various forested ecosystems using quantitative techniques and expert-led qualitative assessments.

2. Materials and Methods

2.1. Study Area: U.S. Department of Agriculture Forest Service (USFS) Forest Cover for the Contiguous United States

The study area covers the contiguous United States. The ForDRI is specifically designed for forested regions utilizing the national forest types and forest groups geospatial dataset obtained from the USFS [33], which has a spatial resolution of 1 km. This forest type group layer was created in 2023 using over 213,000 national forest inventory plots measured between 2014 and 2018 by the USDA Forest Service's Forest Inventory and Analysis (FIA) program, along with other supplementary information [33]. Figure 1 illustrates the forest cover for the CONUS as produced by the USFS. This forest cover map was used to distinguish forest areas from other types of land cover.

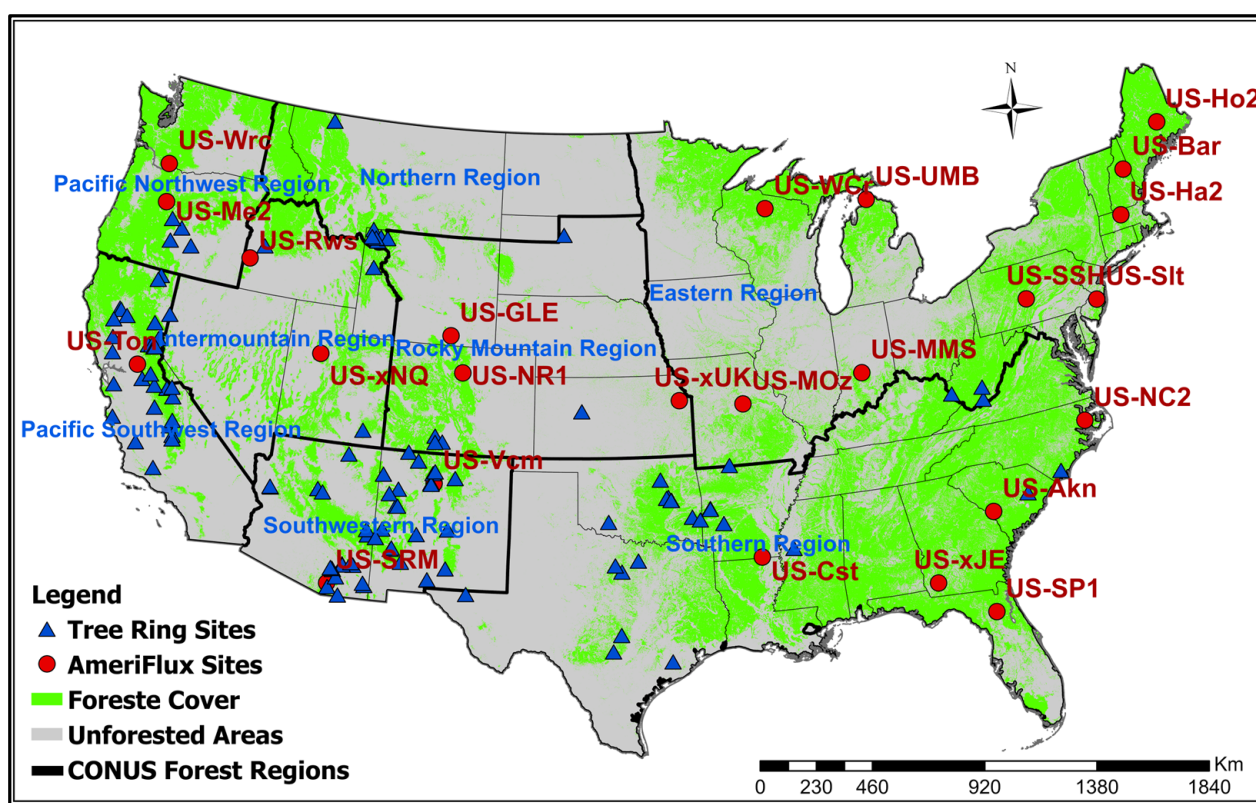


Figure 1. Study area: Forest cover for the contiguous United States (light green) produced by the U.S. Forest Service [33]. The red circle indicates 24 AmeriFlux sites, while the 135 blue-black triangles represent the tree-ring sites used to evaluate the ForDRI in this study.

The ForDRI values for each 12.5 km grid (resampled to 1 km for visualization) were calculated exclusively for forested areas [33]. To evaluate the ForDRI, twenty-four AmeriFlux sites (marked with a red circle in Figure 1) across CONUS. The AmeriFlux network comprises a community of scientists and sites that measure carbon, water, and energy fluxes throughout the Americas, dedicated to producing and sharing high-quality eddy covariance data from AmeriFlux [34]. Additionally, sixty-five tree-ring sites (indicated by blue-black triangles in Figure 1) with relatively long historical records (a minimum of seven years) were included.

2.2. Development of Improved ForDRI Models for the Contiguous United States

Based on the preliminary evaluation of the proof-of-concept ForDRI models for the eastern U.S. [28], we developed enhanced ForDRI weekly models for the contiguous United States by incorporating an additional five years of historical data, now covering 2003 to 2022.

To further improve these models and refine spatial representation, we applied principal component analysis (PCA)'s nearest neighborhood (PCA-nearest) method and integrated local spatial context using a fixed-size spatial kernel uniformly across all datasets [35]. Using a five-by-five sliding window technique, we analyzed the data matrix by extracting five-by-five submatrices and converting each into one-dimensional feature vectors. This method is similar to the receptive field concept used in convolutional neural networks (CNNs) and helps maintain localized spatial variability [36].

The enhanced PCA-nearest method leverages neighborhood-level spatial correlations, addressing limitations in earlier proof-of-concept ForDRI models that treated individual pixels independently. By aggregating information across five-by-five-pixel windows, the improved ForDRI models smooth values, mitigate artifacts from individual data points, and eliminate extreme values that are inconsistent with the surrounding area.

The ForDRI maps were produced at weekly intervals. Table 1 shows the input variables used for developing the ForDRI weekly models. The satellite-based input variables include USGS Earth Resources Observation and Science (EROS) Moderate Resolution Imaging Spectroradiometer (eMODIS) normalized difference vegetation index (NDVI) data and groundwater storage (GWS) measurements at a depth of 1 m from NASA's Gravity Recovery and Climate Experiment (GRACE) satellites [28,37]. The climate component incorporated several Standardized Precipitation Index (SPI) datasets for time frames of 9 months, 12 months, 24 months, and 60 months, as well as Standardized Precipitation-Evapotranspiration Index (SPEI) datasets for 12-, 24-, and 60-month periods. The other environmental input variables included NOAA's NOAH soil moisture estimates (NLDAS-2) for the upper soil layer (10 to 40 cm depth) from NOAA's North American Land Data Assimilation System (NLDAS) Drought Monitor Soil Moisture datasets, Vapor Pressure Deficit (VPD) data from the PRISM Climate Group (Oregon State University) and a 12-month Evaporative Demand Drought Index (EDDI) from the NOAA Physical Sciences Laboratory.

Table 1. Input variables, data types, historical period length, sources, and resolution of the datasets for the ForDRI models.

Original Variables	Data Type	Data Source	Historical Period	Resolution
MODIS-based Normalized Difference Vegetation Index (NDVI)	Satellite	AQUA MODIS NDVI V6	2002–2022	1 km, weekly
Groundwater Storage (GRACE)	Satellite	NASA GSFC Hydrological Sciences Laboratory	2002–2022	0.125 degrees, daily
Standardized Precipitation Index (9-,12-,24-,60-month SPI)	Climate	Applied Climate Information System (ACIS)	1950–2022	Interpolated to 1 km (IDW), weekly
Standardized Precipitation Evapotranspiration Index (12-, 24-, 60-month SPEI)	Climate	Applied Climate Information System (ACIS)	1950–2022	Interpolated to 1 km (IDW), weekly
Soil Moisture	Biophysical	NLDAS Noah	2000–2022	0.125 degrees, monthly
Evaporative Demand Drought Index (12-month EDDI)	Biophysical	NOAA Physical Sciences Laboratory	1980–2022	0.125 degrees, weekly
Vapor-pressure deficit (VPD)	Biophysical	PRISM	1981–2022	0.05 degrees, daily

The ForDRI integrates gridded information on vegetation health, climate, evaporative demand, groundwater, and soil moisture associated with forested areas across the CONUS (Figure 2). To create the ForDRI models, all 12 input datasets were reformatted, reprojected, resampled, and clipped to the areas with forest cover using the forest cover map. Except for the SPI and SPEI datasets, which are already standardized, each input dataset was also standardized (using the z-score method) to ensure consistency before integrating the datasets.

For the weekly ForDRI model, the PCA-nearest neighborhood method was used to determine the weight of each input variable at each grid cell for each week in the year, which reflects their relative (potential) contribution to forest drought conditions, as detailed in Tadesse et al. [28]. After determining the weight for the suite of input variables using the PCA-nearest neighborhood method, the weekly ForDRI values for each grid cell were calculated across the CONUS forest areas. The final ForDRI values are computed by first multiplying the input variables by their respective weights, which are determined through the PCA-nearest neighborhood method. Then, adding all weighted inputs together and standardizing the values at each grid using the z-score. The ForDRI maps are created based on these grid values in the forested areas. Figure 3 illustrates the steps from data processing to generating the ForDRI values and maps.

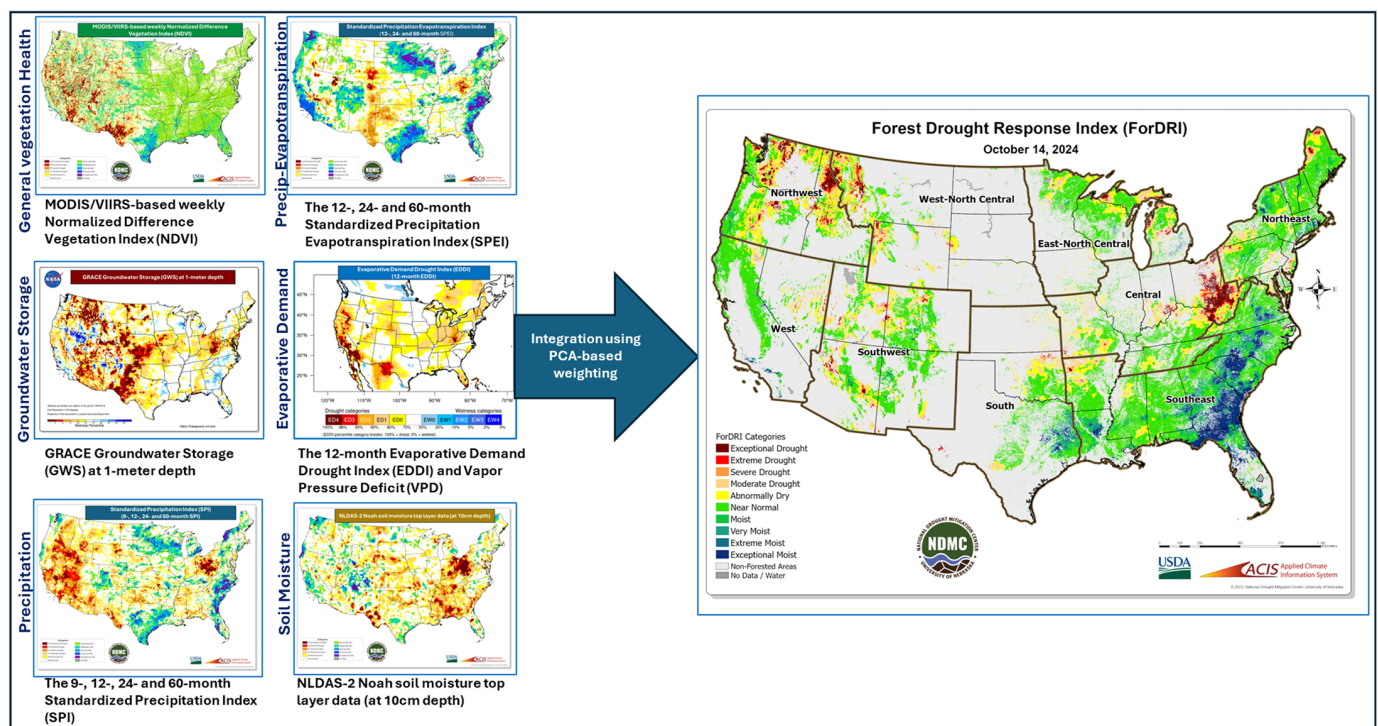


Figure 2. The Forest Drought Response Index (ForDRI) model uses climate, hydrologic, and vegetation-related gridded input variables.

