Artificial Intelligence for Climate Smart Forestry: A Forward Looking Vision

Feng Luo[1,*], Ling Liu[2,*], G. Geoff Wang[3,*], Vijay Kumar[4,*], Mark S. Ashton[5,*]
Jacob Abernethy[2], Fatemeh Afghah[6], Matthew H. E. M Browning[7], David Coyle[3], Philip Dames[8], Tom O'Halloran[3], James Hays[2], Patrick Heisl[3], Chenfanfu Jiang[9], Puskar Khanal[3], Venkat Narayan Krovi[10], Sara Kuebbing[5], Nianyi Li[1], JingJing Liang[11], Ninghao Liu[12], Steve McNulty[13], Christopher M. Oswalt[14], Neil Pederson[15], Demetri Terzopoulos[16], Christopher W. Woodall[17], Yongkai Wu[6], Jian Yang[18], Yin Yang[19], Liang Zhao[20]

[1]School of Computing, Clemson University, Clemson, SC USA, {luofeng, nianyil}@clemson.edu
[2]College of Computing, Georgia Institute of Technology, Atlanta, GA USA, {ling.liu, prof, hays}@cc.gatech.edu
[3]Department of Forestry and Environmental Conservation, Clemson University, Clemson, SC USA, {gwang, dcoyle, tohallo, phiesl, pkhanal}@clemson.edu
[4]School of Engineering and Applied Science, University of Pennsylvania, Philadelphia, PA USA, seasdean@esas.upen.edu
[5]The Forest School, Yale University, New Haven, CT USA, {mark.ashton, sara.kuebbin}@yale.edu
[6]Department of Electrical and Computer Engineering, Clemson University, Clemson, SC USA, {fafghah, yongkaw}@clemson.edu
[7]Department of Parks, Recreation and Tourism Management, Clemson University, Clemson, SC USA, mhb2@clemson.edu
[8]Department of Mechanical Engineering, Temple University, Philadelphia, PA USA, pdames@temple.edu
[9]Department of Mathematics, University of California, Los Angeles, Los Angeles, CA USA, chenfanfu.jiang@gmail.com
[10]Department of Automotive Engineering , Clemson University, Clemson, SC USA, vkrovi@clemson.edu
[11]Department of Forestry and Natural Resources, Purdue University, West Lafayette, IN USA, jjliang@purdue.edu
[12]School of Computing, University of Georgia, Athens, GA USA, ninghao.liu@uga.edu
[13]Northern Research Station, USDA Forestry Service, Durham, NH USA, steven.mcnulty@usda.gov
[14]South Research Station, USDA Forestry Service, Knoxville, TN USA, christopher.oswalt@usda.gov
[15]The Harvard Forest, Harvard University, Petersham, MA USA, neilpederson@fas.harvard.edu
[16]Computer Science Department, University of California, Los Angeles, Los Angeles, CA USA, dt@cs.ucla.edu
[17]Northern Research Station, USDA Forestry Service, Durham, NH USA, christopher.w.woodall@usda.gov
[18]Department of Forestry and Natural Resources, University of Kentucky, Lexington, KY USA, jian.yang@uky.edu
[19]School of Computing, University of Utah, Salt Lake City, UT USA, yin.yang@utah.edu
[20]Department of Computer Science, Emory University, Atlanta, GA USA, liang.zhao@emory.edu

Abstract— **Forests and forest ecosystems are vital to our social, economic, and environmental well-being. However, climate change and climate-driven disturbances (CDDs) are undermining the health and resilience of forests worldwide and pose significant uncertainty to sustainable forest management. Climate-smart forestry (CSF) remains a grand challenge in practice due to our limited knowledge of how forests respond to climate change and our abilities to collect related information to empower decision making. Rapid advances in artificial intelligence (AI) can offer a timely opportunity to address the challenges in CSF. We argue that the AI-enabled, next-generation CSF can be achievable through synergistically coordinated and transdisciplinary efforts that develop and advance foundational and use-inspired AI technologies that can lead to building next-generation forest decision support systems.**

Keywords— artificial intelligence, climate-smart forestry

I. Introduction

Forests cover 33% of the land in the United States, and forest ecosystems are vital to our social, economic, and environmental well-being [1-4]. National forests provide 20% of the nation's freshwater [5], 45% of outdoor recreation jobs [6], and 80% of the wood and fiber products consumed in the US [7]. US forestry is a multi-billion dollar industry [8]. However, climate change has the potential to impact our forests substantially. Forest dynamics are changing because of anthropogenic drivers, such as rising temperature and CO_2 levels [9], as well as the increasing frequency and severity of climate-driven disturbances [10, 11], such as wildfire, drought, ice storms, hurricanes, and insect and disease outbreaks [9]. Collectively, these perturbations have cost the forest industry significant productivity and revenue. For instance, according to data from the National Interagency Fire Center [12, 13], federal wildfire suppression costs in the United States have spiked from an annual average of about \$425M from 1985 to 1999 to \$1.6B from 2000 to 2019. According to [14], "*the total damage and cumulative economic loss for the 2021 wildfire season is estimated between \$70 billion and \$90 billion in the U.S.*" Confronted by climate changes and climate-driven disturbances, both private and public forest landowners seek for timely guidance and tools for multi-objective forest management [15, 16]. Federal and state agencies must accurately assess forest conditions (e.g., tree density, carbon stocks) to develop forest management guidelines and strategies.

Climate-smart forestry (CSF) remains a grand challenge in practice due to 1) our limited knowledge of how different tree species and forests of different scales and their biophysical environments respond to climate changes and disturbances, 2) our limited knowledge of how such changes in climate interact with a multitude of other largely anthropogenic factors affecting our forests (e.g. insects, disease, pollutants, land-use history), and 3) our limited ability to accurately predict forest states and evaluate various harvesting regimes under uncertainties induced by climate change and climate-driven disturbances [17]. Rapid advances in artificial intelligence (AI) and the increased availability of data through ubiquitous network connectivity offer a timely opportunity to address the challenges in CSF. We argue that the vision of AI-enabled, next-generation CSF is only achievable through synergistically coordinated and transdisciplinary efforts that

[*] These authors contributed equally to this paper.

2023 IEEE 5th International Conference on Cognitive Machine Intelligence (CogMI) | 979-8-3503-2383-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/COGMI58952.2023.00011

979-8-3503-2383-2/23/$31.00 ©2023 IEEE
DOI 10.1109/CogMI58952.2023.00011

develop and advance foundational and use-inspired AI technologies that advance a transformative approach toward building next-generation forest decision support systems.

For AI and forestry to work in concert, we argue that three synergistic research endeavors are needed: *First,* we will need to leverage state-of-the-art results in CSF research to characterize the set of pressing forestry challenges where AI technologies may bring significant practical innovations in problem solving through AI-enabled use-inspired forestry research. *Second,* we will need to advance foundational AI algorithms, tools and systems to make them customizable, adaptable, and extensible for tackling complex CSF challenges by integrating human knowledge and inputs, and by facilitating scientific and in-field human experts to provide guidance or to influence the design and development of the forest-use-inspired AI solutions. *Third,* we will need to devise human-centered software service platforms and tools to methodically align foundational AI research and development with forest problems and use-inspired scenarios.

In this paper, we will articulate these three orthogonal yet highly complementary dimensions of the AI–forestry alliance that will fulfill a unique vision and be transformative beyond the scope of existing state-of-the-art research efforts in AI or forestry. They will validate a transdisciplinary, multi-institutional research endeavor that promises to synergistically advance foundational and use-inspired AI research and development in several core areas of CSF.

II. Foundational AI for Climate Smart Forestry

Foundational AI research has the potential to transform US forestry by providing high fidelity, predictive intelligence across diverse spatiotemporal scales under climate change and disturbances. Despite remarkable progress in AI, there remain several open challenges in the adoption and application of AI to CSF. We describe four foundational AI challenges: (i) *The small data problem*: Traditional AI/ML methods for training predictive models with sufficient accuracy require an intractable amount of data. AI learning with limited, sparse, or unlabeled data improves scalability and can establish novel use cases in fields such as forestry where annotations are expensive and differ in scale. (ii) *Heterogeneous information fusion*: Forest data from a plethora of sources and sensors are often collected and studied by forest researchers and field engineers with specific research foci. Applying, adapting, and augmenting AI models for multi-objective learning over heterogeneous and multimodal data is another open challenge. (iii) *Adaptive learning and control*: Autonomous robots can learn to handle numerous edge cases and variations in the field through learning algorithms for agile and robust navigation and control under noisy and dynamically changing uncertainty. (iv) *Human-in-the-loop intelligence*: AI models and algorithms that are explainable and capable of leveraging human-in-the-loop intelligence will increase trust and ease of adoption.

