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Review

Climate-Change-Driven Droughts and Tree Mortality: Assessing the Potential of UAV-Derived Early Warning Metrics

Ewane Basil Ewane [1,2,3], Midhun Mohan [1,2,4,*], Shaurya Bajaj [1,2], G. A. Pabodha Galgamuwa [2,5], Michael S. Watt [6], Pavithra Pitumpe Arachchige [1,2], Andrew T. Hudak [7], Gabriella Richardson [2,8], Nivedhitha Ajithkumar [2,9], Shruthi Srinivasan [10], Ana Paula Dalla Corte [11], Daniel J. Johnson [12], Eben North Broadbent [13], Sergio de-Miguel [14,15], Margherita Bruscolini [1,2,16], Derek J. N. Young [17], Shahid Shafai [2], Meshal M. Abdullah [18,19], Wan Shafrina Wan Mohd Jaafar [20], Willie Doaemo [21,22], Carlos Alberto Silva [23] and Adrian Cardil [14,15,24]

1 Ecoresolve Inc., San Francisco, CA 94105, USA; basil.ewane@ecoresolve.eco or ewane.basil@ubuea.cm (E.B.E.); shaurya.bajaj2014@vitalum.ac.in (S.B.); pavithra.pa@ecoresolve.eco (P.P.A.); margherita@globhe.com (M.B.)
2 United Nations Volunteering Program, via Morobe Development Foundation, Lae 00411, Papua New Guinea; pabodha@tnc.org (G.A.P.G.); gricha06@uoguelph.ca (G.R.); nivedhitha.ajithkumar@uef.fi (N.A.); shafai@skuastkashmir.ac.in (S.S.)
3 Department of Geography, Faculty of Social and Management Sciences, University of Buea, Buea P.O. Box 63, Cameroon
4 Department of Geography, University of California—Berkeley, Berkeley, CA 94709, USA
5 The Nature Conservancy, Maryland/DC Chapter, Cumberland, MD 21502, USA
6 Scion, 10 Kyle St, Christchurch 8011, New Zealand; michael.watt@scionresearch.com
7 USDA Forest Service, Rocky Mountain Research Station, 1221 South Main St, Moscow, ID 83844, USA; andrew.hudak@usda.gov
8 Department of Sociology and Anthropology, University of Guelph, Guelph, ON N1G 2W1, Canada
9 School of Forest Sciences, University of Eastern Finland, 80100 Joensuu, Finland
10 Department of Forest Analytics, Texas A&M Forest Service, Dallas, TX 75252, USA; ssrinivasan@tfs.tamu.edu
11 BIOFIX Research Center, Federal University of Parana, Curitiba 80210-170, Brazil; anacorte@ufpr.br
12 School of Forest, Fisheries, and Geomatics Sciences, University of Florida, Gainesville, FL 32611, USA; johnson.daniel@ufl.edu
13 Spatial Ecology and Conservation Laboratory, School of Forest, Fisheries, and Geomatics Sciences, University of Florida, Gainesville, FL 32611, USA; eben@ufl.edu
14 Department of Agricultural and Forest Sciences and Engineering, University of Lleida, Av. Alcalde Rovira Roure 191, 25198 Lleida, Spain; sergio.demiguel@udl.cat or sergio.demiguel@ctfc.cat (S.d.-M.); adrian.cardil@udl.cat (A.C.)
15 Joint Research Unit CTFC–AGROTECNIO–CERCA, Ctra. Sant Llorenç de Morunys km 2, 25280 Solsona, Spain
16 GLOBHE, Askrikegatan 11, 115 57 Stockholm, Sweden
17 Department of Plant Sciences, University of California Davis, Davis, CA 95616, USA; djyoung@ucdavis.edu
18 Geography of Department, College of Arts and Social Sciences, Sultan Qaboos University, Muscat P.O. Box 50, Oman; m.abdullah1@squ.edu.om
19 Department of Ecology and Conservation Biology, Texas A&M University, College Station, TX 77843, USA
20 Earth Observation Center, Institute of Climate Change, Universiti Kebangsaan Malaysia, Bangi 43600, Selangor, Malaysia; wanshafrina@ukm.edu.my
21 Department of Civil Engineering, Papua New Guinea University of Technology, Lae 00411, Papua New Guinea; willie.doaemo@pnguot.ac.pg
22 Morobe Development Foundation, Doyle Street, Trish Avenue-Eriku, Lae 00411, Papua New Guinea
23 Forest Biometrics, Remote Sensing and Artificial Intelligence Lab, School of Forest, Fisheries, and Geomatics Sciences, University of Florida, Gainesville, FL 32611, USA; c.silva@ufl.edu
24 Tecnosylva, S.L Parque Tecnológico de León, 24004 León, Spain
* Correspondence: mid_mohan@berkeley.edu or mikey@ecoresolve.eco

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Abstract: Protecting and enhancing forest carbon sinks is considered a natural solution for mitigating climate change. However, the increasing frequency, intensity, and duration of droughts due to climate change can threaten the stability and growth of existing forest carbon sinks. Extreme droughts weaken plant hydraulic systems, can lead to tree mortality events, and may reduce forest diversity, making forests more vulnerable to subsequent forest disturbances, such as forest fires or pest infestations. Although early warning metrics (EWMs) derived using satellite remote sensing data are now being tested for predicting post-drought plant physiological stress and mortality, applications of unmanned aerial vehicles (UAVs) are yet to be explored extensively. Herein, we provide twenty-four prospective approaches classified into five categories: (i) physiological complexities, (ii) site-specific and confounding (abiotic) factors, (iii) interactions with biotic agents, (iv) forest carbon monitoring and optimization, and (v) technological and infrastructural developments, for adoption, future operationalization, and upscaling of UAV-based frameworks for EWM applications. These UAV considerations are paramount as they hold the potential to bridge the gap between field inventory and satellite remote sensing for assessing forest characteristics and their responses to drought conditions, identifying and prioritizing conservation needs of vulnerable and/or high-carbon-efficient tree species for efficient allocation of resources, and optimizing forest carbon management with climate change adaptation and mitigation practices in a timely and cost-effective manner.

Keywords: drought-induced tree mortality; climate extremities; climate mitigation potential of forests; drone remote sensing; biotic factors of tree mortality

1. Introduction

The use of forests as a natural solution to mitigate climate change is becoming increasingly popular due to their unparalleled ability to capture and store carbon dioxide (CO_2) [1]. Global forests are a net carbon sink of around 7.6 billion metric tons of CO_2 year^{-1}, which is around one-third of fossil-fuel-based CO_2 emissions [2]. However, human activities, such as fossil fuel use and deforestation, are increasingly adding to the CO_2 concentration in the atmosphere, causing increases in atmospheric temperature and climate change, and consequently increasing the frequency, intensity, and duration of droughts. Climate-change-driven droughts threaten the stability of existing forests as carbon sinks and affect the climate change mitigation potential of forests in the long run [3].

Climate-change-driven droughts, such as the ones observed in Amazonia following the 2015–2016 El Niño event and in California during 2012–2016 and 2020–2022, can result in landscape-scale tree mortality events, a decline in biodiversity, the proliferation of invasive species, and/or loss of ecological functions that can lead to significant increases in carbon emissions from the forest ecosystems to the atmosphere [3–6]. Droughts can stunt plant growth and change plant architecture, resulting in lower primary growth, reduced size/number of leaves, limited fruit production, increased dead/live biomass ratio, and modifications in their reproductive phases [7–9], in addition to increasing autotrophic respiration and promoting wildfires [10,11]. Moreover, plants' responses to drought conditions can vary depending on their stomatal adjustment capabilities—with anisohydric plants continuing the transpiration process irrespective of reduced soil water content, whereas the isohydric plants reduce stomatal conductance to limit transpiration [12]. The age-class and structural diversity of forests, environmental gradients (e.g., topography, temperature, light availability), and competition also play significant roles in determining the impacts of droughts on forest carbon sequestration and storage capacity [13,14].

In addition, drought-induced forest mortality may reduce forest diversity [15], which in turn can be associated with increased vulnerability to future disturbances such as pest outbreaks [16] or the substitution by alternative ecosystems with new species adapted to new fire regimes [17]. Long-term and/or intense droughts have been found to trigger landscape-level tree mortality for years after the drought episode. Drought-associated tree mortality in these cases is referred to as "die-off", whereas partial mortality impacting only peripheral plant parts is usually referred to as forest "dieback" and "decline" [18]. Climate-change-driven droughts and tree mortality entail serious global threats such as decline in ecosystem services and depletion of sequestered forest carbon [19,20], because tree mortality can occur faster than recovery of biomass growth [21].