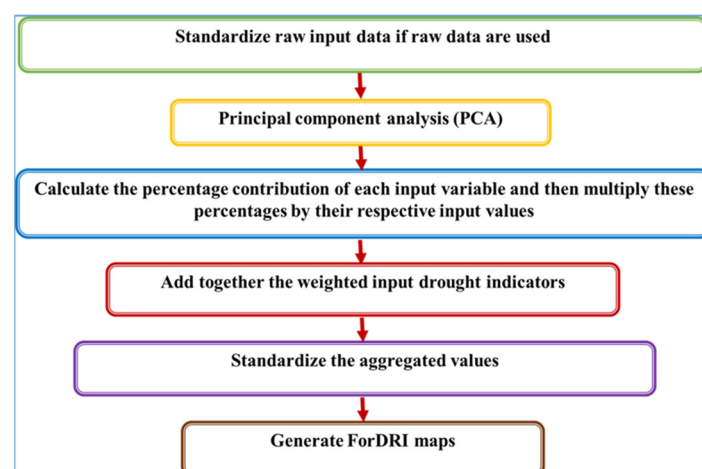


Figure 3. The general flow of the methodology to combine input variables using their contribution/weight using principal component analysis (PCA)'s nearest neighborhood method to generate ForDRI values/maps.

After the ForDRI map is produced, the maps are classified into ten drought categories based on the final weekly ForDRI values of each grid, as shown in Table 2.

Table 2. Forest Drought Index (ForDRI) classification.

ForDRI Values	ForDRI Categories
$\text{ForDRI} \leq -2$	Exceptional Drought
$-2 < \text{ForDRI} \leq -1.5$	Extreme Drought
$-1.5 < \text{ForDRI} \leq -1$	Moderate drought
$-1 < \text{ForDRI} \leq -0.5$	Pre-drought Stress
$-0.5 < \text{ForDRI} \leq 0.5$	Normal
$0.5 < \text{ForDRI} \leq 1$	Moist
$1 < \text{ForDRI} \leq 1.5$	Very Moist
$1.5 < \text{ForDRI} \leq 2$	Extreme Moist
$\text{ForDRI} > 2$	Exceptionally Moist

2.3. Evaluation of Improved ForDRI Models for the Contiguous United States

Over one thousand weekly historical maps (2003 to 2025) were produced for further analysis using fifty-two ForDRI weekly models. After creating these historical weekly ForDRI maps, one of the most critical and challenging tasks was evaluating the modeled products. Evaluation is essential to ensure the accuracy of the ForDRI maps in guiding forest management recommendations and drought response. However, several challenges arise during this process, including the limited availability of ground-truth data in complex forest ecosystems, the difficulty of isolating the impacts of drought from other disturbances such as pests and fires, and the mismatches in scale between coarse satellite inputs (e.g., soil moisture) and localized forest conditions. Model biases may also occur due to oversimplified assumptions about species-specific resilience or delayed effects of drought. The sections below describe the evaluation methods and approaches employed in this study.

The previous study by Tadesse et al. [28] validated the ForDRI model in the eastern United States by comparing output maps and data with the U.S. Drought Monitor (USDM) [38], the normalized Bowen Ratio (BR), and tree-ring data. The results showed that the ForDRI model performed exceptionally well in identifying extreme drought events in forests. Both qualitative and quantitative analyses indicated promising results for expanding the application of the ForDRI proof-of-concept models to other regions of the CONUS.

This research developed the ForDRI tool for the CONUS region and evaluated its performance using both quantitative and qualitative approaches. The quantitative approach compared ForDRI for CONUS forest regions with the Tree-ring Standardized Growth Index (TRSGI) and assessed the relationship between ForDRI and the BR at AmeriFlux sites. The qualitative approach involved gathering expert feedback on ForDRI maps through case studies, which highlight the subjective experiences of forest experts, forest managers, and other stakeholders regarding the impact of drought on forests, collected via a series of webinars in different forest regions of the CONUS.

2.3.1. Evaluating ForDRI with the Tree-Ring Standardized Growth Index (TRSGI)

Numerous studies have shown that tree growth is sensitive to local climate conditions. As a result, tree-ring chronologies (tree growth ring widths) can provide valuable insights for monitoring forest drought because tree-ring widths are reflective of annual climatic conditions and resulting vegetation productivity [39–41]. By comparing series of ForDRI values with tree-ring widths over the same timeframe, we can obtain information about

drought-tree growth interactions that can be used to evaluate the model's performance in identifying forest drought.

According to NOAA's International Tree-Ring Data Bank (ITRDB), the Tree-ring Standardized Growth Index (TRSGI) is calculated by standardizing raw ring-width data from a site by fitting a curve to the data to account for natural growth trends, such as age-related declines [42]. Each ring-width value is divided or subtracted from the corresponding curve value, generating growth indices. This method standardizes samples with different growth rates, eliminating irrelevant trends. For example, if a sample exhibits an exponential decline in growth because of trunk size, a negative exponential function can be used to standardize it. This process results in values that represent deviations from the expected growth. These standardized indices can then be utilized to analyze environmental signals [42]. To evaluate ForDRI, the TRSGI values were calculated for 135 sites with relatively long historical records (more than 7 years) since 2003.

One of the challenges in comparing ForDRI data with the normalized TRSGI is the difference in the frequency of records between the two datasets. TRSGI provides yearly data, while ForDRI operates on a weekly time step. To address this discrepancy, ForDRI data calculated weekly were integrated into growing seasonal (May to October) and yearly values.

2.3.2. Calculation of Integrated ForDRI for Evaluation: Aggregation of ForDRI Values for TSGI Correlation Analysis

To evaluate the ForDRI alongside the TRSGI, we followed these steps: (i) classified the ForDRI values into four levels of dryness/drought (see Table 3), (ii) counted the frequency of each dryness level for each tree site for each year, and (iii) integrated the frequencies using Equation (1), which is based on the Drought Severity and Coverage Index [43]. The weights assigned using Equation (1) were determined based on the empirical knowledge of drought experts, who stated that as the dryness level increased, a higher weight was assigned to the corresponding drought frequency to identify the potentially significant impacts of more severe drought events. If there are few or no minor drought events during a growing season, the yearly ForDRI will equal or be close to 1. Conversely, increasing the number and severity of drought events within a growing season will lead to a higher yearly ForDRI value.

$$\text{Integrated ForDRI} = f_1 \cdot 1 + f_2 \cdot 2 + f_3 \cdot 3 + f_4 \cdot 4, \quad (1)$$

where f_i is the frequency of the i th dryness level.

Table 3. Levels of dryness based on ForDRI values.

Dryness Level	ForDRI	Assigned Weight
1	$\text{ForDRI} \geq 0$	1
2	$0 > \text{ForDRI} \geq -1$	2
3	$-1 > \text{ForDRI} \geq -2$	3
4	$-2 > \text{ForDRI}$	4

Bivariate Spearman correlation and time series analyses were applied in the growing season to evaluate the relationship between the normalized TRSGI and the ForDRI values.

2.3.3. Evaluating ForDRI with Normalized Bowen Ratio (BR) Data

The BR is a key metric for assessing forest drought conditions because it is sensitive to water availability and plant stress [44]. It measures the ratio of sensible heat flux (the energy that warms the air) to latent heat flux (the energy that drives evapotranspiration). A high

BR indicates reduced latent heat flux due to low water availability for evapotranspiration, signaling drought stress in forest ecosystems [45]. This measure complements other drought indices and provides insight into how forests respond to heat and water scarcity [28].

Tadesse et al. [28] demonstrated a significant correlation between ForDRI and the BR during extreme drought events in the eastern U.S. The same approach was used to further investigate the relationship between the normalized BR and the ForDRI across CONUS. In this study, the BR (β) is defined using sensible heat flux (H) and latent heat flux (λL) as shown in Equation (2). Understanding this process allows us to assess forest-related water deficit stress based on changes in stomatal conductance. During periods of forest water deficit stress, characterized by high temperatures and vapor pressure deficits, combined with low precipitation and low soil moisture content, stomatal conductance can be significantly limited. This results in an increase in sensible heat flux and BR values.

$$\beta_i = \frac{\sum H}{\sum \lambda L} \quad (2)$$

The 30 min sensible and latent heat flux datasets (no gap-filled values) were acquired from 24 AmeriFlux sites. The processing and integration of the flux data were the same as in the previous work by Tadesse et al. [28]. The 30 min flux data during the growing season were first aggregated to the 7-day (weekly) scale to match the temporal resolution of the ForDRI with a filter of both H and λL higher than 50 Wm^{-2} to reduce noise in the dataset. To reduce seasonal variations and make values comparable across sites, the integrated BR was log-transformed and normalized based on the weekly mean and standard deviations in the growing season (Equation (3)).

$$\text{Normalized } \beta_i = -\frac{\log_{10}\beta_i - \overline{\log_{10}\beta_l}}{\sigma} \quad (3)$$

In Equation (3), the standard normalization function used to calculate the Z-score was multiplied by -1 to maintain consistency with the interpretation of the ForDRI. Negative values indicate drier conditions, while positive values indicate wet conditions. In this equation, β_l represents the weekly mean of the BR, and σ denotes the weekly standard deviation.

The weekly ForDRI models were quantitatively evaluated using 1040 historical weekly ForDRI maps from 2003 to 2022. In addition, 104 ForDRI weekly maps for 2023–2024 were added for qualitative assessment in recent years' case studies. Because of potential regional differences in the impact of drought on forests across the CONUS, forest regions were categorized into four groups (Figure 4) based on their geographic locations: (i) the West and Pacific Northwest Forest regions, (ii) the Rocky Mountain and Southwest Forest regions, (iii) the East and Northeast Forest regions, and (iv) the South, Central, and Southeast Forest regions.

Spearman and Pearson correlation methods were used for quantitative analysis. Because ForDRI and tree-ring data are assumed to have a monotonic relationship and do not follow a normal distribution, Spearman's correlation method was used, which is more appropriate for measurements from ordinal scales. In contrast, Pearson's correlation was used to compare the ForDRI and BR, which are expected to have a linear relationship. The key findings from the correlation analyses are presented in Section 3 (Results section) for each forest group.

