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Classifying mature federal forests in the United States: The forest inventory growth stage system

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ABSTRACT

President Biden's executive order, *'Strengthening the Nation's Forests, Communities, and Local Economies,'* (EO#14072, April 22, 2022) acknowledges the interest in mature and old-growth (MOG) forests by directing U.S. Federal agencies to define and inventory these resources on United States Forest Service (USFS) and Bureau of Land Management (BLM) lands. We propose using an effective and enduring mature forest classification system that could be adaptable to social paradigms, monitoring data streams, scientific information, and global change factors. We accommodate these design aspects by defining mature forests as a growth stage prior to the onset of old-growth attributes within a proposed Forest Inventory Growth Stage System (FIGSS). FIGSS uses the long-established USFS old-growth assessments often conducted in concert with public dialogues to identify key structural indicators of older forests. The system informs inverse modeling of the prior "mature" stage's structural thresholds enabling initial population estimates of mature forest extent using the USFS' nationally consistent Forest Inventory and Analysis (FIA) program data. With this approach, we estimate that approximately 45 percent of all USFS/BLM forest is mature. The FIGSS system is based on a variety of components that could be used to account for cultural values ascribed to forest conditions which could be refined across future versions such as assumptions about the relative length of growth stages, incorporating data from emerging monitoring technologies along with old-growth/mature field sampling campaigns, accommodating spectrums of site-limited and/or disturbance-driven stand development, refined variable selection processes such as machine-learning, and consideration of traditional ecological knowledge.

1. Introduction

On April 22, 2022, United States' President Biden issued an Executive Order (EO14072, White House, 2022) acknowledging the role that forests play not only at the global level in terms of "clean air and water" but also fundamental to "combating the global climate and biodiversity crisis." Furthermore, the President noted the role that forests play in "the health, prosperity, and resilience of our communities" while indicating that the conservation of "old growth and mature forests on federal Lands while supporting and advancing climate-smart forestry and sustainable forest products is critical to protecting these and other ecosystem services provided by those (sic) forests." Pursuant to these Presidential proclamations, Section 2(b) of EO14072 directs the Secretaries of the Interior (i.e., Bureau of Land Management) and Agriculture (i.e., United States Forest Service, USFS) to "define, identify, and complete an inventory of mature and old-growth (MOG) forests on Federal lands, accounting for regional and ecological variations, as appropriate, and shall make such inventory publicly available" within one year of the order. While USFS regulations have generally approached the concept of mature forest conditions in terms as to when a forest could be harvested and regenerated based primarily on economic and sustained yield principles (NFMA 1976), the USFS does not currently employ a

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definition suitable for a nation-wide inventory of MOG forests based on ecological criteria. In contrast, old-growth assessments on USFS lands were initiated by the Chief of the USFS in 1989 (Supplementary Figure S1) and integrated into Land and Resource Management Plans (LMP's) to various extents across the nine US Forest Service Regions. The resulting old-growth scientific assessments (e.g., Green et al., 1992; Tyrell et al., 1998), modified through the LMP public dialogue, integrating ecological and social values, serve as the most appropriate information for developing old-growth indicators. Coupled with the Nation's strategic-scale forest inventory (Forest Inventory and Analysis program [FIA]; Burrill et al., 2021; Oswalt et al., 2019), these indicators can provide initial, statistically valid population estimates of federal old-growth resources, appropriate for management considerations within the EO's timeframe. Pelz et al. (same issue) details such an approach that forms the technical basis for defining and estimating USFS/BLM old-growth forest resources. This study builds on the paradigm that such a field-intensive survey of old-growth forests coupled with FIA's statistical framework can provide an initial foundation to define USFS and BLM mature forests and associated inventory and estimation techniques.