The increasing frequency and magnitude of drought occurrence and impacts necessitates an increasing need for intensive monitoring and anticipation of drought impacts over multiple scales to understand drought impact at the forest and tree level over time. In this regard, the development of EWMs (early warning metrics) and indicators for monitoring drought impacts and forest and tree mortality using integrated data streams from satellite, UAVs (unmanned aerial vehicles) and ground-based remote sensing techniques is invaluable.

Despite the existence of sufficient research revolving around the impacts of droughts on tree mortality and growth during the dry seasons, early warning metrics (EWMs) for tree physiological stress and mortality after drought scenarios are rarely studied, especially at operational scales [22]. Apart from the highly complex nature of forest–water–climate relations, the paucity of reliable high-quality and continuous data makes it harder for scientists to create dependable predictive models. Given the independent nature of isolated droughts and spatial variability of post-drought tree mortality and tree species' hydraulic traits, field-based methodologies are not practical at regional scales. In addition, climate extremes are not common and are often only able to be studied through retrospective measures. Therefore, recent studies have investigated the possibility of developing EWMs for predicting spatial variability of post-drought tree stress and mortality using satellite remote sensing-based tools [22–24]. However, most of the EWMs are at an early stage and there is a need to bridge the gap between literature and applications through the adoption and integration of state-of-the-art, yet affordable and user-friendly, remote sensing technologies such as UAVs. The advantages of UAVs over satellite imagery and field-based inventory are explained in Section 3.

The integration of the different UAV remote sensing tools to derive and develop EWM frameworks will allow us to address questions such as: What are some tree-level remotely sensed variables that can help us estimate tipping points of plants in post-drought conditions? What happens before a tree of a particular species dies and how can the changes happening at the tree level in terms of physiological structure and leaf traits be captured? Which species are more prone to drought-related tree mortality? What areas were most affected by previous droughts and how are the dynamics of tree mortality and carbon recovery within/across species varying with time? Therefore, in this article, we aim to discuss the status of remote-sensing-based EWMs and the recent advances in UAV applications that could be leveraged for predicting post-drought tree stress and mortality. We outline the most important EWMs derived from ground-based LiDAR (light detection and ranging), aircraft, satellite, and UAV data, and the possible sampling approaches that will allow the integration of UAV data with satellite imagery. We discuss the pathways through which EWMs can push forward precision forestry endeavors, the extension of algorithms for generating modified EWMs from the collected data, and questions of scale and resolution of expected remote sensing products. Lastly, we provide twenty-four approaches, classified into five categories: (i) physiological complexities, (ii) site-specific and confounding (abiotic) factors, (iii) interactions with biotic agents, (iv) forest resource monitoring and optimization, and (v) technological and infrastructural developments to guide the development of EWMs.

2. Status of Remote-Sensing-Based Early Warning Metrics

Various EWMs have been developed and used in recent years using remote sensing data from satellite, airborne, and ground-based (terrestrial) sensors in forest environments. The variables which have contributed towards analysis of drought-induced tree mortality using these remote sensing data can broadly be categorized into the following groups: (i) topographic variables (such as elevation and slope), (ii) vegetation indices (such as the NDVI (Normalized Differential Vegetation Index) and EVI (Enhanced Vegetation Index)), (iii) nonvegetative counterparts (such as NPV (nonphotosynthetic vegetation), and (iv) information on biotic agents (treating them as drivers of tree mortality). Satellite remote sensing data have been used for monitoring drought stress and tree mortality through utilizing reflectance from the visible and infrared spectrums, which can be used to estimate canopy water loss and carbon ecosystem dynamics [25]. Both Landsat and Sentinel-2 series satellite data are widely used due to their relatively high spatial resolution (30 and 10 m pixel resolution, respectively) [23,26]. Moderate Resolution Imaging Spectroradiometer (MODIS) satellite data are also widely used alone or in combination with Landsat data to detect the impacts of drought stress on tree mortality due to their high temporal resolution (1–2 days) [14,27,28].

Using remote sensing satellite data, it is possible to monitor the vegetative condition of large forest areas using derived vegetation indices such as NDVI, NDWI (Normalized Difference Water Index), NDRE (Normalized Difference Red Edge Index), GLI (Green Leaf Index), EVI, GNDVI (Green Normalized Differential Vegetation Index), and GCI (Green Chlorophyll Index). These indices can be used singly or in combination to map drought-induced tree mortality in forests [29–31], where NDVI was identified as an index that differentiates various levels of tree mortality severity arising from droughts [32–34]. Details of such recent studies that have utilized existing or developed new vegetation indices for analyses of drought-induced tree mortality using various remotely sensed data can be found in Supplementary Material Table S1. NDVI has been widely used in various remote-sensing-based studies [35,36] because it is straightforward to interpret and apply and is openly available in a level 2b processed state at a global level at high spatial resolution, with the data freely provided by NASA (National Aeronautics and Spaces Administration) and ESA (European Space Agency).

Nonvegetative metrics, such as NPV, depict the properties of nonphotosynthetic parts of the tree and include information on dead and senescent vegetation, plant litter, and nonphotosynthesizing branch and stem tissues [37], and have been used to gain insights and analyze tree mortality. For example, NPV metrics showed a positive correlation to leaf area index, as well as spatial patterns in tree hydraulic stress underlying mortality, such that NPV-based EWMs were reported to be successful in explaining tree mortality [23]. The spatial pattern of drought-induced AGB (aboveground biomass) loss from sudden aspen decline and tree mortality was more accurately depicted through NPV-related estimations than standard greenness indices (such as NDVI) at a local scale [38]. Subsequent studies further underscored the robustness of NPV measurements in detecting tree mortality at regional scales [39].

Remote sensing data can also be used to account for the influences of biotic agents, and especially pests, which assists with the understanding of spatial patterns of outbreaks and the generation of simulations and predictive models for post-drought tree mortality. For instance, [40] generated budworm infestation maps and spatial patterns from Landsat imagery, and reported that budworm outbreaks (causing defoliation in North American coniferous forests) followed autumn and summer rainfall deficits that were 12% and 20% lower than average, respectively. Other relevant studies include [41–43]. However, few remote sensing studies have examined the influence of biotic factors as co-drivers of post-drought tree mortality [44].

Hydraulic-based approaches that integrate models of plant hydraulics with land surface models can also provide insights into tree mortality by taking into account the water variation in plants, by identifying locations with high drought-induced tree mortality risks. Nonetheless, studies integrating remote sensing data into hydraulic modeling based approaches are very rare. Only a few studies, such as that of [45], have integrated a hydraulic-based threshold approach and Landsat imagery to detect regional patterns of plant water stress thresholds that correspond with the loss of vascular transport capacity from air entry to the xylem leading to tree mortality. The authors of [46] discussed the applicability of microwave remote sensing (e.g., frequencies using active radar and passive radiometry) for retrieving variations in vegetation water content, which were in turn linked to a range of tree responses such as fluxes of water and carbon, mortality, and flammability.

Aerial detection survey data, LiDAR, and topographical variables such as elevation, slope, and aspect have been used to detect seasonal variations in tree status and mortality in drought-prone locations [47–49]. For instance, [50] made use of remote sensing data (aerial photographs, AVIRIS, USGS LiDAR) and derived topographic variables with a random forest algorithm to investigate Bishop pine mortality after a couple of years of intense drought, and observed that dead trees were mostly found on shallow slopes and at the upper elevation limit in the stand where cloud frequency is lowest. Tree survivorship rate was found to be highest for large trees at moderate elevation, and in general, drought or environmental stress agents were most likely to appear at the margins of the climate zone to which the tree is adapted [51,52].

Severe water stress has also been extensively monitored using hyperspectral and, to some extent, multispectral remote sensing of leaf water content to predict both equivalent water thickness and gravimetric water content as indicators of water stress [53,54]. A list of past, current and planned hyperspectral sensors deployed from UAVs, aircraft and satellite is given in Supplementary Tables S2–S5. Canopy water content is closely linked to the equivalent water thickness via leaf area index and is defined as the product of the latter two [55]. The change in canopy water content as an EWM during drought periods, measured using laser-guided imaging spectroscopy, has a strong spatially explicit relationship with post-drought gross conifer mortality [25]. The absorption features in the near-infrared and shortwave-infrared have been exploited in different studies, and strong negative correlations have been observed between leaf water content and reflectance within individual wavelengths [56,57]. A number of studies have used indices derived from near-infrared and shortwave-infrared bands to predict leaf water content [54,58], and a summary of these is given in [59] (Supplementary Material Table S2). Simulations using radiative transfer models that link leaf and canopy physical models have also been widely used to estimate the equivalent water thickness [60,61], and this approach has been successfully used at the canopy level to predict water content using hyperspectral imagery [61]. Recently, microwave remote sensing-derived indicators, such as relative water content, have also been tested for their ability to predict large-scale water stress variations and tree mortality [62]. Although many of the aforementioned studies have been conducted at the leaf level [63] (Supplementary Material Table S3), less research has made predictions at the landscape level.