A. Data-Efficient AI

One of the big challenges in the forest domain is the problem of small and sparse data and the scarcity of quality labeled data. For instance, many forestry datasets are collected over years in different forest regions with relatively little disturbance [18], so the ground truth data about climate-driven disturbances are based on sparsely sampled small footprints, whereas annotations are expensive and vary in spatiotemporal scales. There is a pressing demand for new AI theory and novel AI algorithms that can learn efficiently from data sources with small and limited data, noisy and sparse data, or unlabeled data.

1) Learning with small and sparse data

One approach to quickly learning new concepts in a data-efficient manner is to explore few-shot learning methods [19, 20]. Few-shot learning refers to the ability to classify objects where many predictions are required given a few examples of each category [21, 22]. One-shot learning is a special case of few-shot learning. One-shot learning aims to learn a rich low-dimensional feature representation, called an object embedding, which can be calculated for objects of a given class easily and used as a learned feature vector for the known. Then candidate examples are compared for verification and identification tasks. A deep neural network trained with contrastive loss or the triplet loss function has been shown to perform better in the learning of embeddings for one-shot or few-shot learning problems. Zero-shot learning refers to the ability to learn to predict the correct class without being exposed to any instances belonging to that class in the training dataset. Zero-shot, one-shot, and few-shot learning may be considered as a meta-learning problem where the model learns how to learn to solve the given problem through knowledge transfer [23, 24]. For example, Siamese networks [25, 26] and triplet networks [27, 28] can effectively discriminate two unseen classes, whereas matching networks [21], prototypical networks [29], and relation networks [30] are known to be more effective for discriminating multiple unseen classes.

2) Learning to estimate unknowns through multi-objective and multi-modal representation learning.

One key issue in enabling CSF is the accurate modeling of tree regeneration/growth/death and overall health of tree species under different climate-driven disturbances. Accurate modeling requires integrating known models (e.g., tree growth patterns under no disturbance) with our best estimate of unknowns (e.g., how different tree species respond to the changes in soil condition, water level, and overall stand health under different climate-driven disturbances, such as wildfire, drought, windthrow, and infestation). One approach to tackling the multi-objective learning problem with a large amount of unlabeled data is to integrate multi-modal representational learning, transfer learning, or reinforcement learning with few-shot learning. For example, by combining the Harvard tree growth data network with the FIA database [31, 32]. We can develop multi-modal representation learning algorithms specifically optimized for forest data collections with the temporal alignment of historical weather data. We may utilize the cross-modality retrieval capability of the multi-modal embedding model(s) to extract tree species-specific data over-determined spatial and temporal ranges with corresponding historical weather alignment, and build AI models to learn how different tree species respond to certain climate-driven disturbances, such as fire, drought or insect and disease outbreaks. Based on large-scale, offline model training under non-disturbance and known climate-driven disturbances, we can leverage few-shot learning to elicit unknown patterns under disturbance and make timely response and transform disturbed forest regions into novel ecosystems.

B. *Generalizable AI*

Forest domain-specific AI solutions require the capability of AI models to work effectively under different conditions, including unknowns or evolving conditions. The random forest [33] is a supervised AI learning model widely adopted by forestry researchers [18, 34]. However, compared to prediction quality under no disturbance, the highly uncertain and substantially skewed distribution of forestry data under climate change and climate-driven disturbances renders these models poor in their predictive performance [35-37]. Moreover, prior knowledge and learning experiences are intricately linked to every phase of the complete life cycle of the trees, tree species, and the forest, from getting trees off to a better start to making sure trees are harvested in a way that protects the future of the forest, all demanding generalizable AI solutions.

1) Generalizable AI through robust and prognostic fusion.

An important objective of learning systems is the construction of predictive models with high generalization performance. The most popular approach is to find the best model for a target task. However, it is difficult in general to estimate the best model when given finite samples. Combining multiple neural network predictors has been shown to improve generalization error [38-41]. This is specifically important for enabling climate-smart forestry, which requires learning with limited ground truth data and learning in a changing environment with evolving data streams. We conjecture that ensemble fusion of multiple network predictors with adaptive teaming strategies will bring fresh new solutions to the concept drift problem [42, 43], which is a change in the definition of the concept (class) in data streams because the underlying distribution from which data are drawn for concept learning changes over time.

2) Generalizable AI through reusing and transferring information.

Transfer learning enables the generalization of knowns to learn unknowns by utilizing the transferability of AI models. The main idea is to store knowledge gained while solving one problem and apply it to a different but related problem. For example, knowledge gained while learning to recognize tree growth disturbed under windthrow could apply when trying to recognize tree growth disturbed under ice storm. Transfer learning is an optimization for domain adaptation. It can address the variability and diversity challenges in forest ecosystems by transferring knowledge from existing tree growth processes of certain tree species in specific forest region(s) in order to learn tree growth of other similar species or the same species in a new region, and thus aid in developing digital twin models of diverse tree species across various spatiotemporal scales. A key challenge in transfer learning is to minimize negative transfer where previous data and learned models (knowledge) negatively intervene into the new learning task.

3) Generalizable AI through hierarchical adaptive learning.

The generalizability of an AI model can also refer to its ability to quickly adapt to changing environments. One approach is to model changes in a task environment in terms of state and action spaces relevant to the task and use reinforcement learning (RL) to learn an optimal policy for actions in various states of a task environment, which maximize the cumulative rewards received by the agent [44].

C. *Exploration-Adaptive AI*

Existing forest monitoring with event-triggered sensors and satellite imaging [45, 46] does not offer a low-cost and agile solution with the necessary spatial and spectral resolution to build a digital twin. Flying drones into the forests provides much more detailed information, especially of the underbrush and in remote forest regions. Unmanned Aerial Vehicle (UAV) systems offer the potential for rapid and high-resolution mapping of wide forest areas due to their 3D mobility, flexibility, low flight altitude (below the clouds), and fast and easy deployment. The operation of UAVs in forest monitoring must involve the development of fully autonomous UAVs that can individually or cooperatively operate in unknown and unstructured environments (Figure 1).

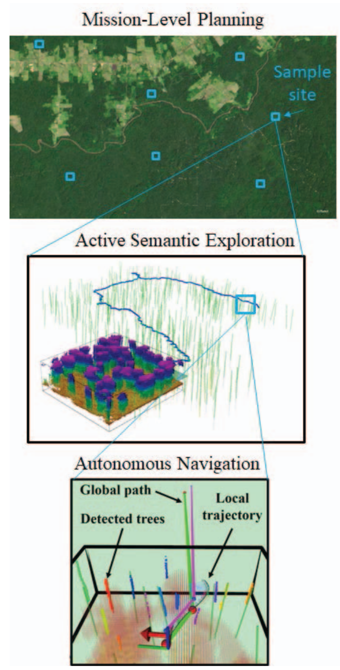

Fig. 1. Hierarchical planning architecture. The *mission planner* (left) determines where to sample the forest (blue squares). The *active semantic exploration* (middle) guides one or more robots to collaboratively build a semantic map of a patch of the forest (*i.e.,* to collect a sample of the biodiversity and structure of part of the forest). The *autonomous navigation* (right) guides robots through the complex 3D geometry of a forest.

1) Mission planner.

The mission planner identifies sampling locations (task identification [47]) and dynamic multi-agent task assignment. A key challenge is to quantify the uncertainty in task locations and durations (i.e., new tasks may be discovered online) in addition to communication constraints [48-54].

2) Active semantic exploration.