Additionally, the summary of the ForDRI-TRSGI Spearman's correlation (ρ) and ForDRI-BR Pearson's correlation (R) are provided in Tables S1 and S2, respectively, as supplementary data to show detailed results. Table S1 presents Spearman's correlation between the ForDRI and the TRSGI at 135 tree-ring sites across CONUS. For each tree-ring

3. Results

3.1. Evaluation of ForDRI for the West and Pacific Northwest Forest Regions

3.1.1. Evaluation of ForDRI Using Tree-Ring and Bowen Ratio for the West and Pacific Northwest Forest Regions

ForDRI-TRSGI Correlation: Forty-two tree-ring sites were analyzed for this forest region group (Figure 4). ForDRI showed a high Spearman correlation (ρ) with TRSGI (tree-ring) in the West and Pacific Northwest Forest regions, notably California and Idaho. For example, in California, strong positive correlations dominate at sites like CA678 (Jeffrey Pine (*Pinus jeffreyi* Balf), $\rho = 0.90$, $p < 0.05$) and CA660 (blue oak (*Quercus douglasii* Hook. & Arn), $\rho = 0.87$, $p < 0.05$), reflecting acute drought sensitivity in shallow-rooted species under the state's Mediterranean climate, particularly during summer dry spells. However, negative correlations at CA665 (blue oak, $\rho = -0.85$, $p < 0.05$) and CA726 (giant sequoia (*Sequoiadendron giganteum* (Lindl.) J. Buchholz), $\rho = -0.66$, $p < 0.05$) suggest buffering that may have resulted from fog or deep soil moisture in certain ecosystems. This may also be due to poor data quality or heavy rainfall, which can saturate the ground with water. Such a condition hinders root growth and ultimately reduces the tree's growth, resulting in narrower tree rings similar to those produced during drought.

In the rest of the Pacific Northwest, the ForDRI-TRSGI generally shows moderate to strong positive correlations, though with slightly more variability, potentially due to maritime influences. Oregon, Idaho, and Montana exhibit consistently strong correlations [$\rho = 0.72$ – 0.91 , $p < 0.05$], primarily in high-elevation coniferous sites where drought stress is a primary constraint on growth. For example, Oregon's semi-arid juniper stands (e.g., OR093, $\rho = 0.86$, $p < 0.05$) and Idaho/Montana's high-elevation conifers (e.g., ID015, ponderosa pine (*Pinus ponderosa* ex C. Lawson), $\rho = 0.68$, $p < 0.05$; MT117, subalpine fir (*Abies lasiocarpa* (Hook.) Nutt), $\rho = 0.71$, $p < 0.05$) show robust correlations, underscoring ForDRI's utility in moisture-limited systems. Utah's UT544 (Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco), $\rho = 0.53$, $p < 0.05$) highlights moderate accuracy in transitional arid zones, suggesting reduced sensitivity compared to drier regions.

Figure 5a illustrates the time series of the ForDRI and TRSGI values to demonstrate the ForDRI-tree ring relationship from 2003 to 2009 for the Frederick Butte Update site (western juniper forest in Oregon, OR093: $\rho = 0.86$, $p < 0.05$), showing strong Spearman's correlation.

ForDRI-BR Correlation: Five AmeriFlux sites were used for the ForDRI-BR correlation (R) in the West and Pacific Northwest Forest regions. This forest region group showed strong seasonal Pearson's correlations between ForDRI and BR, peaking in mid-to-late summer (Weeks 20–35), potentially driven by seasonal aridity and moisture stress. For example, California's US-Ton (Tonzi Ranch) shows peak correlations ($R = 0.73$, $p < 0.05$) in Week 29 (i.e., 15 to 22 July), reflecting its Mediterranean climate where summer droughts sharply reduce latent heat flux. Similarly, Oregon's US-Me2 (Metolius mature ponderosa pine forest) showed a consistent relationship in mid-to late summer, peaking in September (Week 39, $R = 0.61$, $p < 0.05$), as deep-rooted pines access subsurface water during prolonged dry spells. Conversely, a negative ForDRI-BR correlation was observed at Washington's Wind River, US-Wrc (Weeks 25 and 28, $R = -0.72$, $p < 0.05$), revealing ForDRI's inability to resolve BR signals in snow-dominated systems. These discrepancies emphasize the need for region-specific seasonal adjustments in ForDRI's model. This indicates regional limitations, as microclimate variability decouples BR from drought indices, including ForDRI.

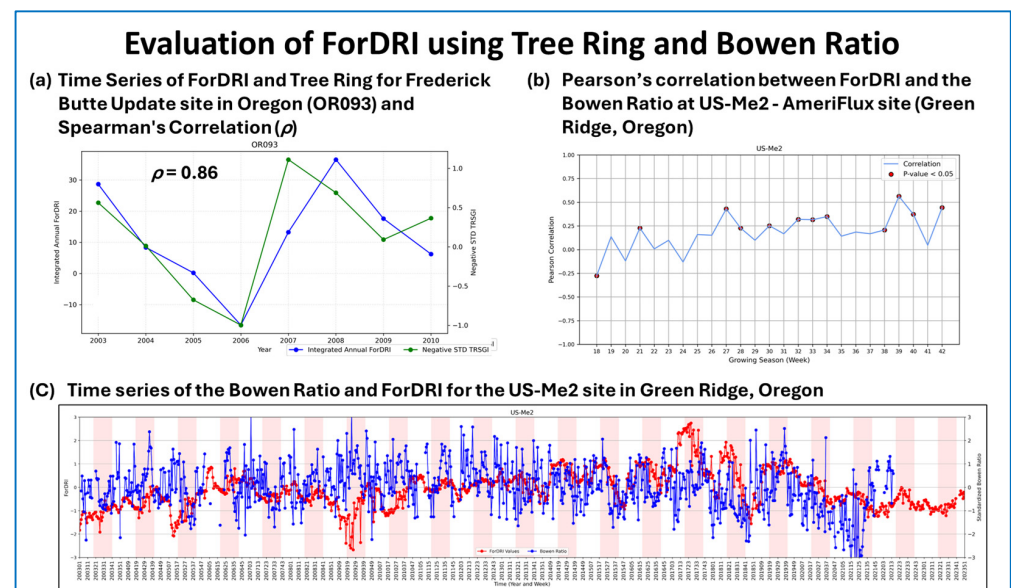


Figure 5. Comparison of the historical records of ForDRI-TRSGI (ForDRI and Tree Ring Standardized Growth Index) and ForDRI-BR (ForDRI and Bowen Ratio): (a) Time series of ForDRI and TRSGI for Frederick Butte Update site (OR093) and FORDRI-TRSGI Spearman's Correlation (ρ), (b) Pearson's correlation between ForDRI and the BR at US-Me2-AmeriFlux site (Green Ridge, Oregon), and (c) Time series of the BR and ForDRI at the US-Me2 site.

An example of Pearson's correlation (R) results between the ForDRI and BR is provided in Figure 5b for the US-Me2 site. The y -axis in Figure 5b represents Pearson's correlation, while the x -axis shows the weeks within the growing season. This ForDRI correlation with the BR was relatively high, reaching correlation values of 0.58 (p -value < 0.05). Figure 5c presents a time series of the BR and ForDRI from 2003 to 2022 for the US-Me2 site in Green Ridge within the eastern Cascade Mountains of Oregon. The rose-colored bars represent the growing season. The correlation graphs indicate that ForDRI and BR values generally followed a similar temporal pattern, especially during the growing season; however, notable differences were observed in some periods.

Generally, ForDRI's incorporation of key variables, including soil moisture values, enhanced its accuracy in the West and Pacific Northwest Forest regions. The strong summer correlations underscore ForDRI's utility in tracking evaporative stress in arid forests. However, micro-climate (e.g., coastal fog) in Washington and rapid wet-season transitions in Oregon slightly dampen late-fall correlations, as intermittent moisture complicates ForDRI-BR linkages. These patterns indicate the need to calibrate ForDRI for topographically complex areas and snow-dominated systems.

3.1.2. Qualitative Evaluation of the Webinar Participants for the West and Pacific Northwest Forest Regions

The qualitative ForDRI evaluation for the West and Pacific Northwest Forest regions covered seven states: Washington, Oregon, California, Idaho, Utah, Montana, and Nevada (Figure 6). For the case studies, weekly ForDRI maps for September 2023–September 2024 and the drought years 2022 and 2015 were included. These ForDRI maps were evaluated using the expert knowledge of the eleven participants during a webinar for this region. Participants noted that the drought depicted on ForDRI during 2023–2024 contributed to increased tree mortality, insect outbreaks, and more intense wildfires. Specifically, 75% of participants observed heightened wildfire activity, while 25% reported intense burns. The ForDRI patterns in the 2023–2024 maps were rated moderately accurate by 67% of participants, though a few discrepancies were highlighted, such as overestimated

drought conditions in western Washington. According to the participants, the 2022 maps effectively depicted the impacts of forest drought in Montana and eastern Oregon, which included issues like insect infestations and tree mortality. However, participants also noted overestimating drought conditions in some local areas during the summer, and ForDRI's delayed response in capturing drought recovery. For the 2015 case study, participants found that ForDRI accurately depicted severe drought conditions in Idaho and Montana. However, they identified an overestimation of drought intensity (i.e., more severe) in California's Sierra Nevada region. The participants noted that the ForDRI did not account for the impact of snowpack drought in Washington's Cascades.

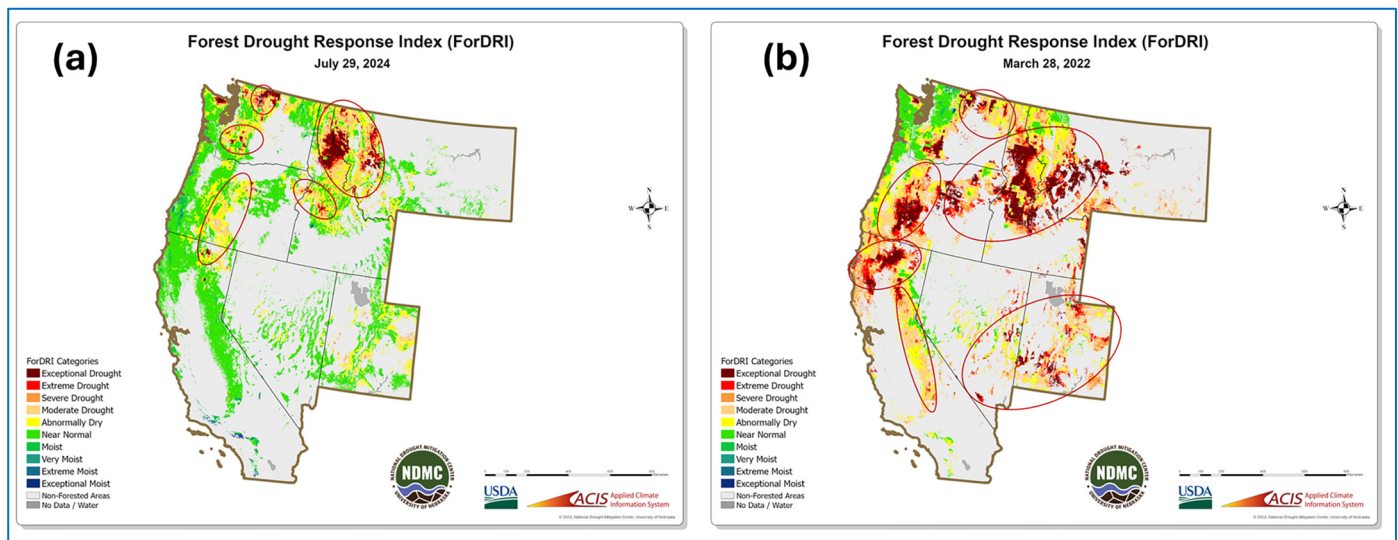


Figure 6. West and Pacific Northwest Forest regions Evaluation: examples of case study maps of Forest Drought Response Index (ForDRI) for (a) 29 July 2024, and (b) 28 March 2022. The red ovals on the maps indicate the specific drought signals considered during the evaluation.