Although there have been notable improvements in the field of airborne and satellite remote sensing-based EWMs in recent years, major gaps exist in operational decision making that impede effective post-drought tree mortality assessment and carbon management, especially at tree-level. However, the use of remote sensing satellite sensors to detect tree stress and mortality is limited to forest areas with open canopies—as in other cases, the mortality signals were often obscured by overlapping crowns and/or understory greenness [30,64]. Landsat images are usually of poor quality due to their moderate spatial and temporal resolution data. Other multispectral satellite remote sensing data sources, such as Worldview, QuickBird, GeoEye-1, Rapideye, etc., with higher spatial and temporal resolution images can be used to more accurately detect tree stress and mortality, but these imageries are expensive for large areas and long-term monitoring studies and affected by cloud cover. Therefore, there is the need for integration of satellite and airborne data with high temporal resolution data from UAVs with a spatial resolution that allows sampling at both the canopy and tree level, to improve on the development of EWMs for tree mortality.

3. Potential of Unmanned Aerial Vehicle (UAV)-Based Endeavors

In addition to satellite remote sensing imagery, UAVs that integrate hyperspectral, thermal, multispectral, and near-infrared sensors have been extensively used in the recent past for local-scale forest monitoring and species-level response to environmental changes to derive EWMs. This is because UAVs provide a cost-effective and easy-to-use alternative high-resolution imagery that ranges from meters to millimeters. This is crucial for studies that require data at high spatial and temporal resolutions, especially in cloudy areas or densely forested landscapes where satellite imagery is not dependable [65–67]. The applications of UAVs in the forest sector have exponentially increased in the past decade due to advancements in the field of robotics, artificial intelligence, sensors, and data science algorithms [68–70]. The advantages of using UAVs in forest management to develop EWMs are shown in Figure 1.

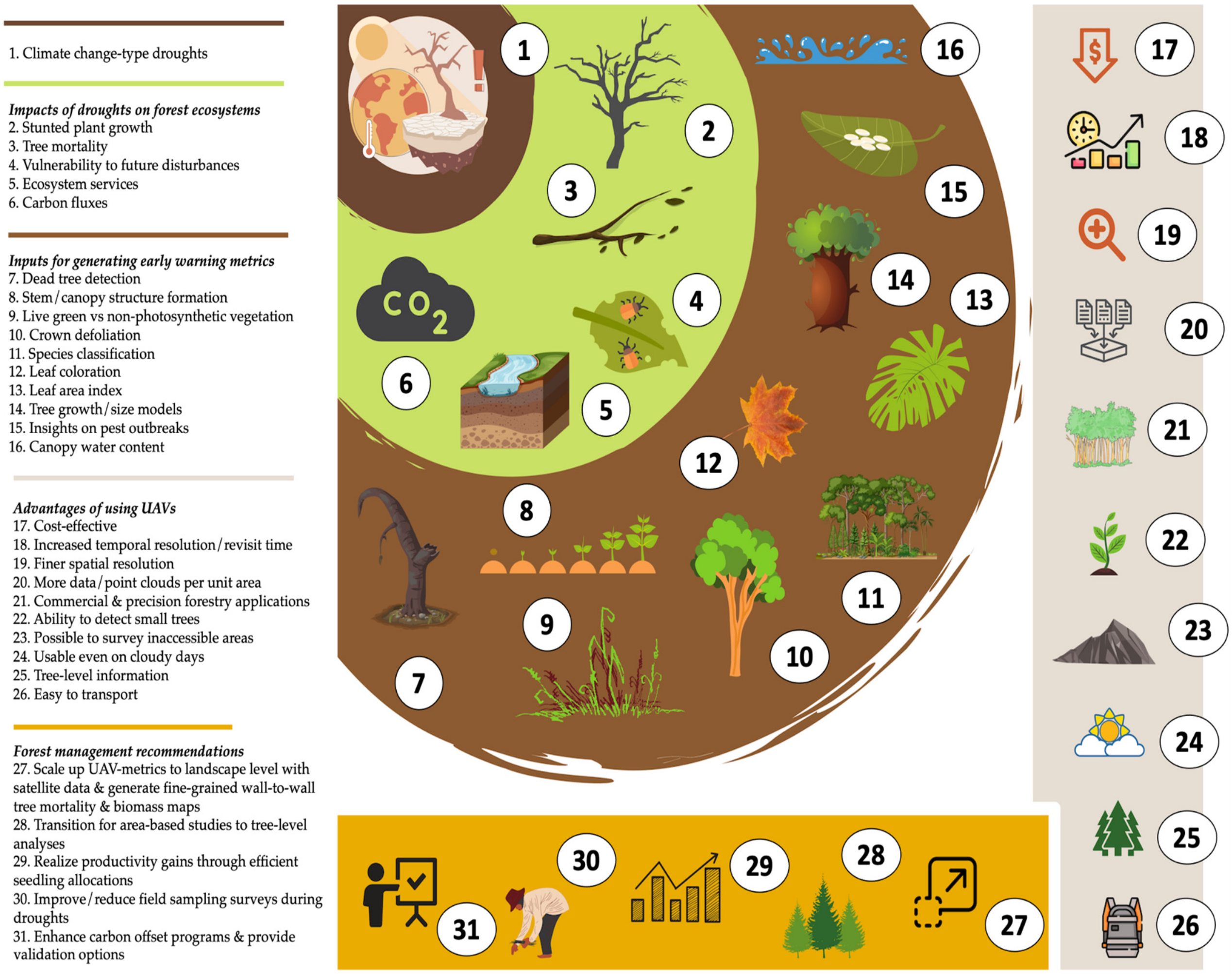

Figure 1. Impacts of climate-change-driven droughts on forests and possible pathways through which operationalization of UAV-derived early warning indicators can assist post-drought tree mortality and biomass assessment.

The implementation of UAVs would allow us to observe the relationship between NDVI and drought, infestations, productivity, leaf senescence, and partial dieback and mortality at a finer resolution (tree level) as well as at more frequent intervals, which are limitations of satellite imagery. Different species display changes in different plant traits under drought conditions, and high-density point clouds/high resolution imagery from UAVs will assist with species classification and species-level analysis information over small areas that can be integrated with satellite and field measurements to produce more reliable data/results. Because satellite-imagery-derived NPV of dying trees shows similar correlation with drought stress and poor site condition, NPV estimated from satellite imagery cannot be generally used as an early warning drought metric in a wide variety of forests. More regular, high-quality time series data acquired over a long-term period from UAVs are necessary to differentiate drought stress from other causal factors such as poor site conditions.

Because UAVs can be used to acquire more data per unit area at small spatial scales, there is more extractable information at the tree level, including reliable vegetation indices. This is extremely beneficial for performing species classification and microscale analysis related to drought responses. Recent improvements in UAV technology, driven by longer flight times and greater carrying capacity, have made them a viable platform for data capture. UAV sensors can be used to characterize indicators of water stress at a fine resolution. For instance, [71] used UAV-acquired multispectral imagery to detect stress in a mature *Pinus radiata* D. Don plantation using the NDVI, GNDVI, and RENDVI (Red Edge Normalized Difference Vegetation Index). Previous research has demonstrated the possibility of operating UAVs fitted with airborne LiDAR for characterizing leaf area index at the landscape level [72]. Similarly, recent advances in UAV hyperspectral sensor technology now allow collection of fine resolution hyperspectral data that are accurately georeferenced, and a list of available sensors is given in [73] (see Supplementary Table S1). Detection of drought stress ideally requires data in the range of 400–2500 nm, as leaf water content has been found to be strongly related with wavelengths from 900–2500 nm.

From an operational standpoint, UAV technology has the potential to fill the data gap between field inventory and satellite remote sensing for assessing forest characteristics and their responses to drought conditions. With the increasing use of UAVs and the greater availability of technologies for data processing, along with robust sampling strategies, we can verify and monitor forest structure at the individual tree scale over tens to hundreds of hectares when integrated with satellite data [74–77]. UAV-derived EWMs can provide detailed assessments and measurements of various tree physiological complexities, site-specific factors, and forest carbon distributions for mitigating the impact of drought and optimizing forest carbon levels at multiple scales depending on supplementary data availability.

The use of UAVs in combination with a wide variety of tools and techniques (e.g., GNSS (Global Navigation Satellite Systems), ground truthing, ground-based LiDAR, GIS (Geographic Information System), etc.) to produce high-resolution data are an essential part of precision forestry and can be extremely useful in detecting early warning signs of droughts, analyzing drought impacts, and helping in tactical and operational decision making [78,79]. In addition, UAVs can play a prominent role in the commercial forestry domain, which is also facing the brunt of climate-change-driven droughts and tree mortality, along with associated events and risks such as wildfires and insect outbreaks [80].