The semantic maps have been shown to improve robot perception [55-61] and autonomy [62-68], along with a novel AI learning strategy to guide robots to autonomously generate these maps, including new neural network architectures to improve the speed and reliability of instance segmentation and classification, and a novel semantic mapping algorithm based on multi-Bernoulli random finite sets [66]. The active exploration strategy will use an information-theoretic objective function with a motion penalty to drive the robots to efficiently construct the semantic maps. In the future, an accurate metric-semantic map, evenwhen individual measurements have high uncertainty, is needed

3) Autonomous navigation

An autonomous robot must use onboard sensing and computation to quickly plan trajectories and safely reach its goal locations, such as those set by the semantic exploration module. Existing autonomous navigation systems for aerial robots [69-72] use signed distance field (SDF) representations of the map, which demands larger storage and computational power and does not account for key platform constraints (e.g., battery life and perception range). In the future, built upon the an autonomous navigation software stack [73-76] in cluttered environments [77]—e.g., under dense forest canopy [65] —novel reinforcement learning algorithms with fast convergence and low computational complexity in high dimensional state-space actions could be developed, which would create a local planner to enhance the safety and speed of ground robot navigation, and to improve generalization to new scenarios [78].

D. Explainable and Trustworthy AI

To facilitate the wide deployment of innovative AI solutions in the forest domain and to gain the trust of public and private forest landowners in AI-enabled CSF developments, we must provide the capability of explaining the reasoning behind predictive models or decisions in a way that humans can understand, the capability of putting the human in the loop for forest decision support systems, and the capability of providing privacy and safety guarantees with respect to the socioeconomic consequences.

1) Feedback-driven learning for human-AI interactive exploration.

Feedback-driven AI promotes human-centric design and human-in-the-loop intelligence by generating feedback based on domain knowledge and the explainability of AI results [79]. Explainability is typically modeled by a set of probabilistic logical formulas summarizing human expert knowledge about causality. A popular approach to explainable AI is to learn an effective surrogate model, which is based on domain knowledge from human experts and hence is intuitive for humans to understand, yet can best approximate the original complex model. In addition, to optimizing the primary loss function by minimizing the difference between the surrogate model and the original model, the explainability learning algorithm will add a regularization term to reward the explainability. Different criteria can be used to measure explainability, such as the number of probabilistic logical formulas (the smaller the better). Explainability can zoom into the causal relationships among variables of interest and reveal how the fundamental design principles and key parameters may impact the convergence and stability of learning.

2) Trustworthy AI through privacy and federated learning

For many private forest landowners, privacy is a primary concern and often one of the biggest deterrents for different stakeholders of the forest system to provide and share data. Federated learning is an emerging distributed learning paradigm that utilizes a distributed population of participants (e.g., individual forest landowners) to collaboratively train a deep neural netowrk model [80-85]. Compelling applications in forest systems include using local data from multiple forest landowners to jointly train predictive models for prediction of tree growth of different tree species under non-disturbance or certain type of climate-driven disturbance. Recent studies show that an honest but curious client may use an inference-based reconstruction attack to derive private client training data based on the local model update shared by the client to the federated server [86, 87].

3) Trustworthy AI through fairness.

Forest datasets are subject to imbalance and sampling or selection bias. For example, compared to the tree growth data acquired under non-climate disturbance, such data collected under climate-driven disturbances has a much smaller sample size. Such biases in training datasets can influence many AI algorithms. Class-weight is a cost-sensitive method to tackle the class imbalance. Re-weighting-based methods reduce selection bias by assigning weight to training errors, where the weights are learned from estimates of sample probabilities, such as clustering-based estimation or kernel mean matching.

III. AI-Enabled Climate-Smart Forestry

Enhancing the resilience of the nation's forests under climate change and climate-driven disturbances through CSF practices remains a tremendous challenge. It is known that certain forest conditions could reduce the occurrence or intensity of certain disturbances (e.g., fire, pestilence, disease) due to their unique characteristics [88]. Here, we argue that AI can help 1) understand tree and forest growth, yield, and vulnerability under climate change and disturbances, 2) assess economic and ecological impacts due to future changes in forest conditions, and 3) measure carbon emissions/removals and associated risks/opportunities across space and time in forests.

A. Climate-Tree Growth Intelligence

Climate has been shown to have a strong impact on tree growth in many parts of the world [89] and climate change strongly influences short- and long-term tree growth [90-93]. Understanding how different tree species respond to climate change and disturbances, projecting tree growth under climate change, and quantifying forest vulnerability can assist risk-averse decision-making for forestry and inform long-term management decisions. First, AI can help *understand the response of tree attributes to climate change and climate-driven disturbances.* Having forest factors, such as forest density, forest composition, the percentage of congeneric trees and species with complementary traits and growth habits, and time since disturbance, as well as having access to physical and geographic data will allow us to investigate the relationships between tree growth and stand factors, local site conditions, and climate. AI models enhance our understanding of the response of trees under a range of local conditions and histories, and under a range of climatic conditions, while at the same time developing the many levels of uncertainty that exist in the productivity of forest ecosystems over time.

Second, AI can help *forest growth and yield projection under climate change.* Projecting forest biomass inclusive of mortality and recruitment under global change is foundational to the quantification of forest ecosystem services. To date, the projection of forest biomass is limited by small geographic coverage, low quality, and incompatibility. By integrating multi-modal forest and climate data from multiple sources, including ground-sourced FIA data, dendrochronological data, and high-resolution remote sensing data from satellite and UAV-based platforms (i.e., GEDI, LANDSAT, MODIS, airborne-LiDAR, etc.) into one universal training dataset, we can adopt multi-modal representation learning algorithms to further enhance the generalization performance and provide data-efficient, generalizable, and explainable climate-smart forest growth and yield projection intelligence.

Third, AI can help *quantification of forest vulnerability*. Quantifying forest vulnerability to climate change and climate-driven disturbances, such as wildfires [94-97], droughts [98, 99], ice storms [100, 101], hurricanes [102], and insect outbreaks [103] is important for CSF practices aimed at reducing the susceptibility or increasing the adaptive capacity of forests. It is necessary to quantify the vulnerability of trees, forest stands, and landscapes at the decadal to centennial temporal scale. By leveraging tree ring and climate change data, we may develop AI methods for quantifying tree vulnerability. The tree ring data can be used to reconstruct past forest disturbances [104] and provide scenarios of forest recovery post-disturbance. We can adopt data-efficient learning to predict past disturbances from tree ring data with higher generalization performance and robustness guarantees. Moreover, we can quantify the vulnerability of forest stands and landscapes using freely available dense LANDSAT time-series stacks (LTSS) and LiDAR point cloud data. Previous methods [105, 106] reconstructed forest disturbance history only from LTSS and failed to detect minor but widespread disturbances that are small in disturbed patch size, less abrupt in impact duration, and more rapid in vegetation regrowth. By incorporating LiDAR point cloud data to provide a more detailed and comprehensive mapping of forest structure (e.g., canopy height, canopy density) to delineate minor disturbance events more effectively, we may develop a 3D deep learning model that integrates LTSS and LiDAR data to improve the efficacy of disturbance detection and the accuracy of disturbance agent classification. By identifying the state before the disturbance and its changes since the disturbance, we can quantify the vulnerability of each stand subject to a historical disturbance event.

B. Multi-Objective Forest Assessment Intelligence

To maintain the resilience of forests, we can develop AI-enabled methods to assess the economic value and tree diversity impact of forests, which will help the development of intervention plans and policies to mitigate the negative effects of climate change and climate-driven disturbances. First, AI can *help forest economic value assessment under climate change.* One of the greatest challenges in forest management and decision-making is designing an optimal harvesting policy to maximize the economic value of forests. This optimization needs to simultaneously account for an array of risks due to natural disturbances, catastrophic events, timber and biomass prices, and interest rates [107]. For instance, changes in species composition would affect biophysical and environmental factors that directly or indirectly affect timber supply [108], such as forest productivity [109], as well as the frequency and severity of forest fires and pest infestations [110, 111]. The prediction will become even more complex in the future because 1) the carbon credit value of forests needs also to be considered, and 2) climate change and disturbances have broad impacts on all parts of the forest sector, from tree growth to timber processing, to transportation costs. To solve this complex, stochastic optimization problem, a deep reinforcement learning (DRL) [112, 113] based method will be useful to learn an optimal harvesting policy using information such as tree diversity and structure, harvest timing and rotation policy, tree growth modeling, carbon credit modeling, climate modeling, and disturbance modeling, as well as economic factors.