Webinar discussions yielded detailed suggestions for improving ForDRI's accuracy and expanding its utility for this region. Participants proposed developing seasonal stress maps, trend comparisons across years, and location-specific time-series maps to better capture the critical dynamics of the growing season. They suggested incorporating additional datasets, such as SNOTEL for snow data, wildfire records, aerial surveys, and information on drought-related tree mortality and insect outbreaks. Emphasis was placed on the need for real-time data access and the integration of long-term drought patterns into analyses. Participants raised questions about the applicability of ForDRI maps in winter, when tree biological activity is minimal, and recommended developing pre-growing season ForDRI maps for wildfire management. They also highlighted the importance of including snow cover, elevation, and post-fire impacts. Additional suggestions included considering the connection between drought stress, defoliation, and insect activity, emphasizing the need to update ForDRI with new data inputs related to these areas as they become available.

3.2. Evaluation of ForDRI for the Rocky Mountain and Southwest Forest Regions

3.2.1. Evaluation of ForDRI Using Tree-Ring and Bowen Ratio for the Rocky Mountain and Southwest Forest Regions

ForDRI-TRSGI Correlation: A total of sixty-seven tree-ring sites were used for the Rocky Mountain and Southwest Forest regions. Many sites exhibit strong positive correlations between ForDRI and TRSGI in the drier interior regions. For example, Colorado's CO588 (ponderosa pine, $\rho = 0.87$, $p < 0.05$) and New Mexico's NM587 (Douglas-fir, $\rho = 0.80$, $p < 0.05$) illustrate the close relationship between ForDRI and tree-ring growth in

high-elevation coniferous forests. This shows ForDRI's accuracy in capturing intra-annual forest drought stress in Rocky Mountain ecosystems. Moderate ForDRI-TRSGI correlation was also observed at Colorado's CO656 (Bristlecone pine (*Pinus longaeva* D.K. Bailey), $\rho = 0.58$, $p < 0.05$), shown in Figure 7a. In addition, Arizona's AZ593 (Douglas-fir, $\rho = 0.76$, $p < 0.05$) and AZ590 (Douglas-fir, $\rho = 0.74$, $p < 0.05$) further validate ForDRI's reliability in semi-arid uplands.

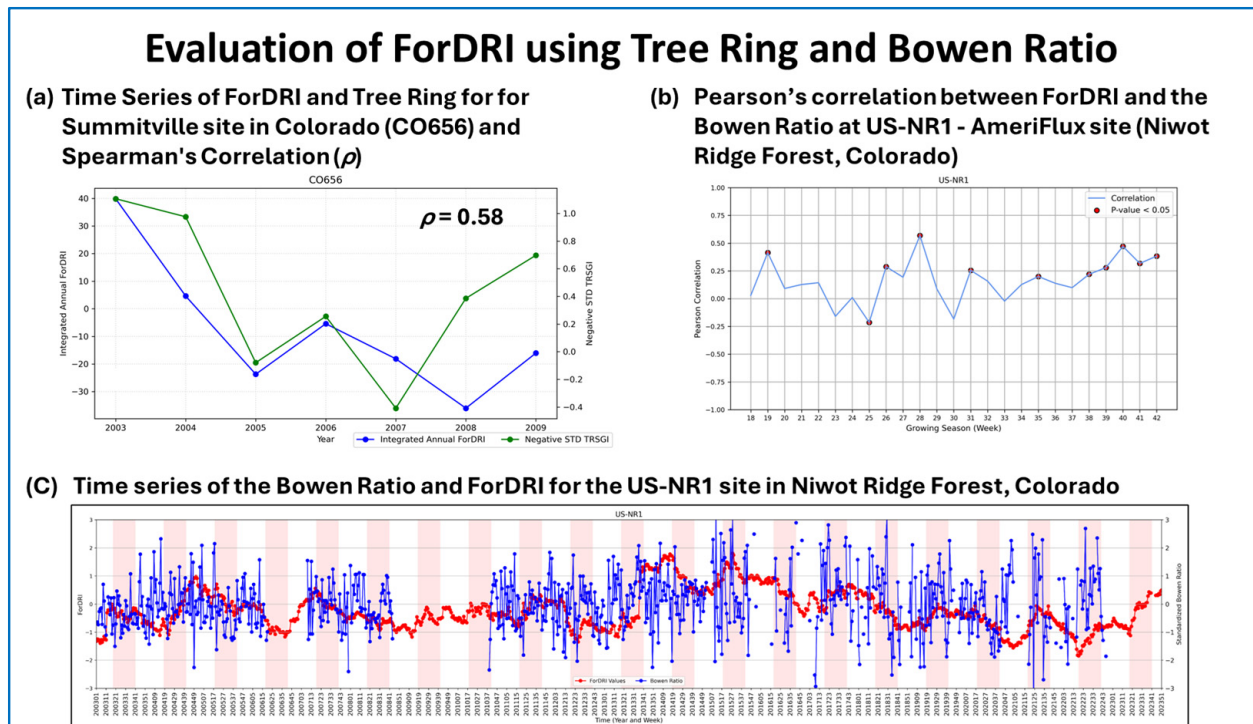


Figure 7. Evaluation of the historical records of ForDRI-TRSGI and ForDRI-BR: (a) Time series of ForDRI and ForDRI-TRSGI Spearman's Correlation for the Summitville site in Colorado (CO656), (b) Pearson's correlation between ForDRI and the Bowen Ratio at US-NR1-AmeriFlux site (Niwot Ridge Forest, Colorado), and (c) Time series of the Bowen Ratio and ForDRI for the US-NR1 site.

Limitations arise in hydrologically complex areas such as Arizona's AZ598 (ponderosa pine, $\rho = -0.18$, $p < 0.05$) and Wyoming's WY051 (lodgepole pine (*Pinus contorta* Douglas ex Loudon), $\rho = -0.42$, $p < 0.05$), which exhibit weak or negative correlations. These discrepancies may be linked to site-specific factors, such as local snowpack influences, groundwater availability, or varying levels of drought stress from year to year. These variations suggest that, although ForDRI generally performs well across the Rockies and Southwest, it could benefit from regional calibration. This would also account for lag effects and the need to incorporate snowpack dynamics, improving accuracy in snow-dependent ecosystems.

ForDRI-BR Correlation: For the Rocky Mountain and Southwest Forest regions, five AmeriFlux sites were used for the ForDRI-BR correlation. This forest region group showed mixed signals. For example, Colorado's Niwot Ridge Forest (US-NR1) showed mid-summer significance, peaking in mid-July (Week 28, $R = 0.58$, $p < 0.05$), which may be tied to intermittent drought stress in subalpine forests located just below the Continental Divide near Nederland, CO. In addition, Arizona's Santa Rita Mesquite (US-SRM: Week 41, $R = 0.57$, $p < 0.05$) and New Mexico's Valles Caldera Mixed Conifer (US-VCM: Week 20, $R = 0.55$, $p < 0.05$) show moderate correlation with ForDRI. Wyoming's US-Rws (Reynolds Creek, Week 36, $R = 0.59$, $p < 0.05$) highlights snowmelt-driven moisture replenishment, which moderately aligns BR with ForDRI. In contrast, the negative linkage at the Glacier Lakes Ecosystem Experiments Site (GLEES), Wyoming (US-GLE), peaks in July (Week 30: $R = -0.50$, $p < 0.05$), likely due to

snowmelt reducing evapotranspiration during drought. Additionally, the GLEES watershed features complex mountainous terrain, ranging from an elevation of 3200 to 3500 m. These results highlight the region's complexity, suggesting that elevation gradients and precipitation timing may be necessary to enhance the ForDRI models.

Figure 7 presents an example of the ForDRI-TSG and ForDRI-BR relationships in the Rocky Mountain and Southwest Forest Regions. Figure 7a shows the time series of the ForDRI and TRSGI values to demonstrate the ForDRI-tree ring relationship from 2003 to 2009 for the Summitville, Colorado (CO656) location. As shown in Figure 7a, Spearman's correlation between ForDRI and tree-ring with a record of CO656 is 0.58 ($p < 0.05$). Figure 7b displays the correlation between ForDRI and BR at the Colorado Niwot Ridge Forest (US-NR1) AmeriFlux site. This correlation with the BR yielded relatively low values, reaching the highest value of 0.58 ($p < 0.05$). Figure 7c shows a time series of the BR at Niwot Ridge Forest and ForDRI from 2003 to 2022. Even though some data were missing, the time-series graph shows a relatively good pattern between ForDRI and the BR across most of the study period.

3.2.2. Qualitative Evaluation of the Webinar Participants for the Rocky Mountain and Southwest Forest Regions

The qualitative evaluation of the ForDRI tool in the Rocky Mountain Forest region focused on eight states (Figure 8), with an emphasis on Colorado and Wyoming, and included case studies for the period from September 2023 to July 2024, as well as the 2022 drought year. For 2023–2024, 58% of the regional experts participating in the webinar did not observe drought impacts on forests, and 70% noted no major wildfire events during that period for the region. However, 25% reported delays and reductions in plant growth in their local area. During the 2022 drought, participants observed changes in vegetation after fires, sapling mortality, and occasional tree mortality, while 22% noted more frequent or intense wildfires. Overall, ForDRI maps for 2023–2024 were deemed very to moderately accurate by 88% of participants, though some noted discrepancies, such as severe drought conditions in areas like the Wind River Range. Similarly, the 2022 maps were found to represent drought conditions well, but they underrepresented the impacts of spring forest drought.

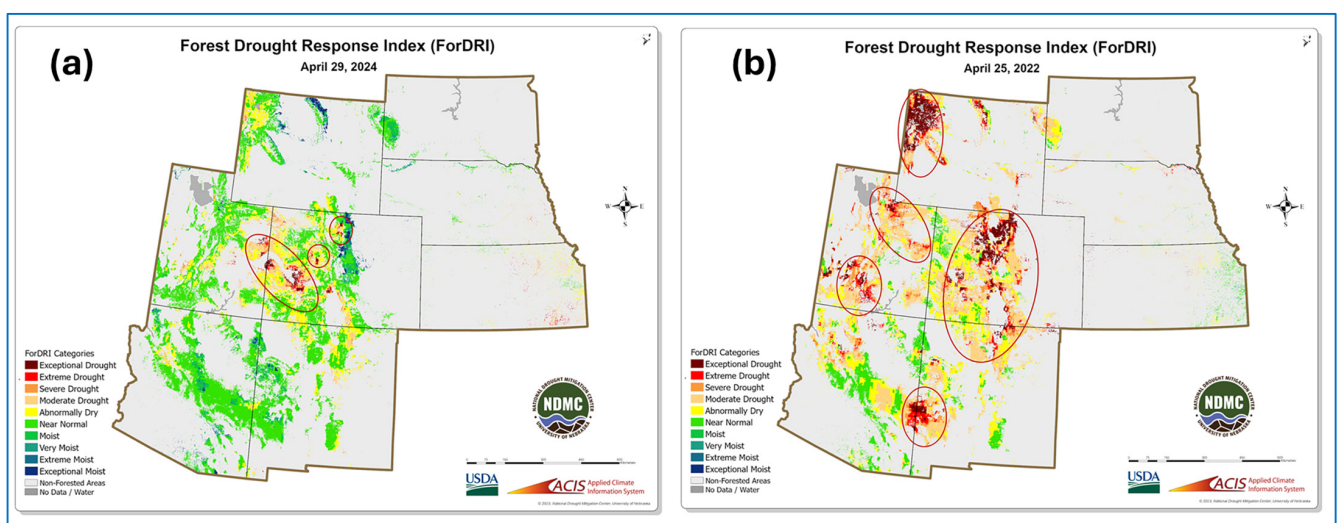


Figure 8. Rocky Mountain and Southwest Forest Region Evaluation: examples of case study maps of Forest Drought Response Index (ForDRI) for (a) 29 April 2024 and (b) 25 April 2022. The red ovals on the maps show the specific drought signals to be considered during the evaluation.