Herein, we argue that UAVs hold immense potential for forest resource management and precision forestry in the event of a drought as UAVs allow us to shift from using remotely sensed data on an area basis (e.g., 20 $\times$ 20 m) to using remotely sensed data on a tree-level basis. Responses of individual species in multiple environments with varying drought intensity can also be measured, providing further insights into the spatial–temporal distribution of tree mortality and drought vulnerability. From UAV-mounted sensors, more usable information (e.g., 3D point clouds) can be obtained per unit area and this can assist with generating new benchmarks for performing cross-validations and for scaling up data from the site level to the landscape level. Figure 1 underscores several possible UAV-based pathways that could be explored for assessing drought-induced tree stress.

4. Prospective Approaches and Recommendations for UAV Applications

In general, the proposed approaches address broader issues in remote sensing and forest ecology and how the recent advances made in the field of UAV-based technologies can be used for bridging the gap between ground-based and satellite remote sensing data and developing new metrics to predict drought-induced tree stress and mortality. The twenty-four prospective approaches and associated recommendations are classified into five categories, including (i) physiological complexities, (ii) site-specific and confounding (abiotic) factors, (iii) interactions with biotic agents, (iv) forest resource monitoring and optimization, and (v) technological and infrastructural developments (Figure 2).

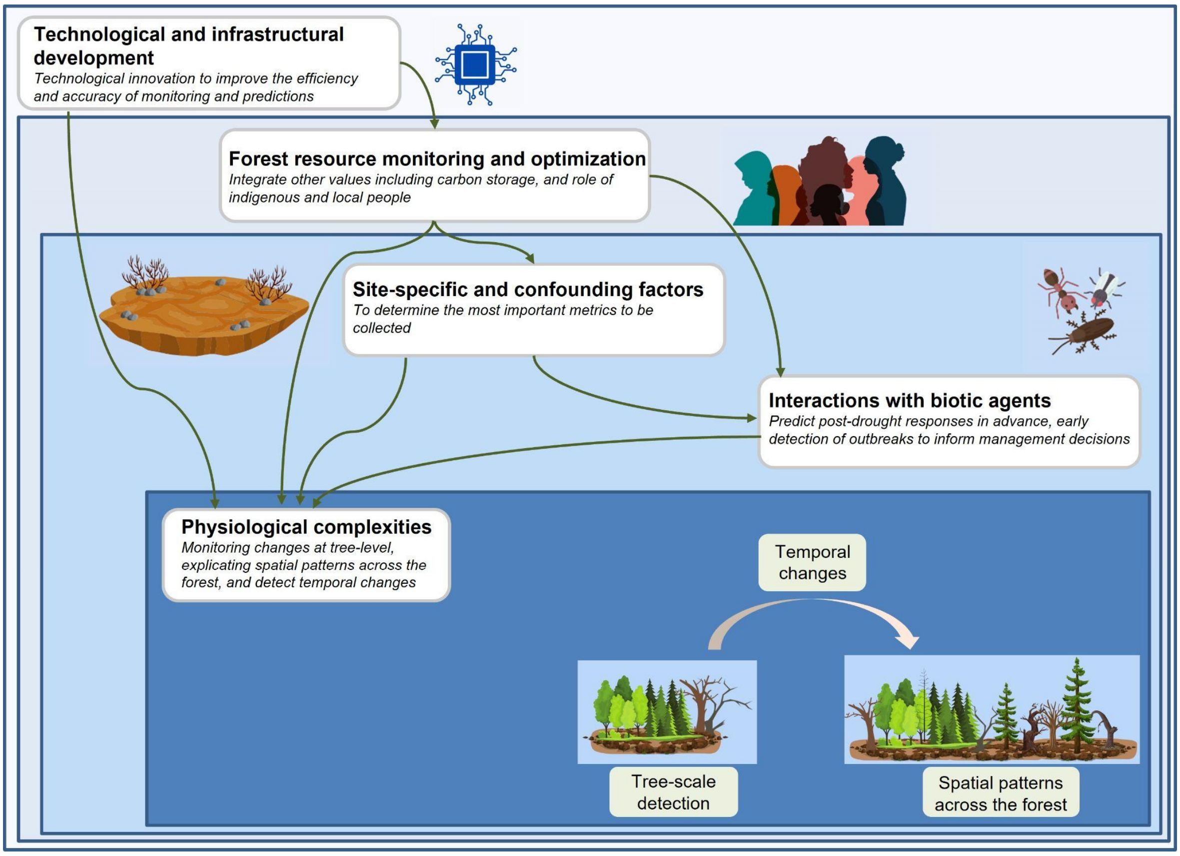

Figure 2. Conceptual framework for the prospective approaches and recommendations for using UAV-based technologies to monitor drought impacts at different scales, early detection of post-drought outbreaks, and how to integrate site-specific, confounding factors and other values in developing the early warning metrics. Also shown are technological innovations that could, in general, improve the efficiency and accuracy of monitoring and prediction of drought impacts.

4.1. Physiological Complexities

4.1.1. Thresholds and Tipping Points

Assessing plant mortality at the tree level is often challenging, mainly due to the complex nature of trees in which hydraulically independent units may survive, while unhealthy parts of the plant die [81]. In parallel, the existence of lag effects adds new constraints to the accurate estimation of drought-induced tree mortality [48]). The concept of a "point of no return" for plants can be used when trying to define or assess the existence of a physiological threshold after which the likelihood of tree mortality progresses irreversibly [82,83]. The point of no return, sometimes called tipping point of the tree, most commonly refers to the cessation of water transport, loss of living aboveground tissue, and/or hydraulic conductivity/water potential gradients which do not recover even when soil moisture increases [22,84].

UAVs can be useful in assessing tipping points of plants, as they allow close to real-time monitoring of changes in forest conditions at a tree scale, thereby recording early warning signals of tree stress. UAVs can overcome the limitations in spatial resolution of satellite data because they better match the scale at which individual tree mortality occurs [22]. The detection of physiological stress at the tree level can assist with the derivation of mortality-related risk factors [22,85]. Physical traits observable from UAVs—such as tree crown defoliation, leaf coloration, canopy loss, leaf area index, stem structure, and tree size—should be utilized as surrogates and be associated with hydraulic failure, carbon starvation, and/or reduced defense [86,87]. This information can also help estimate the change in carbon sequestration capacity of individual trees and thereby assist with updating biomass maps at regional levels.

Detection of reductions in canopy water content, relative water content, and leaf water content using remote sensing techniques is a promising method to detect tree physiological stress (such as hydraulic failure) through the course of a drought and therefore could be used to physiologically monitor, manage, and forecast mortality [25,62,88]. Transferring these technologies to UAV platforms, improving the number of data samples, and analyzing the different species present in the study areas would provide tools to detect gradual/chronic versus short-term/abrupt weakening of plant systems and associated biomass levels. We recommend further research that focuses on deriving integrated quantitative metrics to represent the extent of forest mortality and consider the inclusion of climatic thresholds and lag effects while measuring biophysical parameters.

4.1.2. Canopy Structure and Plant Functional Traits

Hydraulic failure and its interactions with biotic factors have been frequently associated with drought-induced tree mortality. The water potentials (Ψ) at which stem hydraulic conductivity is reduced by, respectively, 50% (Ψ50) and 88% (Ψ88), are suggested as thresholds and probable indicators of hydraulic failure that cause tree mortality [22,89]. However, this tolerance is highly variable both between and within species, and across space and time due to factors such as plant development, seasonality, and life history [45]. Limited knowledge on intraspecific plant functional trait variations and covariations, and interaction among traits, increases uncertainty in model predictions and restricts the assessment of adaptive capacity of trees following stressors such as droughts [90]. Repeated UAV acquisitions of important data can identify and classify tree species based on plant functional traits at the tree level and species level, to characterize within-species trait variation and assist understanding of the transition in properties across age groups and species with high accuracy, and thus improve the accuracy of model predictions.

As drought events have the potential to cause significant reductions in net primary productivity of forests [91], understanding different responses of plant functional traits to droughts is important to predict changes in carbon storage. In this regard, exploration of UAV hyperspectral data and time series images would be beneficial. Leaf area index, which is linked to an apparent ordering of co-occurring species' risks to drought mortality, can be extracted with high confidence using UAV multispectral and/or point cloud data [44,92,93]. UAV-derived biophysical parameters can facilitate the development of direct relationships and improve our understanding of tree size, tree growth and with wood density at the species level, which has been found to have some influence on drought-induced mortality rates [94].