Second, *AI can help map tree species diversity across the nation's forest communities.* Our nation's forests are the most vital repository of terrestrial biodiversity and the provider of a myriad of ecosystem services [114, 115]. With changes in climate and land-use patterns, it has become increasingly urgent to characterize tree species diversity and depict its patterns and main drivers, which are of immense value in devising spatially explicit conservation strategies [116]. In recent years, data and machine learning-based approaches to explore global forest tree species diversity, productivity, and tree symbionts [117, 118] have been developed. By leveraging existing forest and climate data, we can adopt non-parametric deep neural network ensemble learning models to capture the nonlinear relationship between tree species diversity and a large number of predictor variables without statistical assumptions and predetermined mathematical formulas. The AI models will enable us to delineate forest bioregion boundaries, identify expected boundary changes, and estimate potential assemblage shifts under different future climate change scenarios.

C. Forest Carbon Sequestration Intelligence

Forests are a dominant contributor to the terrestrial carbon sink and have been identified as a key component of climate mitigation strategy. Accurately and cost-efficiently measuring the sequestrated carbon is critical for guiding the development and implementation of CSF practices. However, traditional methods for estimating carbon are either empirical or costly and are not scalable to large regions. AI methods can help more accurately predict carbon sequestration. Previously, tree volume has been estimated from the 3D point cloud using an empirical function [119]. One optimization is to develop a volumetric 3D CNN-based method, which represents 3D shapes using 3D occupancy grids and directly applies 3D convolution to this representation to calculate the volume of irregular trees quickly and accurately. With the construction of a lost and damaged tree dataset, the AI method can identify dead and damaged trees from drone images/videos captured after the occurrence of disturbances. By combining the original 3D forest model, we will be able to account for carbon loss. Furthermore, knowledge collected from carbon loss will help us understand how different tree species and stand conditions respond to different types of disturbances.

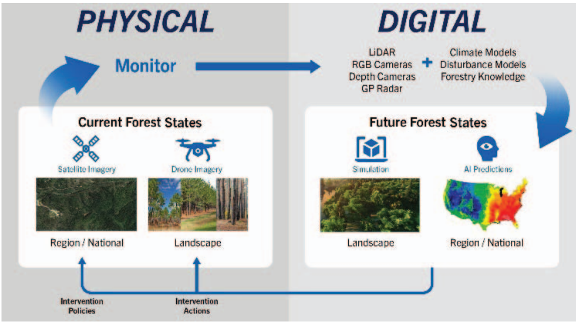

Fig. 2. Forest Digital Twin

IV. AI–Forestry Crosscutting Platforms

To enable CSF, we will need to develop resources and AI tools to support intervention and management decision-making.

A. Forest Digital Twins

A forest digital twin (FDT) (Fig. 2) is a set of virtual models that mimics the structure, composition, dynamics, and states of the forest at the stand, landscape, region, and national scales under different climate changes, climate-driven disturbances, and temporal durations. The FDT will combine forest simulation, forest state prediction, and 3D VR to help predict and visualize the states of future forests. Furthermore, we can also integrate the explainable AI method to help illustrate the factors that are important to the preparation of management policies and strategies.

For 3D virtual forest construction, we can integrate imagery from 3D LiDAR, RGB cameras, and depth cameras of a forest farm collected by drones with other available forest data to generate 3D virtual forests [120]. By leveraging real-world forest data [32], we can further customize the shape, size, orientation, and canopy of the trees, or add other properties such as disease spots and different tree species, through visual and hyperparameter-controlled manipulations provided by our forest digital twins.

Physics simulation of a forest and its interaction with external environments is challenging because 1) material properties of plants are heterogenous and vary significantly from each individual [121-123], 2) the geometries involved are complex—the total number of branches, twigs, and leaves of a tree are usually extremely high [124]; 3) biomechanical simulation is known to be computationally expensive; and 4) it will involve multi-physics interactions and changes. To understand the state of trees, stands, and forest farms over time under climate change and climate-driven disturbances for a range of species compositions, stand/site conditions, and spatiotemporal configurations in the landscape, we will need a multi-scale, multi-physics forest simulation framework. The multi-resolution material point method (MPM) [125], which has shown remarkable flexibility in simulating complex multi-physics scenarios, has the potential for large forest simulation. To overcome the high computational complexity, a scalable GPU implementation will be needed.

The accurate description of current and future forest states is fundamental to CSF. Forest data at the level of individual trees, such as FIA data [32], are useful for forest biomass and terrestrial carbon estimation [126, 127], as well as for guiding forest management practices [128-130]; however, FIA is sparse (one site every 6,000 acres) and delayed (every 5 years for each plot). Satellite and aerial images provide repeatable sensory data to measure the forest tree density [131, 132]; however, current satellite imagery-based estimation methods are not accurate enough for large-scale tree density prediction [133]. New solution that combine satellite images (resolution at 3.7 meters) with FIA data to produce a tree-level forest map will be needed.

B. Forest Data and Knowledge Tool.

Knowledge about tree species response to climate-driven disturbances exists in various forms of published literature, but this knowledge is not structured efficiently for use. In the last decade, the Template for Assessing Climate Change Impacts and Management Options (TACCIMO) [134], a manually curated template tool, was developed to provide information needed for strategic decision making on how near-term and long-term changes in forest composition, structure, and function are impacted by climate change and a variety of climate-driven disturbances. TACCIMO has been used as part of the forest planning process for all R8 National Forests as well as some National Forests outside the R8 Region. However, the manual curation limits TACCIMO to the inclusion of very limited amounts of the available literature. The recent success of large language models (LLMs), such as GPT, demonstrates their knowledge summarization abilities. In the future, it will be very useful to train an LLM specialized to the forestry domain in order to instruct the forest planning process. However, the hallucination shortcoming of LLMs [135] makes it possible for them to generate answers that may cause significant economic loss. Overcoming this shortcoming will be important to putting LLMs into practice.

Furthermore, the majority of traditional silvicultural practices are still applicable under climate change, though the timing and frequency of management may change. However, those practices need to be adjusted or adapted to the disturbed conditions under climate changes. Classic forest management guides such as the USFS Service Forester's Handbook, while useful, is mainly a transposition of charts and figures that offers no interaction. Integrating those guides with an GIS overlay of forest types and forest management guides will provide a default Level 3 ecoregional prescription-level database and default standard management practices. Therefore, the further development of a multimodal LLM for forestry will enable us to create actionable recommendations with sufficient detail.

C. Forest Intelligent Data Acquisition System

Current methods for collecting ground truth data in forestry are labor-intensive and often restricted by road access. This limits researchers' abilities to collect large datasets and to rapidly assess the impact of climate-driven disturbances. Adaptive learning will enable autonomous drone flights through complex forest environments, including under the canopy, which could potentially measure all variables that would be collected by people on the ground yet in a more efficient way, thereby revolutionizing forest data collection. Therefore, it is possible to develop a Forest Intelligent Data Acquisition System (FIDAS) to achieve efficient and accurate forestry data collection. The robotic systems will gather information on canopy trees, live vegetation under the canopy, woody materials on the ground, and the forest floor, using specialty cameras, radar, and other sensors in the autonomous drones. AI will process the collected data to derive accurate measurements about the sampled stand. These measurements will then be validated by actual ground measurements. In addition to routine measurements with FIA plots, the drones can collect data on species identity, forest health or vigor, leaf area, water content of live tissue, standing snags, downed woody materials, forest floor, soil carbon, and soil moisture. Such a FIDAS promises to revolutionize forest data collection and significantly advance forest research and management.