Perhaps the only widely accepted definition of a mature forest is that it is a stage of forest development that precedes the old-growth stage (Frelich and Reich, 2003; D'Amato and Palik, 2021; DellaSala et al., 2022; Barnett et al., 2023). Although past discussions have centered on the final or climax stages of forest development as old growth (Wirth et al., 2009) which includes nuanced semantics (e.g., natural heritage forest; Frelich and Reich, 2003), complementary discourse has included forest conditions prior to onset of old growth (Ducey et al., 2013) as a transition state between stand recovery/development following a disturbance and old-growth (Wirth et al., 2009). D'Amato and Palik (2021) have proposed the concept of "old-stage" forests to suggest there is no climax stage and that growth dynamics that give rise to old-growth structural attributes may be found across numerous stages of stand development. Indeed, Spies and Franklin (1988) decades ago used the term "old-growthness" to refer to this spectrum of old-growth attributes. As Gray et al. (same issue) discusses, mature forests can exhibit a few attributes found in old-growth forests, attributes on the verge of reaching old-growth conditions, or some combination thereof including no old-growth attributes. As old-growth definitions can be subjective against a backdrop of social constructs (e.g., land use change legacies such as primary forest) and empirical observations/data across a landscape-scale shifting mosaic (Frelich and Reich, 2003), the classification of mature forests that do not conflict with old-growth classifications perhaps compound issues associated with uncertainty and subjectivity not to mention global change (Anderegg et al., 2022) that can give rise to future, novel forests (Millar et al., 2007). In the case of the EO14072, because old growth has been investigated and defined across federal lands and elsewhere (e.g., Tyrell et al., 1998), the old-growth information on federal lands can serve as an initial empirical, validated basis to explore classification opportunities for the preceding growth stage considered as a pre-old-growth stage, otherwise termed a "mature" forest recognizing this is a highly uncertain enterprise.

Although a mature class may be bounded by old-growth and a young forest stage (i.e., stem-exclusion or canopy closure stage; Bormann and Likens, 1994; Oliver and Larson, 1996; D'Amato and Palik, 2021), we hypothesize that an initial mature forest classification can be derived from an inverse modeling exercise (e.g., Zhou et al., 2015) using old-growth attributes to estimate preceding forest stand developmental stage attributes. When combining a mature forest inverse modeling exercise with the potential design parameters associated with EO14072, we sought to adhere to a number of principles within a forest structure narrative framework: (1) scientifically rigorous, (2) repeatable and simple, (3) structural metrics are valid across a diversity of forest ecosystems, (4) compatible with use of Forest Inventory and Analysis (FIA) plot data for all stand conditions, (5) applicable across spatial scales and federal jurisdictions, and (6) operational to meet the April 22, 2023 EO14072 deadline and public requests for resource information and inventory refinements into the future.

The goal of this study was to develop a classification system with resulting population estimates of areal extent for USFS/BLM mature forests (as directed by President Biden; EO14072) based on general design parameters associated specifically with federal lands and more broadly with aspects of EO14072. This study explicitly pursued a mature forest classification system that would complement old-growth classification integrated over the past 30 years in current land management planning (see Pelz et al., same issue) while recognizing foundational studies (e.g., Spies and Franklin, 1988) and emerging studies and paradigms (D'Amato and Palik, 2021; Barnett et al., 2023) to effectively support federal studies of MOG forests within a context of global change (e.g., Binkley et al., 2007; Anderegg et al., 2022) and social constructs (e.g., decolonizing paradigms, Reid et al., 2021).

2. Methods

2.1. Study area

As directed by EO14072, the area of interest is all USFS and BLM forest land such that the study area spans portions of the entire US representing a diversity of climates, geophysical domains, and forest ecosystems although the preponderance of federal forest land area is across the western US and coastal Alaska which account for 83% of all USFS forest land (Oswalt et al., 2019). USFS forest land comprises approximately 58 million ha or about 19% of all US forests whereas BLM forest land totals approximately 15 million ha with over 99% in the western US and Alaska (Oswalt et al., 2019). Conducting forest inventories in Alaska is especially challenging due to the remote environment, associated costs, and access restrictions (Cahoon et al., 2022). There is nearly 1.4 million ha of forested NFS land in Alaska not included in this analysis because of permanent field plot monumentation prohibition in Alaskan wilderness areas. There is an additional 11.1 million ha of potentially forested BLM land in interior Alaska that have not yet been inventoried by FIA but are in progress of being inventoried using emerging techniques within a cost-effective survey design (e.g., Babcock et al., 2018). The coastal Alaska inventories of USFS forests are included in this analysis.