4.1.3. Forest Health Mapping

UAV data may be necessary to bridge the resolution gap of satellite-based remote sensing and ground level surveys and improve our predictions of tree health, disturbance regimes, disease spread, and recovery rates [11,95,96]. UAV data over small areas allow us to extract detailed forest metrics at affordable rates and can complement satellite data over larger areas in order to identify coarse and large-scale forest deterioration, stress, and disease progression in post-drought environments. For example, Kattenborn et al. [97] tested the applicability of UAV-based reference data acquisitions as alternatives to traditional field surveys and demonstrated the possibility of scaling up UAV-estimated species cover to spatial scales presented by Sentinel-1 and Sentinel-2. Samiappan et al. [98] utilized UAV-sourced high-resolution multispectral imagery to derive NDVI and SAVI (Soil-Adjusted Vegetation Index) to identify and map Chinese tallow and found greater than 90% consensus between the ground reference data and the tallow identified from the multispectral imagery.

In addition, Watt et al. [99] used multispectral UAV data and satellite data from the WorldView 3 platform to predict weed cover in forest plantations. Similarly, UAV imagery was found to highlight physiological stress caused by herbicide more accurately in comparison to RapidEye imagery [71]. UAV technology has also been used to assess pest damage and identify the threshold of detection of tree crown defoliation in Mediterranean pine forests [11,86]. Dash et al. [85] tracked changes in canopy color and density of herbicide injected trees, on high-resolution time-series UAV data—during a disease outbreak which was simulated in mature *Pinus radiata* (D. Don) trees—and confirmed the utility of UAV data for monitoring the physiological stress in trees. UAV-derived metrics have been used to calibrate measures of burn severity derived from Landsat 8 imagery following a wildfire [100]. Therefore, systematic UAV flights close to ground surveys make it possible to attain consistent data samples explicating spatial patterns of forest health in drought-affected areas.

4.1.4. Nonphotosynthetic Vegetation

The NPV index is a prominent element of vegetation productivity in grasslands, savannas, shrublands, and dry woodlands, and is essential for understanding and assessing carbon sequestration [101]. Measurements of NPV cover can highlight the response of vegetation to drought and mortality caused by disturbance events, and this serves as an essential early warning drought metric of climate change impacts on vegetation in multiple forest ecosystems [23,102]. Long-term drought can result in increased NPV in vegetation across a range of vegetation types from crops to native shrubs and trees, indicating differences in susceptibility to water stress [103]. NPV cover can be estimated utilizing lignin and cellulose absorption features in the shortwave-infrared range. However, since most of the NPV is obscured under longleaf tree canopies, only exposed NPV has an effect on the spectral reflectance [104]. Furthermore, separating NPV and background soil cover is a challenge in the visible and near-infrared wavelength spectrum since they possess identical featureless spectral reflectance curves, and because these bandwidths are used by NDVI and other indices for image classification [100,105]. Higher-resolution images acquired through UAVs can be useful because finer spatial resolution imagery allows the masking of soil layers through various machine learning processes. UAV data could also help improve the accuracy, by differentiating the signals which we take in from nonphotosynthetic vegetation index, to understand the relation between the drought stress signal and poor site vulnerability.

Currently, NPV studies are mostly centered on the estimation of NPV cover using passive optical data rather than NPV biomass; only a few studies have made the best use of hyperspectral, LiDAR, synthetic aperture radar, and data from UAVs. This trend is expected to change in the future with recent advances in extracting and combining multisensor data, and these methodologies include UAV-based frameworks [106]. The combinations of machine learning algorithms and multispectral data from UAVs have been found to detect and quantify the dead canopy woody component (such as dead stands and fallen trees) of secondary dry forest plots with accuracy values higher than 95% [107]. Data from UAVs can also characterize the transition between live to dead biomass pools and identify factors that can quantify compartmentalization of death/senescence of trees.

4.1.5. Spatial Variability

Forest gap formation associated with drought-related tree mortality and forest dieback have been found to be spatially distributed, varying in size and vulnerability based on a multitude of environmental and site-specific parameters [50,108,109]. Spatial attributes of patches related with drought impact can yield significant insights around drought intensity [109]. Satellite/aircraft-based remote sensing provides fundamental underlying data for analysis of spatial patterns and temporal trends related to drought-induced tree mortality [50,110,111]. UAVs are becoming a feasible option for analyzing spatial variation in drought-associated tree mortality, growth rates, resilience, and vulnerability. For example, Buras et al. [112] used UAV-based remote sensing for investigation of Scots pine dieback after drought using parameters such as canopy area, tree height, nearest neighbor distance, and minimum distance to forest edge, and found that dieback (tree mortality) was driven by drought and carbon depletion especially at forest edges. Such findings not only assist with forest management practices but also help elucidate feedback loops related to forest edge effects and identify areas vulnerable to droughts.

UAVs can be used to identify forest gaps and quantify spatial gap patterns at stand levels and/or validate satellite-image-derived gap fraction products [68,113,114]. Zhang et al. [115] demonstrated how UAV-based canopy parameters are able to delineate local biodiversity patterns while assisting several gap dynamics hypotheses and theories within the ecology domain, which otherwise need the existence of expensive long-term monitoring field sites. This highlights the importance of UAV-based metrics in characterizing the status of carbon sinks after formation of forest gaps. The role of drought in creating spatial patterns, age, landscape structure, and changes in other characteristics associated with biomass is yet to be studied and determined for a plethora of different regions and forest types. In this regard, application of UAV swarms and establishment of UAV user networks will be extremely useful for scaling and comparison purposes.

4.2. Site-Specific and Confounding Factors

4.2.1. Secondary Forest Sensitivity

Secondary forests constitute a significant portion of global tropical and temperate forests, possess considerable biomass sequestration capability, and have the potential for cost-effective climate change mitigation and for lessening biodiversity loss [66,116,117]. However, water availability has a significant impact on the biomass resilience of secondary forests, where fewer and/or more variable rainfall patterns in the tropics predicted with climate change may reduce their biomass recovery rates and forest resilience [118]. Elias et al. [117] reported higher vulnerability of secondary forests to drought stress, lower carbon balance, and growth rates in tree species in drier periods in the Brazilian Amazonia, which could diminish the efficiency of the secondary forests carbon sequestration and climate change mitigation capabilities. As large-scale forest landscape restoration efforts are employed around the world it is important to monitor these planted secondary forests and identify their vulnerabilities in the face of climate-change-driven droughts [69].

Given that a lot of secondary forests comprise small trees, UAV-borne sensors (red–green–blue, multispectral, hyperspectral, and LiDAR) have the advantage over coarse-resolution satellite imagery to identify local stand density, tree size distribution, and species diversity of regrowing trees and provide detailed forest monitoring information to assess changes in forest structural attributes, biomass, and tree health in restored secondary forests [66,119]. In addition, if UAV–LiDAR data can be integrated with data from NASA GEDI (Global Ecosystem Dynamics Investigation), it should be possible to investigate how the distance from forest edge—due to ongoing logging and forest fires—affects the degradation, growth rate, and/or carbon sequestered by existing secondary forests of different age groups [120].

4.2.2. Multiple Forest Disturbances Effect

Attribution of causality is a major challenge in detecting climate-change-driven tree mortality through existing monitoring methods [22]. A robust monitoring system should be able to detect forest disturbances, accurately identify proximate causes, and be incorporated into predicting trends [121]. For instance, Maillard et al. [122] investigated the association of forest fragmentation and drought severity patterns with spatial trends in forest fires using precipitation and temperature data, Landsat 8 images, and ultra-high-resolution images from UAVs and found that forest edges and human-utilized zones suffered the greatest impact from forest fires, and spatial trends of drought intensity impacted the extremity of forest fires. Integrating UAV-based remote monitoring protocols with satellite imagery would offer more flexibility with the ability to control temporal and spatial resolution, characterization of disturbances over larger areas in a shorter time period, and for isolating the influence of individual forest disturbance types. Therefore, development of UAV-based novel monitoring networks is essential for a faster, accurate, and more automated detection of multiple disturbance types [66,123].

4.2.3. Species Diversity

High species diversity is widely considered as an element of a climate-resilient forest ecosystem [124]. Studies have shown that forests with high species diversity are also diverse in plant community hydraulics, and these forests are more resilient to drought-related tree mortality compared to species-poor forests [125,126]. However, recent evidence reveals that tree diversity and drought resistance are not always positively correlated [127]. Therefore, understanding tree species interactions and underlying competition among species for resources are important in assessing post-drought tree mortality. We propose using UAV-based remote sensing technology in EWMs to assess positive and negative interactive relationships between different species, which would contribute to the overall resilience and carbon sequestration capacity of the system. Stabilizing feedback may exist where tree mortality increases the survival of neighboring trees due to release from competition for resources [22], and adaptation to drier conditions [128]; these can be tracked in a timely manner using UAV-based frameworks due to the possibility of improved revisit times.