V. Conclusions

AI has the potential to transform US forestry systems by addressing the grand challenges of achieving 21st-century Climate-Smart Forestry (CSF), including assessment and attainment of forest resilience under weather and climate variability, and subject to the scarcity of natural resources. Realizing this potential will require fundamental transformations in how we apply and integrate AI technologies and in how we design and develop AI systems for next-generation CSF systems. Traditionally, AI algorithm and technology designers have been solution and software providers, whereas the domain clients, among them forestry stakeholders and researchers, were end consumers. This is neither adequate nor sustainable, especially within our vision to expand and transform the complex commercial multi-forest-stakeholder enterprise by building future, cyber-physical forest ecosystem supplemented by AI-enabled forest decision support systems and services. We have argued that for AI-driven endeavors to succeed in this complex CSF future, a strong collaboration must be established between the AI researcher/practitioners and a broad range of stakeholders, including forest landowners, forest laborers, consultants, technology service providers, and state and regional policymakers, as well as forestry researchers and scientists.

Acknowledgment

We thank the participants of meetings aimed at developing our CSF vision—Vidya Samadi, Ashok Mishra, Patricia Carbajales, Marzieh Motallebi, Kuangching Wang, Hai Xiao, Ifran Essa, Omar I. Asensio, Molei Tao, Mark Bradford, Karin Riley. We thanks Clemson University administration for their strong support.

References

[1] "The National Wildlife Federation: How Trees Make a Difference, https://www.nwf.org/Trees-for-Wildlife/About/Trees-Make-a-Difference."

[2] "17+ Indigenous Forest Products and Their Various Uses in Our Day-To-Day Life, https://www.conserve-energy-future.com/forest-products.php."

[3] "What is the Greenhouse Effect? https://www.conserve-energy-future.com/greenhouseeffectcauses.php."

[4] "World's Worst Natural Disasters, https://www.conserve-energy-future.com/10-worst-natural-disasters.php."

[5] "Water Facts, https://www.fs.usda.gov/managing-land/national-forests-grasslands/water-facts."

[6] M. Wagner. "National Outdoor Recreation Conference, https://www.fs.usda.gov/speeches/outdoor-recreation-national-forest-system."

[7] "Wood Products in Everyday Life, https://forest-atlas.fs.fed.us/benefits-wood-products.html."

[8] "The National Alliance of Forest Owners (NAFO), https://nafoalliance.org."

[9] N. G. McDowell, C. D. Allen, K. Anderson-Teixeira, B. H. Aukema, B. Bond-Lamberty, L. Chini *et al.*, "Pervasive shifts in forest dynamics in a changing world," *Science,* vol. 368, no. 6494, p. eaaz9463, 2020.

[10] C. Nolan, J. T. Overpeck, J. R. Allen, P. M. Anderson, J. L. Betancourt, H. A. Binney *et al.*, "Past and future global transformation of terrestrial ecosystems under climate change," *Science,* vol. 361, no. 6405, pp. 920-923, 2018.

[11] M. G. Turner, W. L. Baker, C. J. Peterson, and R. K. Peet, "Factors influencing succession: lessons from large, infrequent natural disturbances," *Ecosystems,* vol. 1, no. 6, pp. 511-523, 1998.

[12] "Federal Firefighting Costs, https://www.nifc.gov/fire-information/statistics/suppression-costs."

[13] J. Roman, A. Verzoni, and S. Sutherland, "Greetings from the 2020 Wildfire Season: Five undeniable truths from a pivotal year in the world's growing struggle with wildfire " *NFPA Journal,* vol. November December 2020. [Online]. Available: https://www.nfpa.org/News-and-Research/Publications-and-media/NFPA-Journal/2020/November-December-2020/Features/Wildfire.

[14] M. Puleo, "2021 wildfire season: AccuWeather estimates $70 billion to $90 billion in damages," in *AccuWeather*, ed, 2021.

[15] M. Zhou, "Adapting sustainable forest management to climate policy uncertainty: A conceptual framework," *Forest Policy and Economics,* vol. 59, pp. 66-74, 2015.

[16] J. Buongiorno and M. Zhou, "Adaptive economic and ecological forest management under risk," *Forest Ecosystems,* vol. 2, no. 1, pp. 1-15, 2015.

[17] K. B. Kemp, J. J. Blades, P. Z. Klos, T. E. Hall, J. E. Force, P. Morgan *et al.*, "Managing for climate change on federal lands of the western United States: perceived usefulness of climate science, effectiveness of adaptation strategies, and barriers to implementation," *Ecology and Society,* vol. 20, no. 2, 2015, Art no. 17, doi: 10.5751/ES-07522-200217.

[18] K. L. Riley, I. C. Grenfell, M. A. Finney, and J. M. Wiener, "TreeMap, a tree-level model of conterminous US forests circa 2014 produced by imputation of FIA plot data," *Scientific Data,* vol. 8, no. 1, pp. 1-14, 2021.

[19] Ł. Kaiser, O. Nachum, A. Roy, and S. Bengio, "Learning to remember rare events," *arXiv preprint arXiv:1703.03129,* 2017.

[20] L. Fei-Fei, R. Fergus, and P. Perona, "One-shot learning of object categories," *IEEE transactions on pattern analysis and machine intelligence,* vol. 28, no. 4, pp. 594-611, 2006.

[21] O. Vinyals, C. Blundell, T. Lillicrap, and D. Wierstra, "Matching networks for one shot learning," *Advances in neural information processing systems,* vol. 29, pp. 3630-3638, 2016.

[22] G. Koch, R. Zemel, and R. Salakhutdinov, "Siamese neural networks for one-shot image recognition," in *ICML deep learning workshop*, 2015, vol. 2: Lille.

[23] L. Fei-Fei, "Knowledge transfer in learning to recognize visual objects classes," in *Proceedings of the International Conference on Development and Learning (ICDL)*, 2006, vol. 11.

[24] T. Hospedales, A. Antoniou, P. Micaelli, and A. Storkey, "Meta-learning in neural networks: A survey," *arXiv preprint arXiv:2004.05439,* 2020.

[25] D. Chicco, "Siamese neural networks: An overview," *Artificial Neural Networks,* pp. 73-94, 2021.

[26] J. Bromley, I. Guyon, Y. LeCun, E. Säckinger, and R. Shah, "Signature verification using a" siamese" time delay neural network," *Advances in neural information processing systems,* vol. 6, 1993.

[27] E. Hoffer and N. Ailon, "Deep metric learning using triplet network," in *International workshop on similarity-based pattern recognition*, 2015: Springer, pp. 84-92.

[28] A. Hermans, L. Beyer, and B. Leibe, "In defense of the triplet loss for person re-identification," *arXiv preprint arXiv:1703.07737,* 2017.

[29] J. Snell, K. Swersky, and R. Zemel, "Prototypical networks for few-shot learning," *Advances in neural information processing systems,* vol. 30, 2017.

[30] A. Santoro, S. Bartunov, M. Botvinick, D. Wierstra, and T. Lillicrap, "Meta-learning with memory-augmented neural networks," in *International conference on machine learning*, 2016: PMLR, pp. 1842-1850.

[31] W. T. Tinkham, P. R. Mahoney, A. T. Hudak, G. M. Domke, M. J. Falkowski, C. W. Woodall *et al.*, "Applications of the United States Forest Inventory and Analysis dataset: A review and future directions," *Canadian Journal of Forest Research,* vol. 48, no. 11, pp. 1251-1268, 2018.