2.2. US National forest inventory

The study relied on the plot network and associated land use and forest attribute data collected by the USDA Forest Service's Forest Inventory and Analysis (FIA) program, which is the primary source for information about the extent, condition, status, and trends of forest resources across the U.S. (Oswalt et al., 2019). The FIA program applies a nationally consistent sampling protocol using a systematic design covering all ownerships across the U.S. with a national sample intensity of one plot per 2,428 ha (Bechtold and Patterson, 2005). To improve precision of the field estimates, the population of interest is post-stratified (e.g., forest canopy cover classes from remote sensing) and plots are assigned to strata. Plots are visited if they potentially include forested land which is defined as being at least 10% canopy cover with tree species (currently or recently and not subject to other land uses), at least 0.4 ha in size, and at least 36.6 m wide (Bechtold and Patterson, 2005). Tree and site attributes are measured for plots established in the 2,428-ha hexagons. FIA inventory plots established in forested conditions consist of four, 7.32 m fixed-radius subplots spaced 36.6 m apart in a triangular arrangement with one subplot in the center (USDA, Forest Service, 2021; Burrill et al., 2021). The FIA inventory program delineates spatial "conditions" within each field plot which represent consistent stand size, density, forest type, ownership, and reserve conditions (e.g., half an inventory plot is occupied by a hardwood forest and the other half is occupied by a pine plantation). This term condition is used throughout this study to reflect field plot spatial delineations and is used for inventory classification and population estimation procedures (e.g., Bechtold and Patterson, 2005). All trees (live and standing dead) with a diameter of at least 12.7 cm (at a point 1.37 m above the ground) are inventoried with in situ measurement of diameter, species, height among a host of other attributes (USDA, Forest Service, 2021) on forested conditions within inventory subplots. Due to the abundance of large trees in the west coast states of California, Oregon and Washington, a larger 18 m radius macroplot (0.4 ha total footprint) is used for trees > 76 or 60 cm dbh, depending on location trees). A standing dead tree is considered downed dead wood when the lean angle of its central trunk is >45 degrees from vertical (USDA, Forest Service, 2021). Within each subplot, a 2.07 m microplot offset 3.66 m from subplot center is established where only live and standing dead trees with a diameter between 2.5 and 12.7 cm are inventoried. In this study, all FIA plots that occurred on USFS/BLM land were included with a focus on forested conditions which totaled over 49,000 observations (i.e., unique combinations of plot and mapped conditions within plots; Fig. 1) across all federal regions of the US. All FIA data that was used in this study is available for download at https://apps.fs.usda.gov/fia/datamart/datamart.html (USDA Forest Service, 2022) with the specific FIA inventories by state (i.e., FIA evaluations) identified by Pelz et al. (same issue).

2.3. Overview of forest inventory growth stage classification system

FIGSS defines mature forests as the structural stage of stand development that precedes old growth. Although such a concept of stand development is initially derived from past, frequently used four-stage models of forest development (Fig. 2) (Bormann and Likens, 1994; Hayward, 1991; Oliver and Larson, 1996) contemporary refinements often delineate between young and old-stage forests where structural attributes previously attributed solely to old-growth can be found to varying degrees across all stages (Franklin et al., 2020, D'Amato and Palik, 2021). Hence, FIGSS identifies key structural attributes associated with old-growth forests and "walks down" these metrics by vegetation type to values associated with an onset of maturity (i.e., a prior stage of development) based on assumptions about physiological maximum ages and growth attributes across the US. Recognizing the varying abundance of a variety of mature structural thresholds from young to old-stage forests is highly complex when considering the variety of developmental patterns (e.g., frequent disturbance, dry-site systems; Fig. 2) across the US, a final composite index of structural indicators only requires a minimum number of indicators for mature classification.

The FIGSS workflow (Fig. 3) uses nationally consistent USFS Forest Inventory and Analysis (FIA) program data and stand age (subjectively determined by inventory foresters; Burrill et al., 2021) correlation analysis to identify a set of old-growth structural indicators (Fig. 3, Supplementary Table S2). Inherent in the FIGSS approach is that there are two distinct sets of FIA plots: 1) FIA plots on NFS and BLM lands classified as old growth and 2) FIA plots on NFS and BLM lands not classified as old growth. Using these structural indicators, the 25th percentile of each indicator, stratified by 81 unique USFS Regional vegetation types (Supplementary Table S3) and for all FIA plots classified as old growth (Pelz et al., same issue), is used as the lower threshold of old-growth forest characteristics. These structural metrics and lower old-growth thresholds are then used in a process similar to inverse modeling (e.g., Zhou et al., 2015) to estimate the onset of mature characteristics (i.e., the prior stage of stand development) for each structural indicator. FIGSS uses carbon accumulation curves (Barnett et al., 2023) and maximum physiological ages (Loehle 1988) to estimate the proportion of time from maturity to mortality for each vegetation type (Table 2, Supplementary Table S4). This proportion is used as the "walkdown factor" from the lower threshold of old growth to the onset of mature characteristics for each structural indicator. Lastly, a correlation weighted composite index (a modified version of methods described in Wiréhn et al., 2015) is used to determine the likelihood that a given FIA plot is classified as mature.