4.2.4. Soil Characteristics

Soil characteristics such as the physical, chemical, and biological properties play a major role in determining the drought susceptibility in forests. UAVs allow the monitoring of soil systems temporally and spatially in a satisfactory manner—especially for agroecosystems, forest, and grassland. UAV-based soil moisture estimations can be undertaken using a variety of data sources and methods, including multispectral data and vegetation indices [129], hyperspectral imagery and machine learning algorithms [130], visible images [131], and UAV-borne ground-penetrating radar [132]. The use of UAVs reduces measurement intensity, has zero impact on soils, is relatively low cost, and has high flexibility and efficiency compared to traditional methods [133,134]. UAVs can be used to efficiently detect early changes in stem biomass caused by prolonged drought conditions that lead to drastic biomass reductions (>50%), mainly in the stems [135,136].

Generally, trees grown in soils with high salinity in coastal woodlands/forests are more susceptible to mortality in an event of extreme drought as soil salinization leads to the dispersion of clay particles that reduce drainage. Researchers have highlighted the use of UAV-borne multispectral remote sensing [137] and hyperspectral imaging [138] as powerful tools to determine soil salt content. UAV-mounted multispectral and hyperspectral sensors have been used by previous researchers [139–141] to estimate soil organic carbon in arable/bare soils. However, unlike bare soils, heavy organic matter accumulation in the surface layer of forest soils may interfere with the UAVs' capacity to quantify the aforementioned soil properties, and further research should focus more on drought-related changes in carbon storage and tree mortality.

4.2.5. Topography

Topography (elevation, slope, aspect, and convexity) can influence soil moisture content, leading to variable responses of tree species during drought conditions, especially in mountainous areas. Since topographic convergence (i.e., where the wind flow is, in general, forced up/around a high elevation region resulting in heavier precipitation) is directly linked with plant water demand, it can play a vital role as a predictor of ecosystem productivity and can provide insights to the plants' response to droughts and post-drought conditions [142]. Tai et al. [142] observed less mortality of aspen in topographic convergent areas than that of topographic divergent areas. Trees on ridges and upper slopes are more susceptible to droughts, which is attributable to high drainage and exposure to wind, whereas trees growing in valleys are relatively resistant to droughts due to provision of additional water through lateral hydrologic flow [143,144]. Further, Elliott et al. [145] found slower growth rates of tree species at the upslope position compared to the cove position.

With recent advances, high-resolution/accurate digital elevation models (DEMs) can now be derived from LiDAR mounted on UAVs, which can be used for microscale analysis to obtain greater insight into the role of topography in post-drought tree mortality. These derived DEMs can then be used to calculate changes in various topographic metrics such as slope, terrain curvatures, elevation, etc. [146], at a fine resolution, which are important for understanding the forest response to drought stress. Although global DEMs exist (~30 m pixel resolution), fine resolution DEMs acquired from UAVs can more easily detect newly formed small and manmade changes to the landscape topography [147]. This might be crucial in post-drought studies as these fine level features can affect rainwater trajectories and vertical distribution of below-surface moisture and the ability of the vegetation to tap into this moisture.

4.2.6. Climate Extremities

Climate teleconnections refer to the phenomenon in which climate anomalies are interconnected to each other at large distances. Their occurrences and how they correlate with ecoclimate conditions may be used as an EWM to predict drought-like conditions and drought-induced events. Field et al. [148] found that fires and smoke occurring across the Indonesian Kalimantan region indicated a nonlinear and sensitive relationship to El Niño Southern Oscillation drought conditions. There exist significant relationships between the most relevant climate extremities (Tropical North Atlantic Oscillation) and the area burned by fires, with variations across and within continents and biomes [149]. Studying teleconnections in relation to drought conditions may also provide insight into the conditions that are favorable for ecological growth, versus which climatic conditions would impede growth. For instance, Wharton et al. [150] reported that an increase in the strength or frequency of El Niño Southern Oscillation with Pacific Decadal Oscillation and Pacific/North American Oscillation in phase will increase the variability of CO_2 absorption in conifer trees located in the Pacific Northwest region. Multitemporal application of UAVs should be used for this purpose at local scales, and differences in tree responses during and after (both short and long term to include the lag effects) droughts should be studied in detail. This is because it is extremely difficult to isolate and quantify the impacts of teleconnections and concomitant droughts on tree mortality at local scales from coarse-spatial-resolution satellite imageries.

4.3. Interactions with Biotic Agents

4.3.1. Individual Tree Physical Characteristics

Drought-induced tree mortality usually occurs as a result of hydraulic failure, carbon starvation, and/or insect/pathogen attacks [89]. The effects of water stress have been found to be highly variable among trees within a stand as well as among stands of different forest types and densities [151–153]. Larger trees, in general, are more vulnerable to droughts than smaller trees. Mapping individual trees and stands using vegetation greenness and predicting their drought response in advance using UAVs is important in developing EWMs. Individual tree detection and estimation of forest structural properties can be carried out using UAV–SfM (structure from motion) and UAV–LiDAR to derive relationships between acquisitions of plant resources, interspecies interactions, and the possibility of withstanding droughts [154,155]. UAV-derived tree-level metrics (such as tree crown size and tree heights) could indirectly pinpoint the drought-resistance capability and patterns of mortality outbreaks associated with structural overshoot.

Whole-tree biomass and carbon dynamics can be estimated using UAV–LiDAR, and could be tested for its relationship with tree mortality from carbon starvation to identify the onset of a negative carbon balance during severe drought and in combination with high temperatures and high vapor pressure density [22]. Drought-induced xylem embolism is a prominent factor that is linked to tree mortality. Thus, application of UAVs for characterization of existing species in a forest system would allow the prediction of drought-induced embolism in xylem tissues that can be derived based on the relationship between pit membrane thickness and embolism resistance [156,157]. UAV-based thermal infrared imaging has been used to detect changes in canopy temperature in relation to variation in stomatal conductance, allowing the characterization of genotypic variability under drought conditions [158].

4.3.2. Early Pest Detection and Spatial Distribution of Insects

Above-average temperatures which are characteristic of droughts can directly affect insect and pathogen functional fitness as well as alter tree suitability and predisposition to attacks [22]. The use of UAVs for detection of pest infestations is becoming popular due to advantages/benefits, especially at the individual tree level during early and various other stages of infestation [11,159,160]. For instance, UAVs have been used for detection and quantification of damage from the Eucalyptus Longhorned borers in eucalyptus stands and detection of bark beetle infestation at the individual tree level at different stages of infestation [161]. The increases in plant nutrient concentrations and remobilization of soluble nitrogen forms to younger leaves have been found to be favorable for insect metabolism and population development [162]. In this regard, extraction of leaf area index, understory leaf area index, and/or forest structure—which can provide estimates of younger leaves—from UAV–hyperspectral and/or UAV–LiDAR data can be deemed beneficial for predicting possible threats of insects in drought and post-drought periods. The early detection of pest attacks following droughts is important for implementing management strategies (i.e., phytosanitary cuts, prophylactic treatments) to reduce the danger of elevated tree mortalities, degradation of forest stands, and biomass losses.

4.4. Forest Resource Monitoring and Optimization

4.4.1. High-Priority Carbon Offsets and Role of Indigenous People

UAVs can be used to obtain and validate the satellite-data-based overview of forest attributes and characteristics which can determine aboveground biomass and carbon sequestration levels and thereby support high-quality carbon offset projects. UAV oblique photography was accurately used in the aboveground biomass estimation of subalpine coniferous forests in the region of the Minjiang River [163]. UAVs can be used to obtain time series data over small areas in restoration and afforestation assessment/site selection projects that target high-quality carbon offsets in cooperation with forest local landowners and indigenous communities [69]. This is crucial in establishing successful carbon credit systems as local and indigenous communities possess traditional ecological knowledge and innate understandings of their forests, leading to reduced deforestation and degradation rates [164].

Local projects have been developed to train indigenous communities in UAV mapping and monitoring to identify carbon-efficient trees, vulnerable species, early warning signals of tree mortality, and tree-level parameters that can provide insights into impacts of climate-change-driven droughts [165–167]. Thus, ensuring participation of indigenous/traditional communities in high-quality carbon offsets using UAVs and also redirecting corporate/company carbon offsets to assist Indigenous communities with ecosystem services, soil stabilization, and water purification would help achieve forest regeneration and also improve the livelihoods and rights of forest guardians. However, extra care and attention should be taken to make sure that these technological interventions are not disturbing the living conditions and stability of Indigenous communities.