Participants suggested improving ForDRI for forest management in this region by incorporating additional data inputs, such as snowmelt, elevation, slope, and aspect. They recommended trend maps and an Application Programming Interface (API) for localized analysis, as well as tools for drawing custom polygons to retrieve region-specific time series. ForDRI could support applications such as wildfire management, reforestation planning, and agricultural guidance, addressing questions like the downstream impacts of forest drought on water availability. Validation resources, such as burn severity trends, field plots, aerial surveys, and seedling survival data, were proposed. Participants also highlighted the need for county- or state-level maps and user-defined areas for focused analysis. Other ideas included integrating U.S. Forest Service reforestation and health surveys and offering real-time data for dynamic forest management applications. Breakout discussions emphasized refining the utility of ForDRI maps, particularly for stakeholders such as fire analysts and forest managers.

3.3. Evaluation of ForDRI for the East and Northeast Forest Regions

3.3.1. Evaluation of ForDRI Using Tree-Ring and Bowen Ratio for the East and Northeast Forest Regions

ForDRI-TRSGI Correlation: Spearman's correlation between ForDRI values and tree-ring width demonstrated encouraging results across the East and Northeast Forest regions. Due to data limitations, only four tree-ring sites were used for the ForDRI-TRSGI correlation in this region. For example, Missouri's MO084 (post oak (*Quercus stellata* Wangenh)), $\rho = 0.58$, $p < 0.05$) and West Virginia's WV006 (eastern hemlock (*Tsuga canadensis* (L.) Carrière), $\rho = 0.60$, $p < 0.05$) show moderate correlations, indicating ForDRI's utility during acute droughts in upland forests. However, weak or negative correlations dominate elsewhere. For example, West Virginia's WV009 (pitch pine (*Pinus rigida* Mill), $\rho = -0.07$, $p = 0.005$) reflects growth decoupling from drought in cooler, mesic forests where temperature, not moisture, drives growth cycles. Lacking sufficient tree ring data sites for most Northeastern states (e.g., Maine and New York) limits the ability to draw broader conclusions.

Figure 9a presents a time-series graph that evaluates the ForDRI using Spearman's ForDRI-BR correlation, plotting the time-series data of ForDRI and TRSGI from 2003 to 2012 for the West Virginia Pipestem Resort State Park site (WV006). This graph (Figure 9a) shows a moderate Spearman's correlation of 0.60 between ForDRI and TRSGI. However, the lack of sufficient tree-ring data from other states limits broader regional generalizations, indicating a need for expanded monitoring in eastern deciduous forests and an alternative validation method.

ForDRI-BR Correlation: Nine AmeriFlux sites were used for the ForDRI-BR correlation in the East and Northeast Forest regions. ForDRI shows moderate to strong correlations ($R = 0.4$ – 0.9) in deciduous and mixed forests, with peak accuracy in late summer. For example, the Missouri Ozark Site (US-MOz) shows moderate average correlation between ForDRI and BR ($R \approx 0.34$, $p < 0.05$), with peak correlations in Weeks 31–33 ($R = 0.85$ – 0.86 , $p < 0.05$) during late-summer drought stress in oak-hickory forests. These peaks align with heightened evapotranspiration suppression under seasonal moisture deficits, which ForDRI captured effectively. However, negative correlations in late fall (Week 50: $R = -0.52$, $p < 0.05$) suggest limitations in modeling during the cold season.

In contrast, the Howland Forest site (US-Ho2) in Maine exhibited a weak average correlation between ForDRI and BR ($R \approx -0.01$, $p < 0.05$), with significant seasonal extremes. The strongest positive correlation occurs in Week 51 ($R = 0.57$, $p < 0.05$) during late fall, likely reflecting residual drought stress before winter dormancy. In contrast, the sharpest negative correlation at US-Ho2 is observed in Week 4 ($R = -0.93$, $p < 0.05$), likely due to snowpack insulating soils and masking actual moisture conditions.

Similarly, the Morgan Monroe site (US-MMS) exhibits moderate average correlation between ForDRI and BR ($R \approx 0.28$, $p < 0.05$), with a strong peak in mid-July (Week 28, $R = 0.73$, $p < 0.05$), reflecting drought-driven evapotranspiration suppression in temperate hardwood forests.

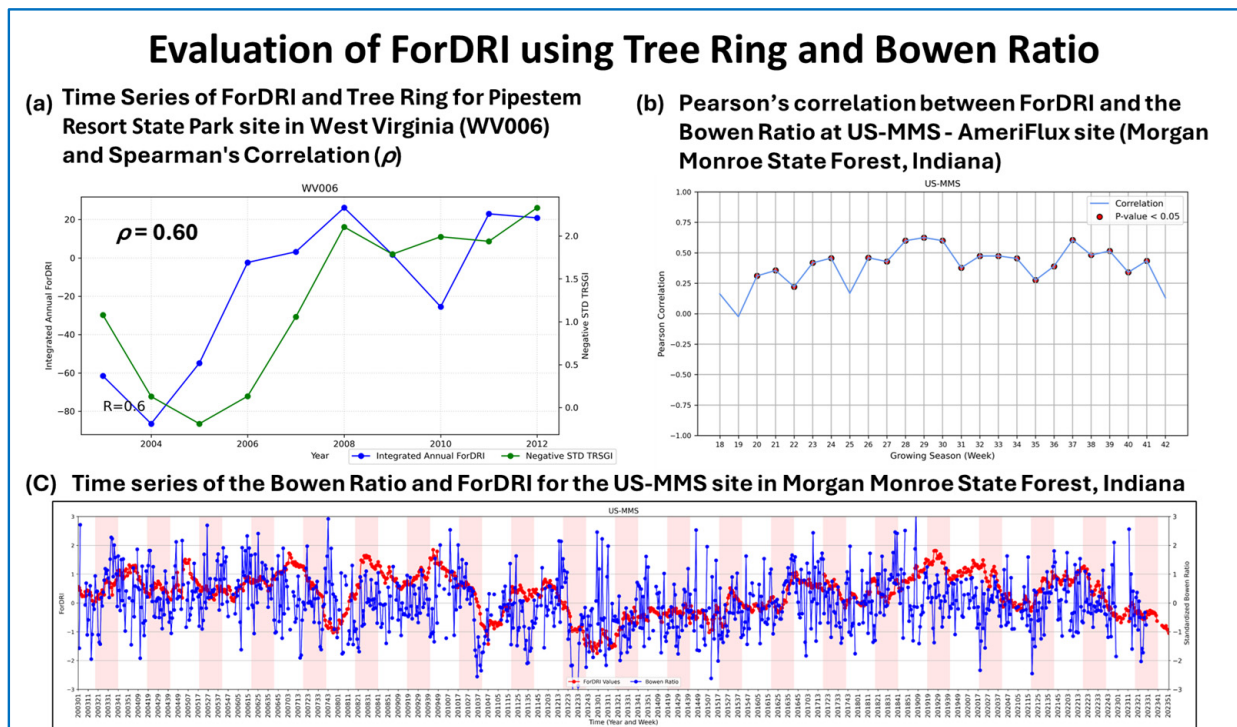


Figure 9. Comparison of the historical records of ForDRI-TRSGI and ForDRI-BR: (a) Time series of ForDRI and TRSGI with ForDRI-TRSGI Spearman's Correlation for Pipestem Resort State Park site in West Virginia (WV006), (b) Pearson's correlation between ForDRI and the Bowen Ratio at US-MMS-AmeriFlux site (Morgan Monroe State Forest, Indiana), and (c) Time series of the Bowen Ratio and ForDRI for the US-MMS site.

Figure 9b illustrates the correlation between ForDRI and BR at the US-MMS AmeriFlux site, revealing a moderate average correlation between ForDRI and BR ($R \approx 0.28$, $p < 0.1$), with a strong peak in mid-July (Week 28, $R = 0.73$, $p < 0.05$), reflecting drought-driven evapotranspiration (ET) suppression in temperate hardwood forests. Additionally, Figure 9c presents a time series analysis of BR and ForDRI from 2003 to 2022 for US-MMS in Indiana, highlighting the relatively similar temporal patterns observed in ForDRI and BR.

3.3.2. Qualitative Evaluation of the Webinar Participants for the East and Northeast Forest Regions

The evaluation webinar for the East and Northeast Forest regions (Figure 10) included 18 participants who provided feedback on ForDRI maps. For the 2023–2024 case study year, most participants (78%) reported that they did not observe any impact of drought on forests. However, a small portion of participants (3%) noted an increase in invasive or non-native plant species and instances of trees dying during this period. A forest health expert participating in the discussion commented that the long-term effects of drought on hardwood trees in this region will not be fully understood until the leaves emerge next spring. The impacts of drought, including tree decline or mortality, are often widespread and challenging for surveyors to measure accurately. In the case study focused on the 2016 drought, many participants reported that they did not observe or recall any effects of the drought on forests.

Overall, the 2024 ForDRI maps have been reasonably representative of the drought conditions. These ForDRI maps also indicate green and moist conditions in the Northeast region during the 2023–2024 period. However, for instance, the upper valley of New Hampshire experienced dry soil conditions in May 2024, as measured by soil moisture at a 1 m depth, which was not reflected on the maps. Participants observed that ForDRI maps are helpful for fieldwork in forested areas by offering insights into site and moisture conditions, as well as expectations regarding whether the site is wetter or drier than usual for the landscape. Additionally, drought-related decisions within the forestry community could benefit from ForDRI data, particularly in determining the timing for prescribed burning (go/no-go decisions) based on current drought conditions. In contrast, for the 2016 drought case study, only 20% of respondents recalled observing tree deaths. Tree mortality due to drought in northeastern US forests is likely rare because temperate deciduous tree species have a strong capacity for carbon storage [46].

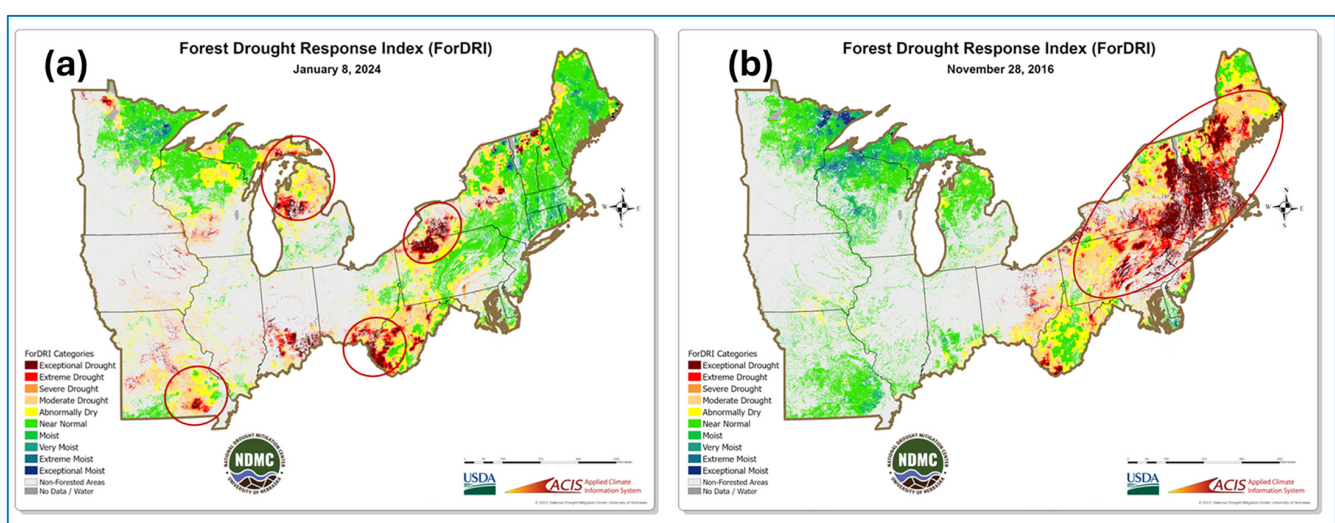


Figure 10. East and Northeast Forest Regions Evaluation: examples of case study maps of Forest Drought Response Index (ForDRI) for (a) 8 January 2024 and (b) 15 August 2016. The red ovals on the maps show the specific drought signals to be considered during the evaluation.