FIGSS is not focused on a singular national definition of mature forests, rather it is a system to estimate forest resource attributes (i.e., extent) using potential indicators of mature forest attributes derived from old-growth characteristics defined by regional USFS old-growth assessments based on decades of field assessment and public engagement that can identify key structural indicators of an advanced stage of stand development (i.e., old forests) (Pelz et al., same issue). FIGSS presents an opportunity for future refinement with stakeholders,

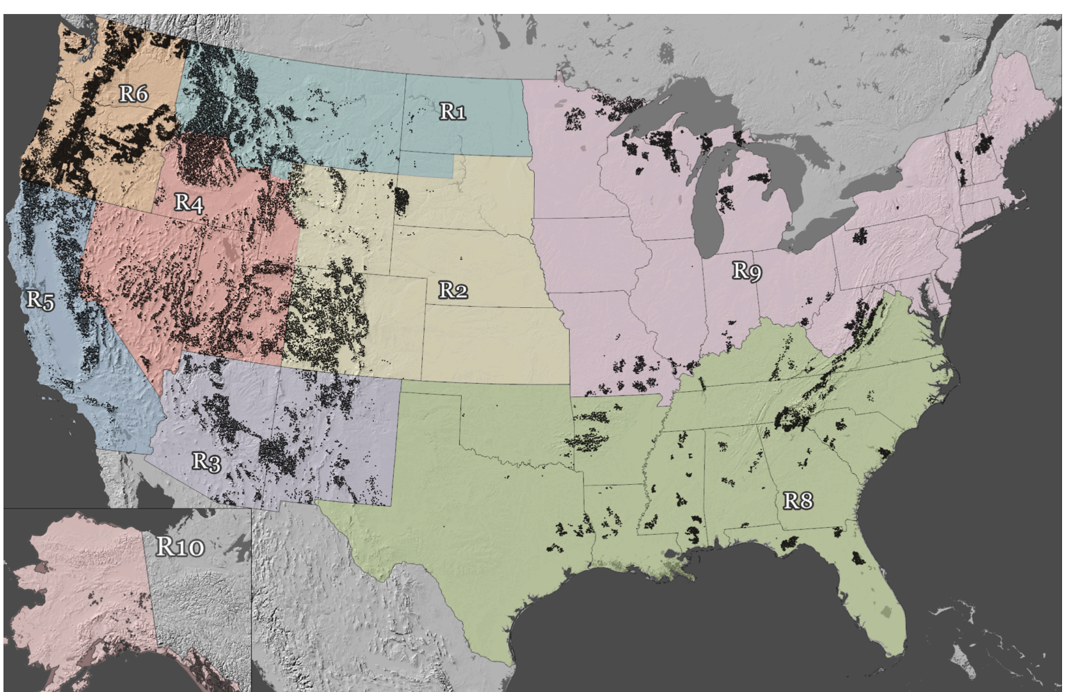

Fig. 1. Spatially perturbed FIA plot locations (49,158 observations) on USFS and BLM lands that were used in this study and identification of federal regions used in summary output (Regions 1–10), US. The black circles broadly illustrate the location of USFS and BLM forest lands.