[32] A. N. Gray, T. J. Brandeis, J. D. Shaw, W. H. McWilliams, and P. Miles, "Forest inventory and analysis database of the United States of America (FIA)," *In: Dengler, J.; Oldeland, J.; Jansen, F.; Chytry, M.; Ewald, J., Finckh, M.; Glockler, F.; Lopez-Gonzalez, G.; Peet, RK; Schaminee, J. HJ, eds. Vegetation databases for the 21st century. Biodiversity and Ecology. 4: 225-231.,* pp. 225-231, 2012.
[33] L. Breiman, "Random forests," *Machine learning,* vol. 45, no. 1, pp. 5-32, 2001.
[34] W. Ma, G. Lin, and J. Liang, "Estimating dynamics of central hardwood forests using random forests," *Ecological modelling,* vol. 419, p. 108947, 2020.
[35] I. Fayad, D. Ienco, N. Baghdadi, R. Gaetano, C. A. Alvares, J. L. Stape *et al.*, "A CNN-based approach for the estimation of canopy heights and wood volume from GEDI waveforms," *Remote Sensing of Environment,* vol. 265, p. 112652, 2021.
[36] D. P. Roy, H. B. Kashongwe, and J. Armston, "The impact of geolocation uncertainty on GEDI tropical forest canopy height estimation and change monitoring," *Science of Remote Sensing,* p. 100024, 2021.
[37] J. Chen, J. Chen, D. Zhang, Y. Sun, and Y. A. Nanehkaran, "Using deep transfer learning for image-based plant disease identification," *Computers and Electronics in Agriculture,* vol. 173, p. 105393, 2020.
[38] G. Huang, Y. Li, G. Pleiss, Z. Liu, J. E. Hopcroft, and K. Q. Weinberger, "Snapshot ensembles: Train 1, get m for free," *arXiv preprint arXiv:1704.00109,* 2017.
[39] R. Caruana, A. Niculescu-Mizil, G. Crew, and A. Ksikes, "Ensemble selection from libraries of models," in *Proceedings of the twenty-first international conference on Machine learning*, 2004, p. 18.
[40] T. G. Dietterich, "Ensemble methods in machine learning," in *International workshop on multiple classifier systems*, 2000: Springer, pp. 1-15.
[41] N. El Gayar, J. Kittler, and F. Roli, *Multiple Classifier Systems: 9th International Workshop, MCS 2010, Cairo, Egypt, April 7-9, 2010, Proceedings*. Springer, 2010.
[42] A. Tsymbal, "The problem of concept drift: definitions and related work," *Computer Science Department, Trinity College Dublin,* vol. 106, no. 2, p. 58, 2004.
[43] R. Elwell and R. Polikar, "Incremental learning of concept drift in nonstationary environments," *IEEE Transactions on Neural Networks,* vol. 22, no. 10, pp. 1517-1531, 2011.
[44] R. A. Monserud, "Evaluating forest models in a sustainable forest management context," *Forest Biometry, Modelling and Information Sciences,* vol. 1, no. 1, pp. 35-47, 2003.
[45] R. J. Lisle, "Google Earth: a new geological resource," *Geology today,* vol. 22, no. 1, pp. 29-32, 2006.
[46] N. Gorelick, M. Hancher, M. Dixon, S. Ilyushchenko, D. Thau, and R. Moore, "Google Earth Engine: Planetary-scale geospatial analysis for everyone," *Remote sensing of Environment,* vol. 202, pp. 18-27, 2017.
[47] O. Maimon and L. Rokach, "Data mining and knowledge discovery handbook," 2005.
[48] G. Neville, H. Ravichandar, K. Shaw, and S. Chernova, "Approximated dynamic trait models for heterogeneous multi-robot teams," in *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2020: IEEE, pp. 7978-7984.
[49] P. Ghassemi and S. Chowdhury, "Multi-robot task allocation in disaster response: Addressing dynamic tasks with deadlines and robots with range and payload constraints," *Robotics and Autonomous Systems,* vol. 147, p. 103905, 2022.
[50] S. Choudhury, J. K. Gupta, M. J. Kochenderfer, D. Sadigh, and J. Bohg, "Dynamic multi-robot task allocation under uncertainty and temporal constraints," *Autonomous Robots,* pp. 1-17, 2021.
[51] K. Lerman, C. Jones, A. Galstyan, and M. J. Matarić, "Analysis of dynamic task allocation in multi-robot systems," *The International Journal of Robotics Research,* vol. 25, no. 3, pp. 225-241, 2006.
[52] H. Ravichandar, K. Shaw, and S. Chernova, "STRATA: unified framework for task assignments in large teams of heterogeneous agents," *Autonomous Agents and Multi-Agent Systems,* vol. 34, no. 2, pp. 1-25, 2020.
[53] M. Koes, I. Nourbakhsh, and K. Sycara, "Constraint optimization coordination architecture for search and rescue robotics," in *Proceedings 2006 IEEE International Conference on Robotics and Automation, 2006. ICRA 2006.*, 2006: IEEE, pp. 3977-3982.
[54] A. Prorok, M. A. Hsieh, and V. Kumar, "The impact of diversity on optimal control policies for heterogeneous robot swarms," *IEEE Transactions on Robotics,* vol. 33, no. 2, pp. 346-358, 2017.
[55] R. F. Salas-Moreno, R. A. Newcombe, H. Strasdat, P. H. Kelly, and A. J. Davison, "Slam++: Simultaneous localisation and mapping at the level of objects," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2013, pp. 1352-1359.
[56] D. Maturana and S. Scherer, "3d convolutional neural networks for landing zone detection from lidar," in *2015 IEEE international conference on robotics and automation (ICRA)*, 2015: IEEE, pp. 3471-3478.
[57] S. L. Bowman, N. Atanasov, K. Daniilidis, and G. J. Pappas, "Probabilistic data association for semantic slam," in *2017 IEEE international conference on robotics and automation (ICRA)*, 2017: IEEE, pp. 1722-1729.
[58] N. Atanasov, S. L. Bowman, K. Daniilidis, and G. J. Pappas, "A Unifying View of Geometry, Semantics, and Data Association in SLAM," in *IJCAI*, 2018, pp. 5204-5208.
[59] S. Yang and S. Scherer, "Cubeslam: Monocular 3-d object slam," *IEEE Transactions on Robotics,* vol. 35, no. 4, pp. 925-938, 2019.
[60] L. Nicholson, M. Milford, and N. Sünderhauf, "Quadricslam: Dual quadrics from object detections as landmarks in object-oriented slam," *IEEE Robotics and Automation Letters,* vol. 4, no. 1, pp. 1-8, 2018.
[61] A. Rosinol, A. Violette, M. Abate, N. Hughes, Y. Chang, J. Shi *et al.*, "Kimera: From SLAM to spatial perception with 3D dynamic scene graphs," *The International Journal of Robotics Research,* vol. 40, no. 12-14, pp. 1510-1546, 2021.
[62] D. Maturana, P.-W. Chou, M. Uenoyama, and S. Scherer, "Real-time semantic mapping for autonomous off-road navigation," in *Field and Service Robotics*, 2018: Springer, pp. 335-350.
[63] M. Ryll, J. Ware, J. Carter, and N. Roy, "Semantic Trajectory Planning for Long-Distant Unmanned Aerial Vehicle Navigation in Urban Environments," in *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2020: IEEE, pp. 1551-1558.
[64] V. Vasilopoulos, Y. Kantaros, G. J. Pappas, and D. E. Koditschek, "Reactive planning for mobile manipulation tasks in unexplored semantic environments," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*, 2021: IEEE, pp. 6385-6392.
[65] X. Liu, G. V. Nardari, F. C. Ojeda, Y. Tao, A. Zhou, T. Donnelly *et al.*, "Large-scale autonomous flight with real-time semantic slam under dense forest canopy," *IEEE Robotics and Automation Letters,* vol. 7, no. 2, pp. 5512-5519, 2022.
[66] B.-T. Vo, B.-N. Vo, R. Hoseinnezhad, and R. P. Mahler, "Robust multi-Bernoulli filtering," *IEEE Journal of Selected Topics in Signal Processing,* vol. 7, no. 3, pp. 399-409, 2013.
[67] I. Kostavelis and A. Gasteratos, "Semantic mapping for mobile robotics tasks: A survey," *Robotics and Autonomous Systems,* vol. 66, pp. 86-103, 2015.
[68] D. Maturana, S. Arora, and S. Scherer, "Looking forward: A semantic mapping system for scouting with micro-aerial vehicles," in *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2017: IEEE, pp. 6691-6698.
[69] Y. Lin, F. Gao, T. Qin, W. Gao, T. Liu, W. Wu *et al.*, "Autonomous aerial navigation using monocular visual‐inertial fusion," *Journal of Field Robotics,* vol. 35, no. 1, pp. 23-51, 2018.
[70] X. Zhou, Z. Wang, H. Ye, C. Xu, and F. Gao, "Ego-planner: An esdf-free gradient-based local planner for quadrotors," *IEEE Robotics and Automation Letters,* vol. 6, no. 2, pp. 478-485, 2020.
[71] X. Zhou, J. Zhu, H. Zhou, C. Xu, and F. Gao, "Ego-swarm: A fully autonomous and decentralized quadrotor swarm system in cluttered environments," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*, 2021: IEEE, pp. 4101-4107.
[72] H. Oleynikova, C. Lanegger, Z. Taylor, M. Pantic, A. Millane, R. Siegwart *et al.*, "An open‐source system for vision‐based micro‐aerial vehicle mapping, planning, and flight in cluttered environments," *Journal of Field Robotics,* vol. 37, no. 4, pp. 642-666, 2020.
[73] S. W. Chen, G. V. Nardari, E. S. Lee, C. Qu, X. Liu, R. A. F. Romero *et al.*, "Sloam: Semantic lidar odometry and mapping for forest inventory," *IEEE Robotics and Automation Letters,* vol. 5, no. 2, pp. 612-619, 2020.
[74] R. Bähnemann, N. Lawrance, J. J. Chung, M. Pantic, R. Siegwart, and J. Nieto, "Revisiting boustrophedon coverage path planning as a generalized traveling salesman problem," in *Field and Service Robotics*, 2021: Springer, pp. 277-290.
[75] K. Sun, K. Mohta, B. Pfrommer, M. Watterson, S. Liu, Y. Mulgaonkar *et al.*, "Robust stereo visual inertial odometry for fast autonomous flight," *IEEE Robotics and Automation Letters,* vol. 3, no. 2, pp. 965-972, 2018.
[76] S. Liu, K. Mohta, N. Atanasov, and V. Kumar, "Search-based motion planning for aggressive flight in se (3)," *IEEE Robotics and Automation Letters,* vol. 3, no. 3, pp. 2439-2446, 2018.