3.4. Evaluation of ForDRI for the South, Central, and Southeast Forest Regions

3.4.1. Evaluation of ForDRI Using Tree-Ring and Bowen Ratio for the South, Central, and Southeast Forest Regions

ForDRI-TRSGI Correlation: Twenty-two tree ring study sites were utilized for the ForDRI-TRSGI correlation in this region. The ForDRI-TRSGI data showed a strong Spearman's correlation in these regions where tree-ring (TRSGI) data aligns closely with ForDRI's drought signals in the South and Central Forest regions, particularly in Oklahoma and Texas. For example, Oklahoma's shortleaf pine (OK038, $\rho = 0.92$, $p < 0.05$) and Texas's post oak (TX051, $\rho = 0.85$, $p < 0.05$) showed high correlation between ForDRI and growth suppression. In addition, Mississippi's MS003 (baldcypress (*Taxodium distichum* (L.) Rich.), $\rho = 0.47$, $p < 0.05$) shows moderate correlations and may be suitable for upland monitoring. However, floodplain ecosystems like South Carolina's baldcypress (SC007, $\rho = 0.06$, $p < 0.05$) and Arkansas's AR078 (shortleaf pine, $\rho = 0.21$, $p < 0.05$) exhibit minimal correlations likely due to groundwater buffering, where persistent soil moisture decouples growth from drought. This contrast highlights ForDRI's strengths in arid systems but weaknesses in hydrologically dynamic regions. Moreover, the limited availability of data, particularly short overlap periods in tree-ring records for southeastern states like Florida, reduces the reliability of ForDRI-TRSGI correlations in these areas. This suggests that the

ForDRI could be a complementary tool, requiring integration with local hydrological data to enhance interpretation.

ForDRI-BR Correlation: Five AmeriFlux sites were used for the ForDRI-BR correlation in the South, Central, and Southeast Forest regions. Due to contrasting drivers, these forest regions displayed highly variable correlations ($R = 0.60\text{--}0.99$). For example, the NC-Loblolly Plantation in North Carolina (US-NC2) sites showed relatively strong early-summer (May to June) correlations ($R = 0.68$, $p < 0.05$), reflecting natural drought cycles in unirrigated forests. Similarly, Florida's subtropical forests (US-SP1) exhibit moderate correlations ($R = 0.67$, $p < 0.05$) as high humidity buffers ET loss, reducing ForDRI's sensitivity to forest drought (Figure 11b). In addition, hurricane volatility and humidity-driven buffering could underscore the region's challenges for consistent drought monitoring.

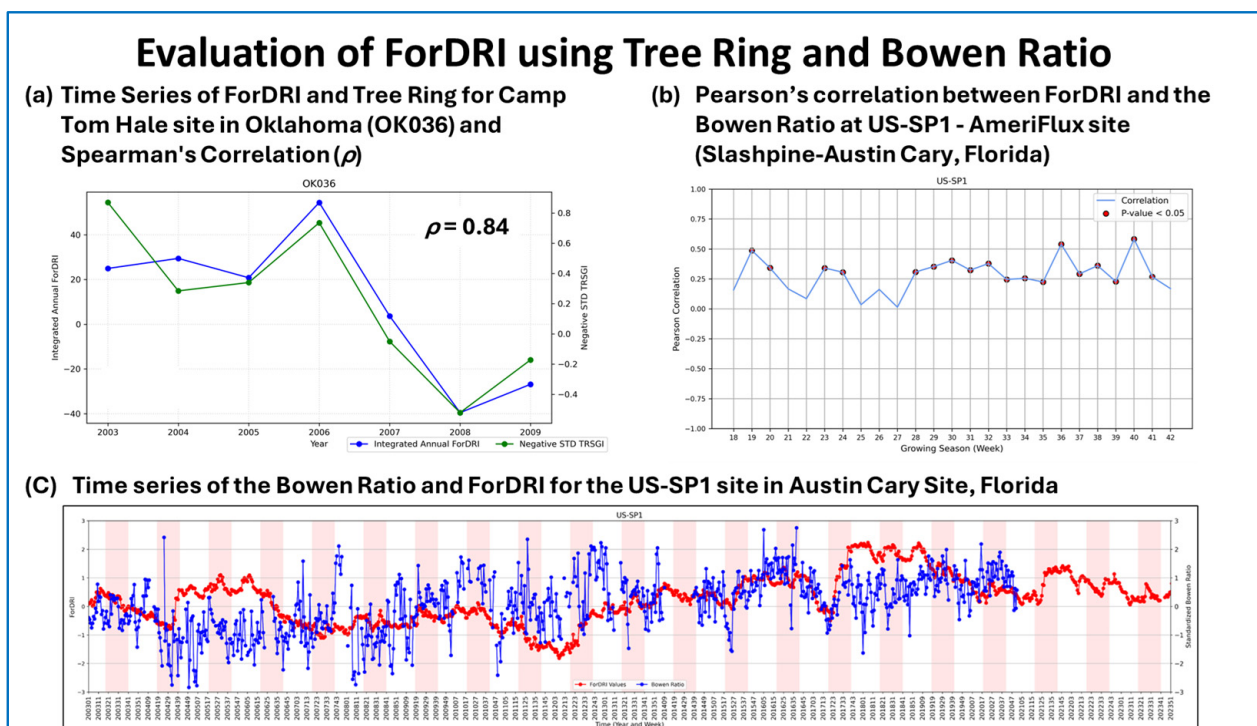


Figure 11. Comparison of the historical records of ForDRI-TRSGI and ForDRI-BR: (a) Time series of ForDRI and TRSGI with FORDRI-TRSGI Spearman's Correlation for Camp Tom Hale site in Oklahoma (OK036), (b) Pearson's correlation between ForDRI and the Bowen Ratio at US-SP1-AmeriFlux site (Austin Cary Site, Florida), and (c) Time series of the Bowen Ratio and ForDRI for the US-SP1 site.

Figure 11a presents a time-series graph analyzing the ForDRI in relation to tree-ring data at the Camp Tom Hale site in Oklahoma (OK036) from 2003 to 2013 using Spearman's correlation, which yields a correlation coefficient of 0.84. Figure 11b depicts Spearman's correlation between the BR at the US-SP1-AmeriFlux site (Slashpine-Austin Cary, Gainesville, FL, USA) and the ForDRI, showing a correlation of 0.67 ($p < 0.05$) in early September (during the growing season). Figure 11c provides a time-series comparison of the BR and ForDRI from 2003 to 2022 at the US-SP1 AmeriFlux site, highlighting their relatively similar temporal patterns.

3.4.2. Qualitative Evaluation of the Webinar Participants for the South, Central, and Southeast Forest Regions

Forest conditions during the 2023–2024 and 2016 drought years were assessed across 19 states, including Florida, Georgia, Kentucky, Missouri, and North Carolina (Figure 12).

Twelve participants provided feedback, reporting that in the 2023–2024 drought, 58% observed significant tree mortality and insect outbreaks, while 17% noted delays in plant growth and occurrences of tree blowdowns that align with the forest drought conditions depicted by the ForDRI maps. In addition, wildfires were a significant focus, with half of the participants in 2023–2024 reporting that wildfires burned more intensely than expected, 33% noting increased wildfire frequency, and 17% indicating adverse effects of smoke on wildlife and people.

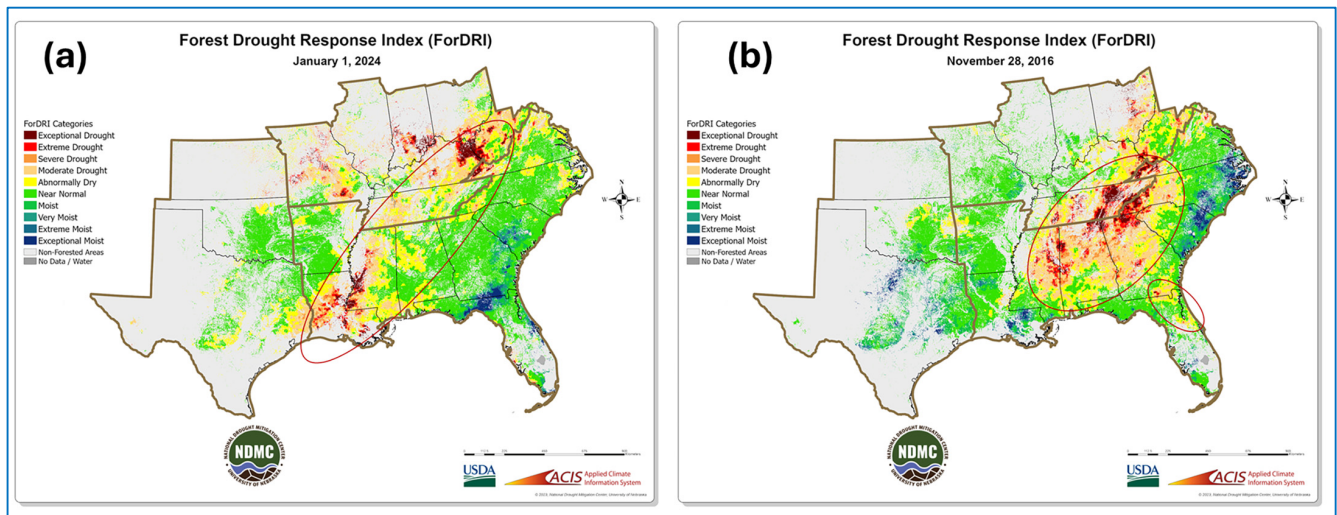


Figure 12. South, Central, and Southeast Forest Regions Evaluation: examples of case study maps of Forest Drought Response Index (ForDRI) for (a) 1 January 2024 and (b) 28 November 2016. The red ovals on the maps show the specific drought signals to be considered during the evaluation.

For the 2016 drought, 64% observed tree mortality, and 45% reported insect outbreaks, with additional impacts such as vegetation composition changes post-fire and increased erosion. Similarly, in the 2016 drought year, 67% of participants observed intensified wildfires and related smoke impacts. A participant noted that fires in the southern Appalachian region were particularly significant during 2016. Heavy smoke extended far south into central Georgia, enveloping the Atlanta-Athens area for many days in November 2016. Overall, participants rated the accuracy of the 2023–2024 ForDRI maps positively, with 67% stating they reflected conditions very accurately, compared to 50% for 2016 maps.

Discussions during the breakout session emphasized regional ForDRI drought patterns and their ecological impacts. For example, participants linked the 2023 drought in southwest Mississippi and Louisiana to Ips beetle outbreaks and significant wildfires, notably the Tiger Island fire, the largest in the state's history [47]. Historical trends from the 2016 ForDRI maps highlighted the role of drought in delayed leaf drop and its effects on wildfire severity in the Southern Appalachian region. Participants suggested enhancing ForDRI maps with Sentinel-2 data, trend visualization, and integration of forest mortality metrics. Key recommendations included analyzing seasonal indicators like early leaf senescence, distinguishing drought from excessive moisture impacts, and refining hotspot analysis to identify key drought-affected regions. Further, integrating forest inventory data, such as FIA, to evaluate drought tolerance among tree species was highlighted as critical to improve ForDRI. This shows the significance of refining the ForDRI model and improving its potential for ForDRI to inform stakeholders and enhance forest management practices.