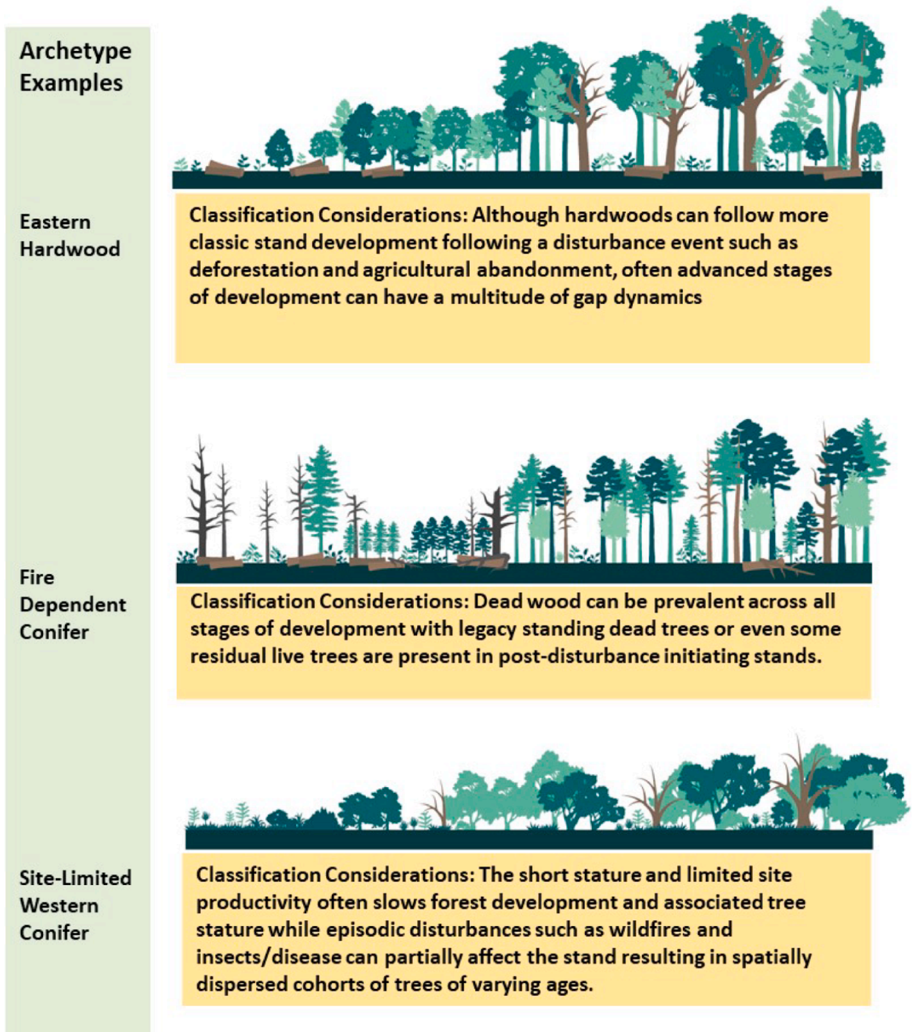

Fig. 2. Mature forest classification considerations when considering a few example forest ecosystem archetypes across the United States: Eastern hardwood, fire-dependent conifers, and site-limited western conifers.

emerging science, and empirical data due to lack of available literature and data to fully develop some components of this system.

2.3.1. *Old-growth inventories as means to define mature forests*

FIGSS does not define/prescribe old-growth attributes but instead uses FIA inventory observations classified as old growth (Pelz et al., same issue) to inform the classification of mature forests. Because this study is focused on mature classification, we will only briefly outline old-growth estimation procedures. USFS National Forest System (NFS) regional definitions of old-growth forest were compiled for all nine NFS Regions, based on foundational documentation, including General Technical Reports, Land Management Plans, and other supporting documents (e.g., Tyrell et al., 1998). The degree of development and management implementation of old-growth definitions varies widely among regions due to different approaches, from an extensively developed exercise (see Northwest Forest Plan; Davis et al., 2022) to a survey/documentation effort decades ago where old-growth forest may be rare (eastern US; Tyrell et al., 1998; Pelz et al., same issue). The regional definitions of old growth, defined by vegetation types, were cross-walked into FIA forest types and nationally consistent FIA attributes (e.g., minimum stand age and minimum number of large trees per unit area) to derive consistent estimation of population attributes (e.g., forest area) for all USFS/BLM ownerships while aligning with National Forest System planning documents to the extent possible. The FIA plots in USFS/BLM ownerships that were identified as old growth are used in FIGSS to inform estimation of mature forests.