[77] K. Mohta, M. Watterson, Y. Mulgaonkar, S. Liu, C. Qu, A. Makineni *et al.*, "Fast, autonomous flight in GPS‐denied and cluttered environments," *Journal of Field Robotics,* vol. 35, no. 1, pp. 101-120, 2018.

[78] Z. Xie and P. Dames, "DRL-VO: Using Velocity Obstacles to Learn Safe and Fast Navigation."

[79] M. Du, N. Liu, and X. Hu, "Techniques for interpretable machine learning," *Communications of the ACM,* vol. 63, no. 1, pp. 68-77, 2019.

[80] B. McMahan and D. Ramage, "Federated Learning: Collaborative Machine Learning without Centralized Training Data " in *Google AI Blog*, ed, 2017.

[81] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-efficient learning of deep networks from decentralized data," in *Artificial intelligence and statistics*, 2017: PMLR, pp. 1273-1282.

[82] H. B. McMahan, E. Moore, D. Ramage, and B. A. y Arcas, "Federated learning of deep networks using model averaging," *arXiv preprint arXiv:1602.05629,* 2016.

[83] Y. Zhao, M. Li, L. Lai, N. Suda, D. Civin, and V. Chandra, "Federated learning with non-iid data," *arXiv preprint arXiv:1806.00582,* 2018.

[84] V. Smith, C.-K. Chiang, M. Sanjabi, and A. S. Talwalkar, "Federated multi-task learning," *Advances in neural information processing systems,* vol. 30, 2017.

[85] K. Bonawitz, H. Eichner, W. Grieskamp, D. Huba, A. Ingerman, V. Ivanov *et al.*, "Towards federated learning at scale: System design," *Proceedings of Machine Learning and Systems,* vol. 1, pp. 374-388, 2019.

[86] J. Geiping, H. Bauermeister, H. Dröge, and M. Moeller, "Inverting gradients-how easy is it to break privacy in federated learning?," *Advances in Neural Information Processing Systems,* vol. 33, pp. 16937-16947, 2020.

[87] W. Wei, L. Liu, M. Loper, K.-H. Chow, M. E. Gursoy, S. Truex *et al.*, "A framework for evaluating client privacy leakages in federated learning," in *European Symposium on Research in Computer Security*, 2020: Springer, pp. 545-566.

[88] J. Lecina‐Diaz, J. Martínez‐Vilalta, A. Alvarez, M. Banqué, J. Birkmann, D. Feldmeyer *et al.*, "Characterizing forest vulnerability and risk to climate‐change hazards," *Frontiers in Ecology and the Environment,* vol. 19, no. 2, pp. 126-133, 2021.

[89] H. Fritts, *Tree rings and climate*. Elsevier, 2012.

[90] K. J. Anderson-Teixeira, V. Herrmann, C. R. Rollinson, B. Gonzalez, E. B. Gonzalez-Akre, N. Pederson *et al.*, "Joint effects of climate, tree size, and year on annual tree growth derived from tree-ring records of ten globally distributed forests," *Global Change Biology,* vol. 28, no. 1, pp. 245-266, 2021.

[91] E. R. Cook and N. Pederson, "Uncertainty, emergence, and statistics in dendrochronology," in *Dendroclimatology*: Springer, 2011, pp. 77-112.

[92] L. D'Orangeville, J. Maxwell, D. Kneeshaw, N. Pederson, L. Duchesne, T. Logan *et al.*, "Drought timing and local climate determine the sensitivity of eastern temperate forests to drought," *Global Change Biology,* vol. 24, no. 6, pp. 2339-2351, 2018.

[93] L. J. Graumlich, "Response of tree growth to climatic variation in the mixed conifer and deciduous forests of the upper Great Lakes region," *Canadian Journal of Forest Research,* vol. 23, no. 2, pp. 133-143, 1993.

[94] T. Shearman, G. Wang, P. Ma, and S. Guan, "Patterns of bark growth for juvenile trees of six common hardwood species in the eastern United States and the implications to fire-tolerance," *Trees,* vol. 32, no. 2, pp. 519-524, 2018.

[95] L. S. Pile, G. G. Wang, B. O. Knapp, G. Liu, and D. Yu, "Comparing morphology and physiology of southeastern US Pinus seedlings: implications for adaptation to surface fire regimes," *Annals of forest science,* vol. 74, no. 4, pp. 1-12, 2017.

[96] E. S. Wenk, G. G. Wang, and J. L. Walker, "Within-stand variation in understorey vegetation affects fire behaviour in longleaf pine xeric sandhills," *International Journal of Wildland Fire,* vol. 20, no. 7, pp. 866-875, 2011.

[97] G. Wang, "Fire severity in relation to canopy composition within burned boreal mixedwood stands," *Forest Ecology and Management,* vol. 163, no. 1-3, pp. 85-92, 2002.

[98] R. J. Klos, G. G. Wang, W. L. Bauerle, and J. R. Rieck, "Drought impact on forest growth and mortality in the southeast USA: an analysis using Forest Health and Monitoring data," *Ecological Applications,* vol. 19, no. 3, pp. 699-708, 2009.

[99] H. Hu, G. G. Wang, W. L. Bauerle, and R. J. Klos, "Drought impact on forest regeneration in the Southeast USA," *Ecosphere,* vol. 8, no. 4, p. e01772, 2017.

[100] D. Lu, L. S. Pile, D. Yu, J. Zhu, D. C. Bragg, and G. G. Wang, "Differential responses of tree species to a severe ice storm and their implications to forest composition in the southeast United States," *Forest Ecology and Management,* vol. 468, p. 118177, 2020.

[101] L. S. Pile, C. A. Maier, G. G. Wang, D. Yu, and T. M. Shearman, "Responses of two genetically superior loblolly pine clonal ideotypes to a severe ice storm," *Forest Ecology and Management,* vol. 360, pp. 213-220, 2016.

[102] S. Guan and G. G. Wang, "Post-hurricane fuel dynamics and implications for fire behavior (Project SO-EM-F-12-01)," *In: Potter, Kevin M.; Conkling, Barbara L., eds. 2018. Forest health monitoring: national status, trends, and analysis 2017. General Technical Report SRS-233. Asheville, NC: US Department of Agriculture, Forest Service, Southern Research Station.,* vol. 2018, pp. 157-160, 2018.

[103] H. Xie, J. E. Fawcett, and G. G. Wang, "Fuel dynamics and its implication to fire behavior in loblolly pine-dominated stands after southern pine beetle outbreak," *Forest Ecology and Management,* vol. 466, p. 118130, 2020.