4.4.2. Scaling Strategies

Previous studies have tested various multiscale approaches using UAVs in association with satellite imagery for scaling up plant water content and vegetation fractional cover [168,169]. In these cases, collection of samples from several UAV sites were proposed to be used for training satellite data to examine vegetation at larger extents. This can further help the scaling of prevalent UAV-based workflows to drought prone ecosystems as long as UAV datasets are sampled across a large study domain, capturing diverse features/signals present within the landscape, and appropriate inferences are made with respect to observations from satellite imagery. For example, comparison of aggregated classified high-resolution pixels from UAV orthomosaics with the values extracted from satellite imagery for the corresponding pixel area could provide insights into the applicability of the data collected.

UAVs have been successfully used with NASA GEDI spaceborne LiDAR for large-scale multilayer fuel components measurements and load model characterization using sample plots [170]. Similarly, UAV thermal infrared sensors could also serve as potential scaling tools when integrated with ECOSTRESS data as they can bridge the disparities arising from the scales (i.e., in situ data versus ~69 m cross-track × 38 m in-track spatial resolution of ECOSTRESS). However, we need to analyze the within-pixel estimates of spatial and temporal variability offered by UAVs (as they fly low and can be used based on our demands) in a diligent manner to better understand and improve scaling issues, if any [171].

4.4.3. Pandemic–Vulnerability Metrics

In the midst of a pandemic, UAV monitoring of forested areas and mapping of tree mortality is ideal—given the limitations on fieldwork and available labor—to identify degraded and deforested areas which have previously undergone drought periods. The COVID-19 pandemic led to a reduction in conservation funding in many parts of the world and a decrease in forest monitoring due to pandemic restrictions [172,173]. The lack of forest monitoring and regulation also means that there is a high chance of losing all the carbon sequestered through forests due to illegal logging and fire activities. For example, lockdown during COVID-19 was associated with an upsurge of forest fires in Colombia's Amazon, which was correlated with an increase in the presence of armed groups in these areas [174]. Such anthropogenic activities harm ecological diversity and threaten forest resilience, making the forests more vulnerable to droughts in the future. UAV technology was successfully used to assess and monitor forests and identify reductions in canopy coverage and density associated with tree mortality during pandemic restrictions [88,175,176].

4.4.4. Input to Earth System Science Models

In the last few decades, there has been an increasing focus on development of Earth system models owing to the need for better comprehension related to feedback between climate change and the carbon cycle [177]. Several Earth system models that exist today incorporate numerous biogeochemical processes and offer important insights into climate variation, role of anthropogenic undertakings, and decision making in the form of climate adaptation and mitigation actions [177,178]. In the context of this review, several forest and environmental attributes captured via remote sensing/UAVs related to tree mortality and droughts can aid in improving these models, making them more efficient and sensitive to short-term climate anomalies and scales. UAV-derived plant physiological traits can be included in Earth system models for simulation of land–plant–atmosphere feedbacks and extreme climate phenomenon, since they have a direct influence on drought intensification. Spectral and structural data collected using UAVs can also possibly serve as dependable Earth system model validation data in post-drought scenarios.

4.4.5. Post-Drought Species Community Trajectory

Post-drought species community dynamics have the potential for ecosystem reorganization at least in the short-term, and are dependent on multiple factors, including drought characteristics, environmental requirements of the species, plant traits, and ecosystem legacies, of which several are trackable using existing UAV technologies [179]. This can have major implications for biomass levels, biodiversity, and ecosystem services; therefore, understanding regeneration dynamics and vulnerability for future stressors is important. These post-drought ecological trajectories are influenced by management intensity and other stressors, such as when pathogens act as co-drivers of tree mortality [179]. However, it should also be noted that a positive indication of certain characteristics for some plant communities might mean a negative indication in others [35]. UAVs could assist with development of methods to identify which behavior could imply an appropriate signal when approaching a novel post-drought plant community, given the flexibility it can offer in terms of data sampling frequency and enhanced data quality.

4.4.6. Optimizing Field Data Collection

Previous studies have suggested that a coordinated monitoring network which combines inventory plot data with satellite imagery data is a suitable method to detect changes in forest coverage and potential drought areas [22]. UAV applications in forest monitoring would help optimize field data collection one step further—in particular, with the minimization of manual labor required and timely identification of tree mortality hotspots. UAV–LiDAR data will be able to provide site specific information such as changes in terrain, forest characteristics, and conditions which may be indicative of tree mortality and drought and are useful for reducing sample size and for filling data gaps in field surveys [97,180]. Once drought-prone areas are identified and/or validated using the UAV data, experimental studies measuring physiological and ecological interactions could be conducted, allowing inferences to be drawn regarding how current climate conditions are impacting the mortality rate of various tree species [175,181]. This would help address several scales and time-related EWMs limitations that researchers [22,182] have faced while attempting to study and predict tree mortality and determine the location of drought prone areas.

4.5. Technological and Infrastructural Developments

4.5.1. Deep Learning and Object Identification

Neural networks and corresponding deep learning algorithms have been identified as a key technology for object detection using UAVs, given the detail of forest- and tree-level information that can be extracted from the fine-resolution images and 3D point clouds. When UAV imagery is used as input to deep learning, it is possible to detect small newly planted trees [66,183], accurately classify tree classes [184,185], identify tree species in secondary forests, and map tree trunks after logging, which are crucial steps towards quantifying post-drought tree mortality patterns and biomass recovery rates [65,66,186,187]. The use of these approaches facilitates tree-level detection, which opens up a range of additional applications (e.g., development of tree level growth models). The advantage of using UAV data for deep learning—over airborne or satellite systems—is that we can acquire more pixels per tree, which makes tree-level detection more robust as there is usually a minimum number of pixels required for accurate object identification. Further research should extend these deep learning applications to detect mortality of the newly planted trees from drought.

4.5.2. Data Fusion

Data fusion is driven by the need to overcome spatial and temporal resolution limitations associated with moderate- to high-spatial-resolution data (e.g., Landsat and UAV data, respectively), while simultaneously making use of the advantages offered by both. High-spatial-resolution data are generally acquired over small areas using UAVs and these datasets offer improved sampling characteristics compared to satellite imagery. Collection of such data also requires appropriate timing and knowledge of when tree mortality occurs so that data can be collected before, during, and after mortality occurs [188]. However, UAVs' ability to map tree mortality at larger spatial scales is limited, and even if such remotely sensed data are available via specific satellites, these can be costly, may not be open-access, and/or their availability may be geographically limited. In addition, moderate-resolution and time series satellite data, which cover broader spatial scales, may not be able to provide the resolution to accurately detect and map changes/parameters related to drought-induced tree mortality.

These issues could be addressed through adoption of a multisensor, multiscale approach, which can make use of data derived from in situ measurements, UAVs, and satellites, among various other instruments, in a holistic way to address the several challenges posed in mapping the extent and severity of tree mortality [168,169,188]. Using a data fusion approach, UAV data have been used to analyze individual tree mortality; airborne LiDAR data were employed for delineation of the canopy crown, calculating canopy cover and relative mortality proportion; and Landsat imagery was used for scaling up estimates of tree mortality to a greater spatial scale at the regional level [188]. Data fusion has also shown potential for understanding the effects of droughts on forests, in terms of increased mortality, weak plant hydraulic systems, stunted growth, and changes in biomass and carbon sequestration capability [189–191].

4.5.3. Operational Aspects

Remote sensing applications are a vital source of timely, cost-effective, and comprehensive information required for sustainable forest management. However, improving the operationalization of remote sensing research, data, and algorithms is essential for maximizing the utilization of these tools and technologies in applied forest management [192]. Data integration and coordination is another important aspect of operationalization of forest monitoring systems as part of an EWMs framework. Many existing operational forest monitoring systems track only a few specific attributes at national to global scale, but to effectively monitor structural, functional, and compositional attributes of a forest system, integration of multiple sources of data is needed [193]. UAVs can be used in remote and inaccessible areas with several revisit times to sample data/areas with more flexibility and efficiency to help address the limited sample size and sampling biases from field surveys.

For effective carbon management and for enhanced resource-use efficiency in managing threats, EWMs should have a regional-scale focus. The challenge in developing UAV-based EWMs for post-drought forest management is to balance the need for regional-scale-focus satellite data with local-scale inputs from higher-accuracy UAV data. Presently, there are numerous platforms for remotely sensed data from satellites but this is not the case for UAVs, most probably as a significant proportion of data collection is undertaken at the individual/enterprise level. Thus, the creation of an online UAV open-source platform and database would be useful. Within such a system, academic and industry researchers, forest managers, and related professionals could voluntarily upload their data associated with different forest types and different UAV-mounted sensors. They could also engage in data aggregation, sharing, visualization, and analysis for post-drought mortality detection and carbon assessment.