2.3.2. *Selection of old-growth structural indicators*

FIGSS used an initial list of 36 possible structural indicators that can be used to describe old-growth forests (Gray et al., same issue) that can be calculated from USFS FIA plots (Supplementary Table S2). Of these initial 36 indicators, the following guiding principles were used to select a subset of structural indicators to use in FIGSS:

1. Ecologically relevant to forest stand development,
2. Scalable from old growth to mature developmental stages for identifying classification thresholds (i.e., indicators are numerically relevant before and after scaling),
3. Minimal multicollinearity between indicators, and
4. Indicators can be measured in the field (or subsequently calculated) and applied at various scales (e.g., field plots or remote sensing).

To avoid multicollinearity among indicators (e.g., Pearson's $R > 0.7$; Dormann et al., 2012), we tested the correlation between each pair of indicators and retained the indicator most correlated with stand age (Kamoske et al., 2022; Povak et al., 2020). Of these remaining indicators, the correlation between that indicator and stand age was estimated, stratified by the 81 USFS Regional vegetation groups, with

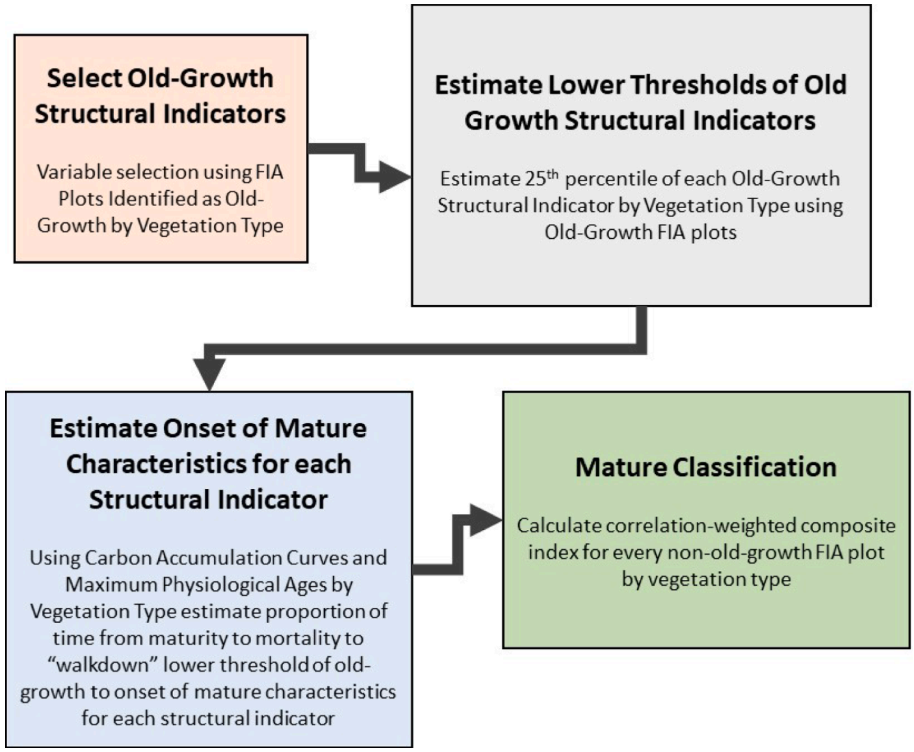

Fig. 3. Major components of Forest Inventory Growth Stage System (FIGSS) for classifying mature federal forests, US.

indicators being retained when their Pearson's R correlation was ≥ 0.20 (or when the indicator declines as stand development proceeds, $\leq$ Pearson's R of -0.20). The minimum correlation of 0.20 was chosen because machine learning approaches used to evaluate large sets of FIA variables (Smith et al., 2022) suggest that a correlation of 0.2 has a reasonable explanatory power given the tremendous breadth of the FIA national inventory program not only across stand conditions but in terms of the number of variables. Moreover, it has been found that most correlations among FIA variables are below 0.1, with the remainder often being autocorrelated (Woodall and Westfall, 2012). This multi-collinearity analysis coupled with the above guiding principles resulted in a set of seven structural indicators used for estimating forest growth stage thresholds (Table 1).

For vegetation types that had less than 10 FIA plots/conditions (six forest type groups representing 2.9% of the 49,000+ plots used in this analysis), the more inclusive FIA forest type group that was most closely related to the vegetation type was used to derive indicator thresholds (Supplementary Table S3). A minimum number of at least 10 FIA conditions per vegetation type was used to align with FIA post stratification procedures (minimum of 12 plots, page 46 of Bechtold and Patterson, 2005) and other applied research studies suggesting at least eight FIA plots per estimation unit (carbon research polygons; Woodall et al., 2015). This selection process resulted in a subset of structural indicators used to classify each vegetation type as mature (V).