3.5. Summary of Evaluation of the ForDRI Models and Products Through Regional Webinars

Fifty-eight participants attended the four webinars to evaluate the ForDRI qualitatively. Overall, when participants reviewed and discussed the case study drought years of ForDRI maps, the majority responded that the maps were very to moderately accurate in reflecting the drought (or non-drought) conditions they remembered and experienced in their local forest region. Participants also discussed specific forest drought impacts they observed and experienced in their area. Participants also identified various forest-related applications for the ForDRI tool and product requirements for specific decision-making activities. For example, the participants indicated that ForDRI maps are helpful for forest management decisions, such as determining tree planting timelines in the spring, identifying fire danger, making decisions about wildfire management and prescribed burns, and determining the appropriate times for seed collection. In addition, ForDRI maps can help determine recommendations and share forest health conditions with agricultural producers, other land managers, and individuals conducting fieldwork or with interests in forested areas.

Participants expressed specific regional concerns regarding the current ForDRI model and its effectiveness in characterizing forest-related droughts. These insights can be valuable for improving and tailoring the index across the CONUS in future work. A significant concern was the lack of elevation and snow cover data in the ForDRI model, especially for mountainous regions in the western United States. Drought affects higher elevations differently, and runoff from snowpacks is a crucial water source that helps mitigate some of the drought's effects. For instance, during the case study years of 2023–2024 in western Washington and the Wind River Range, the ForDRI model slightly overestimated drought conditions and showed delays in drought recovery.

4. Discussion

The ForDRI is specifically designed to improve upon existing drought monitoring tools for forests. While traditional climate indices like the PDSI and KBDI quantify moisture deficits, they do not assess forest health [27]. Remote sensing methods, such as the NDVI, offer spatial data but often struggle to distinguish drought stress in dense forests [40]. Hybrid tools, such as VegDRI, integrate satellite data and climate information for seasonal vegetation monitoring [32], but they primarily focus on agriculture and lack forest-specific parameters. In contrast, ForDRI combines 12 environmental variables, including vegetation health, climate, and soil moisture, into a comprehensive index tailored for forests [28]. Offering weekly updates at a 1 km resolution, ForDRI provides a targeted approach to monitor forest drought more effectively than existing drought monitoring tools.

To evaluate ForDRI's performance across the CONUS, quantitative comparisons of ForDRI with tree-ring width (TRSGI) and Bowen Ratio (BR) measurements were conducted. Additionally, qualitative feedback was gathered during regional webinars, where experts shared insights on ForDRI's accuracy and potential applications. This combined approach provided a well-rounded evaluation of ForDRI across various U.S. Forest regions.

Generally, ForDRI showed significant regional variability in accuracy, validated through correlations with BR and tree-ring data. Strong positive correlations (Spearman- $\rho > 0.7$, $p < 0.05$) were found in the Western, Rocky Mountain, Southwest, and Pacific Northwest states, highlighting the tool's effectiveness in monitoring forest drought. These regions benefit from clear drought signals driven by seasonal aridity and monsoon variability, where soil moisture deficits amplify sensible heat fluxes (BR) and suppress tree growth. In contrast, ForDRI's performance declines in humid and human-altered landscapes (e.g., urbanization), such as those in southern and eastern states, suggesting that other factors may also influence forest drought conditions.

Feedback from 58 webinar participants, including representatives from the U.S. Forest Service, indicated that ForDRI maps were generally accurate and helpful; however, several improvements were suggested. These included adding trend maps, enhancing visualizations, and integrating additional datasets, such as snow cover and elevation. Additionally, participants identified potential applications of ForDRI for guiding prescribed burns, tracking moisture conditions, and monitoring seasonal trends. They recommended incorporating features such as dynamic zooming and regional datasets to improve usability and emphasized the importance of nuanced modeling for canopy microclimates and species composition.

Future research directions: The ForDRI is designed to monitor drought conditions across U.S. forests, which is essential for managing and preserving forest ecosystems across the CONUS. However, several gaps and areas need improvement in the ForDRI tool to improve monitoring and the successful implementation of drought management strategies. In future studies, the following gaps and improvements are recommended to be addressed:

- **Data availability and accessibility:** Inconsistent ground truth data collection and the lack of long-term forest-related datasets hinder the ForDRI model's ability to track changes over time effectively. Building partnerships with local forest experts for data sharing and collaborative research could help identify available and accessible data to develop new and improved ForDRI models;
- **Leveraging Advances in Machine Learning:** Using machine learning (ML) to combine multiple datasets (e.g., integrating remote sensing and climate data) can enhance the precision of forest drought stress monitoring and support forest managers in making informed decisions. We plan to consider adding more hydrologic and environmental datasets using various ML methods to improve the ForDRI models;
- **Incorporating Ecosystem-Specific Metrics:** Developing tailored indices for different forest types (e.g., tropical vs. boreal; evergreen vs. deciduous) and integrating environmental information such as elevation and improved soil moisture measurements (or data). Including snow and temperature extremes data in ForDRI models would provide a more specific and tailored indicator for different regions and seasons.

5. Conclusions

The ForDRI tool integrates hydrological, climatic, and vegetation-related indices into a comprehensive forest drought index. ForDRI is a robust tool for monitoring forest drought in moisture-limited western forests. Thus, ForDRI's utility is best in arid and semi-arid zones, where drought remains the dominant driver of tree growth. It can also be effective in eastern, humid forest environments during periods of extended extreme drought, including hotter droughts. However, ForDRI requires complementary data (e.g., local hydrology, species traits) to improve accuracy in regions with complex microclimates, non-climatic stressors, or cold and wet ecosystems. In addition, while stakeholders view ForDRI as a valuable tool for monitoring forest drought, they recommend further refinement to enhance its accuracy and effectiveness in forest management.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/f16071187/s1>, Table S1: Spearman's correlation between Forest Drought Response Index (ForDRI) and Tree-Ring Growth Index (TRSGI) at 135 tree-ring sites for CONUS; and Table S2: Pearson's correlation between ForDRI and Bowen Ratio at twenty-four AmeriFlux sites for CONUS.

Author Contributions: Conceptualization, T.T., B.W., M.S. and B.A.F.; methodology, T.T., B.Z. and H.A.; evaluation, T.T., S.C., B.W., M.S., B.Z., B.A.F., C.A., F.H.K., T.B., I.R., K.V., L.J. and C.R.; formal analysis, T.T.; investigation, T.T., B.W., M.S., B.A.F. and B.Z.; resources, M.S.; data curation, T.T., B.Z.,

H.A., C.P., J.W. and J.N.; writing—original draft preparation, T.T.; writing—review and editing, T.T., S.C., B.W., M.S., B.A.F., C.A., F.H.K. and K.V.; visualization, T.T., J.N. and I.R.; supervision, M.S.; project administration, M.S. and B.A.F.; funding acquisition, M.S., B.A.F., B.W. and T.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the United States Department of Agriculture (USDA) Cooperative Agreement, Federal Award Identification Number 58-0111-23-011.

Data Availability Statement: The authors will make the data available upon request.

Acknowledgments: The authors thank the USDA, U.S. Forest Service, NASA, and USGS for providing satellite and model products, and the Department of Energy AmeriFlux Network Management Project for the AmeriFlux data. We want to acknowledge the contributions of Jessica Halofsky, Director of the Northwest Climate Hub and the Western Wildland Environmental Threats Assessment Center, as well as Katie Nigro from the USDA Northern Plains Climate Hub and the USDA Forest Service at the Oak Ridge Institute for Science and Education. Their invaluable help in evaluating the ForDRI and revising the manuscript has greatly enhanced our work.

Conflicts of Interest: The authors declare no conflicts of interest. The funder (USDA) had no role in the design of the study, the collection, analysis, or interpretation of data, the writing of the manuscript, or the decision to publish the results.

References

1. Oldekop, J.A.; Rasmussen, L.V.; Agrawal, A.; Bebbington, A.J.; Meyfroidt, P.; Bengston, D.N.; Blackman, A.; Brooks, S.; Davidson-Hunt, I.; Davies, P.; et al. Forest-Linked Livelihoods in a Globalized World. *Nat. Plants* **2020**, *6*, 1400–1407. [CrossRef] [PubMed]
2. Lewis, S.L.; Edwards, D.P.; Galbraith, D. Increasing Human Dominance of Tropical Forests. *Science* **2015**, *349*, 827–832. [CrossRef] [PubMed]
3. Mo, L.; Zohner, C.M.; Reich, P.B.; Liang, J.; De Miguel, S.; Nabuurs, G.J.; Renner, S.S.; van den Hoogen, J.; Araza, A.; Herold, M.; et al. Integrated Global Assessment of the Natural Forest Carbon Potential. *Nature* **2023**, *624*, 92–101. [CrossRef] [PubMed]
4. Zhang, W.; Luo, G.; Hamdi, R.; Ma, X.; Termonia, P.; De Maeyer, P. Drought Changes the Dominant Water Stress on the Grassland and Forest Production in the Northern Hemisphere. *Agric. For. Meteorol.* **2024**, *345*, 109831. [CrossRef]
5. Luo, H.; Zhou, T.; Liu, X.; Shi, P.; Mao, R.; Zhao, X.; Xu, P.; Yu, P.; Liu, J. Dual Roles of Water Availability in Forest Vigor: A Multiperspective Analysis in China. *Remote Sens.* **2021**, *13*, 91. [CrossRef]
6. USDA Forest Service. *Forest Health*; USDA Forest Service: Washington, DC, USA, 2025. Available online: <https://www.fs.usda.gov/science-technology/forest-health> (accessed on 4 April 2025).
7. Shi, H.; Peng, X.; Zhou, Y.J.; Wang, A.Y.; Sun, X.K.; Li, N.; Bao, Q.S.; Buri, G.; Hao, G.Y. Resilience and Response: Unveiling the Impacts of Extreme Droughts on Forests Through Integrated Dendrochronological and Remote Sensing Analyses. *For. Ecosyst.* **2024**, *11*, 100209. [CrossRef]
8. Asif, Z.; Chen, Z.; Sadiq, R.; Zhu, Y. Climate Change Impacts on Water Resources and Sustainable Water Management Strategies in North America. *Water Resour. Manag.* **2023**, *37*, 2771–2786. [CrossRef]
9. Wehner, M.F.; Arnold, J.R.; Knutson, T.; Kunkel, K.E.; LeGrande, A.N. Droughts, Floods, and Wildfires. In *Climate Science Special Report: Fourth National Climate Assessment*; Wuebbles, D.J., Fahey, D.W., Hibbard, K.A., Dokken, D.J., Stewart, B.C., Maycock, T.K., Eds.; U.S. Global Change Research Program: Washington, DC, USA, 2017; Volume I, pp. 231–256. Available online: <https://ntrs.nasa.gov/api/citations/20180001310/downloads/20180001310.pdf> (accessed on 2 July 2025).
10. Knutson, T.R.; Zeng, F.; Wittenberg, A.T. Seasonal and Annual Mean Precipitation Extremes Occurring During 2013: A U.S. Focused Analysis. *Bull. Am. Meteorol. Soc.* **2014**, *95*, S19–S23. [CrossRef]
11. Hegerl, G.C.; Zwiers, F.W.; Braconnot, P.; Gillett, N.P.; Luo, Y.; Orsini, J.A.M.; Nicholls, N.; Penner, J.E.; Stott, P.A. Understanding and Attributing Climate Change. In *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*; Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M., Miller, H.L., Eds.; Cambridge University Press: Cambridge, UK, 2007; pp. 663–745.
12. Thrippleton, T.; Bugmann, H.; Folini, M.; Snell, R.S. Overstorey—Understorey Interactions Intensify After Drought-Induced Forest Die-Off: Long-Term Effects for Forest Structure and Composition. *Ecosystems* **2018**, *21*, 723–739. [CrossRef]
13. Bréda, N.; Huc, R.; Granier, A.; Dreyer, E. Temperate Forest Trees and Stands Under Severe Drought: A Review of Ecophysiological Responses, Adaptation Processes and Long-Term Consequences. *Ann. For. Sci.* **2006**, *63*, 625–644. [CrossRef]
14. Coomes, D.A.; Grubb, P.J. Impacts of Root Competition in Forests and Woodlands: A Theoretical Framework and Review of Experiments. *Ecol. Monogr.* **2000**, *70*, 171–207. [CrossRef]