4.5.4. Technical Advancements, Market Integration, Scope, and Collaborations

Emerging technologies, such as UAVs, can help map and predict changes related to the Earth's ecosystems and climate to assist decision making for a sustainable future. Depending on their intended use, UAVs can be manufactured in a lightweight and energy-efficient way by using different energy sources such as wireless charging and solar power [194]. More recently, UAVs can also be modified and customized for post-drought tree mortality assessment and carbon management. Conceiving new policy designs, business models, financing options, and certification standards will be necessary to help us acquire a better understanding of physiological drought vulnerability at multiple spatial, temporal, ecological, and evolutionary scales. In parallel, this activity will encourage collaboration between foresters, biologists, anatomists, environmental modelers, researchers, policymakers, and other stakeholders.

One method used to combat climate change is carbon offsets, where businesses that have high emissions and are unable to reduce emissions pay to keep trees from being cut down elsewhere, which helps cancel out their carbon emissions. However, estimating how forests around the world are offsetting emissions at various spatial scales is challenging. Integrating UAVs/satellite-based remote sensing along with artificial intelligence can be used to measure forest characteristics, stored carbon, reforestation, and deforestation for various forest projects [195]. Companies can adopt UAV services cost-effectively by offering discounts based on carbon credits, and this type of initiative can encourage landowners, individuals, private entities, and enterprises to use UAVs for reforestation and forest monitoring to promote voluntary participation in carbon markets. Efforts need to be made to make high-resolution data more accessible as a tool to keep companies and individuals more engaged and ensure accountability. New applications that can derive and use a multitude of data from the UAVs and compile them into a user-friendly interface should be developed along with rigorous quality assurance control protocols that support automation and standardization.

4.5.5. UAVs for Sowing Seeds and Plant Characterization

Recent research highlights the importance of planting trees for mitigating future droughts, as reforestation increases local and downwind summer rainfall [196]. UAV-supported seed sowing, with support from seed enablement technology, is a suitable type of technology which may be used to improve seedlings' survival rates in water-stressed environments and protect forest biomass of secondary forests in response to EWMs. UAV-supported seed sowing uses high-resolution UAV mapping and optimization of target areas based on machine learning techniques, which then informs the UAV flight plan [173]. UAVs are then dispatched in "swarm operations" over target areas in a predetermined, optimized, and efficient pattern in order to disperse seed pods, which contain nutrients, biochar, and other ingredients to ensure the survival of the seedling [197]. UAVs could be used to sow seeds and track the growth of seedlings of selected species in post-drought conditions according to EWMs (including edaphic properties). This will help to improve forest diversity and increase forest resilience and carbon sequestration, which will thereby contribute to mitigating climate change and drought impacts.

Data collected from UAVs also allow for more robust characterization of drought resistance at the individual tree level. This type of assessment could be achieved through tree delineation using LiDAR 3D point clouds from UAVs and then characterization of leaf water content using hyperspectral imagery or stomatal closure through thermal imagery. The characterization may enable the identification of clones or genotypes that are more drought-resistant, which will allow managers to realize productivity gains through allocating these drought-resistant clones to areas that are likely to suffer from drought at the present time or in the future.

5. Limitations of UAV-Based Endeavors

Although UAVs are an alternative remote sensing tool for aircraft and satellite for small forest areas and tree-level monitoring, for most practical applications in large-scale forest monitoring, UAVs remain a poor choice relative to aircraft and ground-based measurements, including ground-based LiDAR. Importantly, for most jurisdictions, UAVs cannot be used in forests without a line of sight from the drone to the UAV operator/pilot. To operate UAVs with line of sight in forests, the highest levels of pilot certification (equivalent to a full UAV pilot's license) and the highest level (aircraft certification) for the UAV is required. Operating such UAV and sensors are more time-consuming and expensive than aircraft, as even the largest civilian UAVs can cover only relatively small areas. The deployment of a UAV with professional components such as an initial measurement unit (IMU) and Global Positioning System (GPS) often results in a far higher cost per hectare evaluated, compared to more traditional products derived from satellites or manned aircraft. Although UAVs offer higher spatial and temporal resolution imageries, only a few forest management schemes can afford such expensive investment costs in forest monitoring. Thus, satellite and aircraft remain a more practical and cheaper option for monitoring of larger areas.

The practical implementation of UAVs in forest monitoring requires a dense network of forest roads accessible by vehicles, and such a road network is absent in most forests. Carrying and operating a UAV to locations remote from vehicle access becomes very challenging; this problem is exacerbated by the inability to recharge batteries in remote areas unless batteries, generators, and fuel are available or taken by the operator. UAVs need open spaces to launch and land, and such gaps are difficult to locate in dense forest and may be large distances from areas of interest. These operational limitations highlight the relative advantages of undertaking biomass assessment using field observations and terrestrial LiDAR, that can be scaled through sensors mounted on fixed wing aircraft or satellite.

Image spectroscopy and LiDAR sensors that are small and light enough to fit on UAVs remain extremely expensive and difficult to operate. Operationally, these UAV-based systems are not "plug-and-play" equipment and pose significant constraints in terms of the economics of data acquisition and data volumes generated over larger areas. In addition, UAVs that are capable of longer flights (20–30 min) and operating with image spectrometers and LiDAR are heavy (approximately 25 kg) and awkward to transport in extensive and remote forest environments. Although UAVs can be used for developing operational frameworks and models of EWMs at a local scale, this is only a part of the information required for an EMW framework that can also be filled with aircraft and terrestrial LiDAR. These limitations explain why UAVs are not commonly used to characterize EWMs for larger-spatial-scale mapping, but are highly useful at small spatial scales. Despite the observed limitations of using UAVs in forest management, we argue that, with careful improvements, UAVs could be used for early identification of variation in physiological traits of plants resulting from drought stress and for improving tree-level sample collection.

6. Conclusions

In this review article, we discussed several potential forest management and remote sensing applications where UAVs can play a crucial role in overcoming operational limitations of contemporary data collection models/sampling approaches, provide greater insights into forest carbon reserves, and contribute towards generating EWMs with regard to climate-change-driven droughts and related tree mortality. Although UAVs, at the moment, cannot be treated as a panacea for prediction of EWMs, we provide prospective approaches and future directions to researchers for advancing the field. UAVs can easily collect repeated data at a high temporal and spatial resolution to characterize EWMs within predrought, drought, and post-drought environments. Scaling UAV-collected datasets in conjunction with global/satellite remote sensing data should be treated as a priority. Reproducible, seasonal, and transferable datasets can be generated using UAVs that are applicable to a broad range of forest systems experiencing droughts. Data fusion strategies combining multisensor, multiscale approaches that can integrate data derived from in situ measurements, UAVs, and satellites in effective ways should be formulated. These frameworks should be used to capture and quantify post-drought tree mortality and forest carbon allocation in vivo and could greatly assist development of wall-to-wall maps of biomass densities. However, case-by-case analysis and/or site-specific background information might be required to determine the most important metrics to be collected using UAVs.

The results of our literature survey underscore that various biotic and abiotic factors such as topography, hydrology, tree size, pests, etc., play a significant role in drought-induced tree mortality. It may become difficult to consider these factors in isolation or identify all the parameters that would be relevant for prediction models given the complex interactions between them. However, UAVs—in association with robust sampling strategies—can bridge the gap between labor-intensive field surveys and spaceborne mapping of tree mortality. The amalgamation of data from different UAV platforms and sensors could produce a wealth of information that can be used to understand mortality patterns at different scales. Advances in artificial intelligence and biostatistical models can further increase the efficiency in mapping and monitoring forest health data collected by UAVs and are expected to drive forward research related to climate-change-driven droughts and forest carbon management. Most importantly, making predictions at the tree level is a major shift that UAVs will facilitate and is certainly not possible using satellite data. Hence, the use of UAVs in commercial forestry and their utilization for precision forestry applications need to be expanded from a drought-monitoring perspective. We hope that future research endeavors in this field will encourage and support researchers, policymakers, and forest ecologists to translate the ideas presented in this paper into practical outcomes.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs15102627/s1, Table S1: Recent research studies related to development of early warning metrics of drought-induced stress and mortality in forests using remote sensing-based data; Table S2: List of available UAV-compatible hyperspectral sensors and their specifications. Table S3: List of other available airborne hyperspectral sensors and their specifications; Table S4: List of decommissioned or inactive satellite missions carrying hyperspectral sensors and their specifications; Table S5. List of launched, operational and planned satellite missions carrying hyperspectral sensors and their specifications. References [198–233] are cited in the supplementary materials.

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