FIA plot-level conditions classified as nonstocked forest land (n = 2,121) were removed from the structural indicator analysis because those conditions have less than 10 percent canopy cover and cannot be classified as mature. The HT_{sd} indicator (Table 1) contains some null values that were converted to zeros because these null values indicate no tally trees existed within any FIA plot/condition.

2.3.3. *Determining the onset of mature structural characteristics*

To determine the lower old-growth threshold, we calculated the 25th percentile of values for each structural indicator (Supplementary Table S3) from the old growth set of FIA plots. This threshold value was calculated for each of the 81 vegetation types and is assumed to correspond to the transition zone from mature to old growth conditions. The 25th percentile was chosen as a consistent approach of dealing with outliers and heavy-tailed distributions warranting future empirical refinement given the lack of mature definitions and consensus in the scientific literature.

Next, we used inverse modeling to estimate the onset of mature characteristics for each structural indicator by using a walkdown factor and the lower old growth threshold calculated above (Fig. 3). The walkdown factor represents the proportion of time from maturity to mortality for each vegetation type and is based on ages associated with the onset of mature forest condition derived from carbon accumulation curves (Barnett et al., 2023; Table 2) and mean maximum physiological ages expected for common trees species of the US that were related to FIA forest type groups (Supplementary Table S4). We used the following equation to estimate this walkdown factor:

$$M_{st} = OG_{25}\left(\left[M_{mort} - CMAI_{age}\right]/M_{mort}\right)$$

where M_{st} is the threshold representing the onset of mature structural characteristics for each structural indicator by vegetation type, OG_{25} is the value of the structural indicator for the onset of old-growth, M_{mort} is max age (MAXMORT; Loehle, 1988) and $CMAI_{age}$ is the age of the onset of maturity derived from culmination mean annual increment of carbon (Barnett et al., 2023). This equation resulted in a list of walkdown factors for each FIA forest type (Table 2). For forest types that did not have a maximum age value, we used the median walkdown value derived from all forest types that had a walkdown value (i.e., 0.80). To crosswalk these FIA forest type walkdown factors to regional vegetation types we identified all of FIA forest types contained within a regional vegetation type and took the mean value of those walkdown values. Like the selection of the 25th percentile of old-growth structural attribute values, the estimation of mature ages and associated walkdown factors is based on initial empirical observations warranting further exploration.

2.3.4. *Multifactor mature classification and population estimates*

Using all non-old growth FIA plots and the above onset of mature

Table 1
Structural indicator variables used in the FIGSS analysis selected from a wider set of structural indicators (see Supplementary Table S2) which were used to "walk down" to the prior stage of development assumed to be mature. For FIA database definitions and associated codes please refer to Burrill et al., 2021. All units are imperial to align with the units within FIA's national database to avoid unintended errors regarding interpretation and associated code (see Supplementary Material).

Variable	Description	Ecological Significance	Calculation from FIA data
tpadom	Total dominant trees per acre (TPA)	Abundance of large trees in the upper layers of the canopy serves to indicate stage of stand development	Sum of live trees per acre, where diameter >=1 in. and crown class code (CCLCD) is 1, 2, or 3
HTsd	Standard deviation of height of all trees (TPA-weighted) (ft)	The variation in tree height in a stand is an indicator of extended periods of stand development and differentiation of tree sizes in the canopy	Calculated from HT for all live trees from the FIA tree table, weighted by tpa_unadj
QMDdom	Quadratic mean diameter of overstory trees (in)	The average size of trees that dominate the canopy is highly correlated with stand development because dominant trees in the stand continue to add diameter growth as they age	QMD_DOM = √((BA_DOM /(TPA_DOM* 0.005454)))
snagbatot	Total basal area of standing dead trees with dbh ≥ 5 in. (ft2/ac)	Dead wood resources can indicate stand development processes such as self-thinning and/or disturbance related tree mortality	Sum of Basal Area for all standing dead trees from the FIA tree table. BA = tpa_unadj*3.141593*(dia/24)*2
badom	Total basal area of dominant trees (ft2/ac)	Indicates the site occupancy of the dominant, large trees in a stand	BALIVE where diameter >=1.0″ and crown class code(CCLCD) is 1,2, or 3
ddiscore	Diameter diversity score (NWFP, Davis et al., 2022)	Indicates the variation in tree size in a stand and is an indicator of cohorts developing over time and differentiation of tree sizes in the canopy	Calculate the 4 TPA classes: Class_0 = 2–9.8″ d.b.h. Class_1 = 9.9–19.7″ d.b.h. Class_2 = 19.8–39.4″ d.b.h. Class_3 = 39.5+" d.b.h. Calculate index values from TPA classes, then calculate DDI from index values. https://lemma.forestry.oregon state.edu/data/structure-maps
HTquart	Mean height of tallest 25% of trees (TPA-weighted) (ft)	Height development in a stand indicates stage of stand development	Calculated from HT for all live trees from the FIA tree table, weighted by tpa_unadj