[104] V. Trotsiuk, N. Pederson, D. L. Druckenbrod, D. A. Orwig, D. A. Bishop, A. Barker-Plotkin *et al.*, "Testing the efficacy of tree-ring methods for detecting past disturbances," *Forest Ecology and Management,* vol. 425, pp. 59-67, 2018.

[105] C. Huang, S. N. Goward, J. G. Masek, N. Thomas, Z. Zhu, and J. E. Vogelmann, "An automated approach for reconstructing recent forest disturbance history using dense Landsat time series stacks," *Remote Sensing of Environment,* vol. 114, no. 1, pp. 183-198, 2010.

[106] R. E. Kennedy, Z. Yang, and W. B. Cohen, "Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr—Temporal segmentation algorithms," *Remote Sensing of Environment,* vol. 114, no. 12, pp. 2897-2910, 2010.

[107] M. Zhou, J. Liang, and J. Buongiorno, "Adaptive versus fixed policies for economic or ecological objectives in forest management," *Forest ecology and management,* vol. 254, no. 2, pp. 178-187, 2008.

[108] T. O. Ochuodho and V. A. Lantz, "Economic impacts of climate change in the forest sector: a comparison of single-region and multiregional CGE modeling frameworks," *Canadian journal of forest research,* vol. 44, no. 5, pp. 449-464, 2014.

[109] J. Liang, T. W. Crowther, N. Picard, S. Wiser, M. Zhou, G. Alberti *et al.*, "Positive biodiversity-productivity relationship predominant in global forests," *Science,* vol. 354, no. 6309, p. aaf8957, 2016.

[110] M. D. Flannigan, K. A. Logan, B. D. Amiro, W. R. Skinner, and B. J. Stocks, "Future Area Burned in Canada," *Climatic Change,* vol. 72, no. 1, pp. 1-16, 2005/09/01 2005, doi: 10.1007/s10584-005-5935-y.

[111] T. Lempriѐre, P. Bernier, A. Carroll, M. Flannigan, R. Gilsenan, D. McKenney *et al.*, "The importance of forest sector adaptation to climate change," 2008.

[112] Y. Li, "Deep reinforcement learning: An overview," *arXiv preprint arXiv:1701.07274,* 2017.

[113] D. Silver, T. Hubert, J. Schrittwieser, I. Antonoglou, M. Lai, A. Guez *et al.*, "A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play," *Science,* vol. 362, no. 6419, pp. 1140-1144, 2018.

[114] N. M. Haddad, L. A. Brudvig, J. Clobert, K. F. Davies, A. Gonzalez, R. D. Holt *et al.*, "Habitat fragmentation and its lasting impact on Earth's ecosystems," *Science advances,* vol. 1, no. 2, p. e1500052, 2015.

[115] H. Ter Steege, N. C. Pitman, D. Sabatier, C. Baraloto, R. P. Salomão, J. E. Guevara *et al.*, "Hyperdominance in the Amazonian tree flora," *Science,* vol. 342, no. 6156, p. 1243092, 2013.

[116] H. Ter Steege, N. C. Pitman, T. J. Killeen, W. F. Laurance, C. A. Peres, J. E. Guevara *et al.*, "Estimating the global conservation status of more than 15,000 Amazonian tree species," *Science advances,* vol. 1, no. 10, p. e1500936, 2015.

[117] B. S. Steidinger, T. W. Crowther, J. Liang, M. E. Van Nuland, G. D. Werner, P. B. Reich *et al.*, "Climatic controls of decomposition drive the global biogeography of forest-tree symbioses," *Nature,* vol. 569, no. 7756, pp. 404-408, 2019.

[118] R. Cazzolla Gatti, P. B. Reich, J. G. Gamarra, T. Crowther, C. Hui, A. Morera *et al.*, "The number of tree species on Earth," *Proceedings of the National Academy of Sciences,* vol. 119, no. 6, p. e2115329119, 2022.

[119] X. Guo, F. Wang, Y. Ma, and D. Du, "Research on three-dimensional point clouds processing for standing tree volume based on laser

scanner," in *2009 Second International Symposium on Knowledge Acquisition and Modeling*, 2009, vol. 3: IEEE, pp. 206-208.

[120] X. Liu, S. W. Chen, C. Liu, S. S. Shivakumar, J. Das, C. J. Taylor *et al.*, "Monocular camera based fruit counting and mapping with semantic data association," *IEEE Robotics and Automation Letters,* vol. 4, no. 3, pp. 2296-2303, 2019.

[121] P. Schopfer, "Biomechanics of plant growth," *American journal of botany,* vol. 93, no. 10, pp. 1415-1425, 2006.

[122] B. Wang, Y. Zhao, and J. Barbič, "Botanical materials based on biomechanics," *ACM Transactions on Graphics (TOG),* vol. 36, no. 4, pp. 1-13, 2017.

[123] K. J. Niklas, H. C. Spatz, and J. Vincent, "Plant biomechanics: an overview and prospectus," *American journal of botany,* vol. 93, no. 10, pp. 1369-1378, 2006.

[124] G. P. Asner, J. M. Scurlock, and J. A. Hicke, "Global synthesis of leaf area index observations: implications for ecological and remote sensing studies," *Global ecology and biogeography,* vol. 12, no. 3, pp. 191-205, 2003.

[125] K. Abe, K. Soga, and S. Bandara, "Material point method for coupled hydromechanical problems," *Journal of Geotechnical and Geoenvironmental Engineering,* vol. 140, no. 3, p. 04013033, 2014.

[126] J. C. Jenkins, R. A. Birdsey, and Y. Pan, "Biomass and NPP estimation for the Mid‐Atlantic region (USA) using plot‐level forest inventory data," *Ecological Applications,* vol. 11, no. 4, pp. 1174-1193, 2001.

[127] J. Blackard, M. Finco, E. Helmer, G. Holden, M. Hoppus, D. Jacobs *et al.*, "Mapping US forest biomass using nationwide forest inventory data and moderate resolution information," *Remote sensing of Environment,* vol. 112, no. 4, pp. 1658-1677, 2008.

[128] J. O'Neil-Dunne, S. MacFaden, and A. Royar, "A versatile, production-oriented approach to high-resolution tree-canopy mapping in urban and suburban landscapes using GEOBIA and data fusion,"*Remote sensing,* vol. 6, no. 12, pp. 12837-12865, 2014.

[129] R. W. Guldin, "Forest science and forest policy in the Americas: building bridges to a sustainable future," *Forest Policy and Economics,* vol. 5, no. 4, pp. 329-337, 2003.

[130] E. E. Oldfield, A. J. Felson, D. N. Auyeung, T. W. Crowther, N. F. Sonti, Y. Harada *et al.*, "Growing the urban forest: tree performance in response to biotic and abiotic land management,"*Restoration Ecology,* vol. 23, no. 5, pp. 707-718, 2015.

[131] M. C. Hansen, P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina *et al.*, "High-resolution global maps of 21st-century forest cover change," *science,* vol. 342, no. 6160, pp. 850-853, 2013.

[132] M. Pfeifer, M. Disney, T. Quaife, and R. Marchant, "Terrestrial ecosystems from space: a review of earth observation products for macroecology applications," *Global Ecology and Biogeography,* vol. 21, no. 6, pp. 603-624, 2012.

[133] T. W. Crowther, H. B. Glick, K. R. Covey, C. Bettigole, D. S. Maynard, S. M. Thomas *et al.*, "Mapping tree density at a global scale,"*Nature,* vol. 525, no. 7568, pp. 201-205, 2015.

[134] E. Treasure, S. McNulty, J. M. Myers, and L. N. Jennings, "Template for assessing climate change impacts and management options: TACCIMO user guide version 2.2," *Gen. Tech. Rep. SRS-GTR-186. Asheville, NC: USDA-Forest Service, Southern Research Station. 33 p.,* vol. 186, pp. 1-33, 2014.

[135] Z. Ji, N. Lee, R. Frieske, T. Yu, D. Su, Y. Xu *et al.*, "Survey of hallucination in natural language generation," *ACM Computing Surveys,* vol. 55, no. 12, pp. 1-38, 2023.