15. Zamora-Pereira, J.C.; Hanewinkel, M.; Yousefpour, R. Robust Management Strategies Promoting Ecological Resilience and Economic Efficiency of a Mixed Conifer-Broadleaf Forest in Southwest Germany Under the Risk of Severe Drought. *Ecol. Econ.* **2023**, *209*, 107825. [\[CrossRef\]](#)
16. Joyce, L.A.; Coulson, D. *Climate Scenarios and Projections: A Technical Document Supporting the USDA Forest Service 2020 RPA Assessment*; General Technical Report RMRS-GTR-413; U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station: Fort Collins, CO, USA, 2020; p. 85. [\[CrossRef\]](#)
17. Allen, C.D.; Breshears, D.D.; McDowell, N.G. On Underestimation of Global Vulnerability to Tree Mortality and Forest Die-Off from Hotter Drought in the Anthropocene. *Ecosphere* **2015**, *6*, 1–55. [\[CrossRef\]](#)
18. Bennett, A.C.; McDowell, N.G.; Allen, C.D.; Anderson-Teixeira, K.J. Larger Trees Suffer Most During Drought in Forests Worldwide. *Nat. Plants* **2015**, *1*, 1–5. [\[CrossRef\]](#) [\[PubMed\]](#)
19. U.S. Department of Agriculture Forest Service (USDA-FS). *New Aerial Survey Identifies More Than 100 Million Dead Trees in California*; USDA-FS: Washington, DC, USA, 2024. Available online: <https://www.usda.gov/about-usda/news/press-releases/2016/11/18/new-aerial-survey-identifies-more-100-million-dead-trees-california> (accessed on 18 November 2024).
20. Stephens, S.L.; Collins, B.M.; Fettig, C.J.; Finney, M.A.; Hoffman, C.M.; Knapp, E.E.; North, M.P.; Safford, H.; Wayman, R.B. Drought, Tree Mortality, and Wildfire in Forests Adapted to Frequent Fire. *BioScience* **2018**, *68*, 77–88. [\[CrossRef\]](#)
21. Breshears, D.D.; Cobb, N.S.; Rich, P.M.; Price, K.P.; Allen, C.D.; Balice, R.G.; Romme, W.H.; Kastens, J.H.; Floyd, M.L.; Belnap, J.; et al. Regional Vegetation Die-Off in Response to Global-Change-Type Drought. *Proc. Natl. Acad. Sci. USA* **2005**, *102*, 15144–15148. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Yu, X.; Orth, R.; Reichstein, M.; Bahn, M.; Klosterhalfen, A.; Knohl, A.; Koebisch, F.; Migliavacca, M.; Mund, M.; Nelson, J.A.; et al. Contrasting Drought Legacy Effects on Gross Primary Productivity in a Mixed Versus Pure Beech Forest. *Biogeosciences* **2022**, *19*, 4315–4329. [\[CrossRef\]](#)
23. Flach, M.; Brenning, A.; Gans, F.; Reichstein, M.; Sippel, S.; Mahecha, M.D. Vegetation Modulates the Impact of Climate Extremes on Gross Primary Production. *Biogeosci. Discuss.* **2020**, *2020*, 1–20. [\[CrossRef\]](#)
24. Kukowski, K.R.; Schwinning, S.; Schwartz, B.F. Hydraulic Responses to Extreme Drought Conditions in Three Co-Dominant Tree Species in Shallow Soil over Bedrock. *Oecologia* **2013**, *171*, 819–830. [\[CrossRef\]](#) [\[PubMed\]](#)
25. Mildrexler, D.; Yang, Z.; Cohen, W.B.; Bell, D.M. A Forest Vulnerability Index Based on Drought and High Temperatures. *Remote Sens. Environ.* **2016**, *173*, 314–325. [\[CrossRef\]](#)
26. Gazol, A.; Camarero, J.J.; Anderegg, W.R.L.; Vicente-Serrano, S.M. Impacts of droughts on the growth resilience of Northern Hemisphere forests. *Glob. Ecol. Biogeogr.* **2017**, *26*, 166–176. [\[CrossRef\]](#)
27. AghaKouchak, A.; Huning, L.S.; Sadegh, M.; Qin, Y.; Markonis, Y.; Vahedifard, F.; Love, C.A.; Mishra, A.; Mehran, A.; Obringer, R.; et al. Toward Impact-Based Monitoring of Drought and Its Cascading Hazards. *Nat. Rev. Earth Environ.* **2023**, *4*, 582–595. [\[CrossRef\]](#)
28. Tadesse, T.; Hollinger, D.Y.; Bayissa, Y.A.; Svoboda, M.; Fuchs, B.; Zhang, B.; Demissie, G.; Wardlow, B.D.; Bohrer, G.; Clark, K.L.; et al. Forest Drought Response Index (ForDRI): A New Combined Model to Monitor Forest Drought in the Eastern United States. *Remote Sens.* **2020**, *12*, 3605. [\[CrossRef\]](#)
29. Norman, S.P.; Koch, F.H.; Hargrove, W.W. Review of Broad-Scale Drought Monitoring of Forests: Toward an Integrated Data Mining Approach. *For. Ecol. Manag.* **2016**, *380*, 346–358. [\[CrossRef\]](#)
30. Zhang, X.; Zhang, X.; Terfa, B.K.; Nam, W.H.; Zeng, J.; Ma, H.; Gu, X.; Du, W.; Wang, C.; Yang, J.; et al. Mapping Global Drought-Induced Forest Mortality Based on Multiple Satellite Vegetation Optical Depth Data. *Remote Sens. Environ.* **2024**, *315*, 114406. [\[CrossRef\]](#)
31. Yang, Y.; Anderson, M.C.; Gao, F.; Wood, J.D.; Gu, L.; Hain, C. Studying Drought-Induced Forest Mortality Using High Spatiotemporal Resolution Evapotranspiration Data from Thermal Satellite Imaging. *Remote Sens. Environ.* **2021**, *265*, 112640. [\[CrossRef\]](#)
32. Brown, J.F.; Wardlow, B.D.; Tadesse, T.; Hayes, M.J.; Reed, B.C. The Vegetation Drought Response Index (VegDRI): A New Integrated Approach for Monitoring Drought Stress in Vegetation. *GIScience Remote Sens.* **2008**, *45*, 16–46. [\[CrossRef\]](#)
33. USDA Forest Service Forest Inventory & Analysis Program (USFS). Science by Barry, T. Wilson (USFS), Cartography by Emily Meriam (ESRI). Forest Type Groups of the Continental United States. Available online: <https://www.arcgis.com/home/item.html?id=10760c83b9e44923bd3c18efdaa7319d> (accessed on 11 November 2024).
34. AmeriFlux. *About AmeriFlux*; AmeriFlux: Berkeley, CA, USA, 2025. Available online: <https://ameriflux.lbl.gov/about/about-ameriflux/> (accessed on 4 April 2025).
35. Jolliffe, I.T.; Cadima, J. Principal component analysis: A review and recent developments. *Philos. Trans. R. Soc. A Math. Phys. Eng. Sci.* **2016**, *374*, 20150202. [\[CrossRef\]](#) [\[PubMed\]](#)
36. Gu, J.; Wang, Z.; Kuen, J.; Ma, L.; Shahroudy, A.; Shuai, B.; Liu, T.; Wang, X.; Wang, G.; Cai, J.; et al. Recent advances in convolutional neural networks. *Pattern Recognit.* **2018**, *77*, 354–377. [\[CrossRef\]](#)

37. Sproles, E.A.; Leibowitz, S.G.; Reager, J.T.; Wigington, P.J., Jr.; Famiglietti, J.S.; Patil, S.D. GRACE Storage-Runoff Hystereses Reveal the Dynamics of Regional Watersheds. *Hydrol. Earth Syst. Sci.* **2015**, *19*, 3253–3272. [[CrossRef](#)]
38. Svoboda, M.; LeComte, D.; Hayes, M.; Heim, R.; Gleason, K.; Angel, J.; Rippey, B.; Tinker, R.; Palecki, M.; Stooksbury, D.; et al. The drought monitor. *Bull. Am. Meteorol. Soc.* **2002**, *83*, 1181–1190. [[CrossRef](#)]
39. Xue, R.; Jiao, L.; Zhang, P.; Wei, M.; Wang, X.; Li, Q.; Qi, C. Response Sensitivity Processes of Conifer Radial Growth to Climate Factors Based on Tree Ring Width Variations. *Glob. Ecol. Conserv.* **2023**, *48*, e02743. [[CrossRef](#)]
40. Pompa-García, M.; Camarero, J.J.; Colangelo, M.; González-Cásares, M. Inter and Intra-Annual Links Between Climate, Tree Growth and NDVI: Improving the Resolution of Drought Proxies in Conifer Forests. *Int. J. Biometeorol.* **2021**, *65*, 2111–2121. [[CrossRef](#)] [[PubMed](#)]
41. Peltier, D.M.; Ogle, K. Tree Growth Sensitivity to Climate Is Temporally Variable. *Ecol. Lett.* **2020**, *23*, 1561–1572. Available online: <https://onlinelibrary.wiley.com/doi/full/10.1111/ele.13575> (accessed on 2 July 2025). [[CrossRef](#)] [[PubMed](#)]
42. National Oceanic and Atmospheric Administration (NOAA). *The World Data Service for Paleoclimatology—The International Tree-Ring Data Bank (ITRDB)*; NOAA: Washington, DC, USA, 2024. Available online: <https://www.nci.noaa.gov/products/paleoclimatology/tree-ring> (accessed on 11 November 2024).
43. Akyuz, F.A. *Drought Severity and Coverage Index*; United States Drought Monitor: Lincoln, NE, USA, 2025; Available online: <https://droughtmonitor.unl.edu/About/AbouttheData/DSCI.aspx> (accessed on 4 May 2025).
44. Ren, X.; Zhang, Q.; Yue, P.; Yang, J.; Wang, S. Environmental and Biophysical Effects of the Bowen Ratio Over Typical Farmland Ecosystems in the Loess Plateau. *Remote Sens.* **2022**, *14*, 1897. [[CrossRef](#)]
45. Richter, R.; Ballasus, H.; Engelmann, R.A.; Zielhofer, C.; Sanaei, A.; Wirth, C. Tree Species Matter for Forest Microclimate Regulation during the Drought Year 2018: Disentangling Environmental Drivers and Biotic Drivers. *Sci. Rep.* **2022**, *12*, 17559. [[CrossRef](#)] [[PubMed](#)]
46. Coble, A.P.; Vadeboncoeur, M.A.; Berry, Z.C.; Jennings, K.A.; McIntire, C.D.; Campbell, J.L.; Rustad, L.E.; Templer, P.H.; Asbjornsen, H. Are Northeastern US forests vulnerable to extreme drought? *Ecol. Process* **2017**, *6*, 1–13. [[CrossRef](#)]
47. Norman, S.P.; Christie, W.M.; Asaro, C. Mapping the 2023–2024 pine mortality event in Mississippi and Louisiana driven by an extreme hot-drought, pine bark beetle outbreaks, and wildfire. In *Forest Health Monitoring: National Status, Trends, and Analysis 2024*; Pandit, K., Lim-Hing, S., Eds.; US Department of Agriculture, Forest Service: Washington, DC, USA, 2025; Chapter 2.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.