structural characteristic thresholds, we calculated a correlation weighted composite index using a modified version of methods described in Wiréhn et al. (2015) to determine the likelihood that a given FIA plot is classified as mature for each vegetation type (Supplementary Table S3). For each vegetation type, the composite index was derived by taking the absolute value of the correlation between each structural indicator and stand age and dividing that value by the sum of all correlation absolute values (i.e., all structural indicators used in a

Table 2
Walkdown factors for the onset of mature structural characteristics were calculated with equation described above (M_{st}). Max Age is derived from Loehle, 1988 (MAXMORT); Mature Age is derived from Barnett et al., 2023; Vegetation Type is based on FIA forest types. In situations where a Mature or Max age was not available, the median walkdown factor of all complete data was used – this is indicated by the * symbol in the Walkdown Factor column.

Vegetation Type	Mature Age	Max Age	Walkdown Factor
Alder / maple group	36	200	0.82
Aspen / birch group	91	185	0.51
California mixed conifer group	129	NA	*0.80
Douglas-fir group	166	1200	0.86
Elm / ash / cottonwood group	62	241	0.74
Exotic softwoods group	24	NA	*0.80
Fir / spruce / mountain hemlock group	167	799	0.79
Hemlock / Sitka spruce group	119	867	0.86
Loblolly / shortleaf pine group	20	230	0.91
Lodgepole pine group	152	300	0.49
Longleaf / slash pine group	21	400	0.95
Maple / beech / birch group	73	270	0.73
Oak / gum / cypress group	55	525	0.90
Oak / hickory group	66	281	0.76
Oak / pine group	53	263	0.80
Other eastern softwoods group	45	300	0.85
Other hardwoods group	85	NA	*0.80
Other western softwoods group	313	NA	*0.80
Pinyon / juniper group	111	544	0.80
Ponderosa pine group	102	594	0.83
Redwood group	NA	NA	*0.80
Spruce / fir group	68	257	0.74
Tanoak / laurel group	59	300	0.80
Tropical hardwoods group	70	NA	*0.80
Western larch group	68	915	0.93
Western oak group	140	340	0.59
Western white pine group	NA	NA	*0.80
White / red / jack pine group	66	425	0.85
Woodland hardwoods group	158	NA	*0.80

vegetation type classification). If the measured structural indicator value of a given FIA plot exceeded the onset of mature structural characteristic threshold (i.e., M_{st} in Section 2.4.2) that plot was assigned the correlation weighted value previously derived. For each of the non-old growth FIA plots this process was completed for each subset of structural indicators, resulting in a final mature composite index value between 0 and 1. If a plot's composite index exceeded, or was equal to 0.5 it was classified as mature. Within the general FIGSS framework (Fig. 3), all the preceding analytical steps (Fig. 4) offer a variety of opportunities for subsequent improvement while being closely linked to the publicly available FIA inventory to enable transparency, repeatability, and verification. As a final component of executing an initial MOG inventory, the design-based population attribute estimation procedures (Bechtold and Patterson, 2005) were applied to the plots classified as mature, old growth, and non-MOG such that the extent and associated sampling errors could be determined. Using this approach, the proportion of MOG classifications was determined in terms of USFS areal extent by USFS firesheds as an initial examination of the spatial distribution of USFS MOG resources. Firesheds are spatial containers of landscape variation in wildfire risk connecting social and biophysical conditions at scales meaningful for management (Ager et al., 2021). Natural breaks classification was used to create three different classes of mature and old-growth forests into low, intermediate, and high groups of population totals (i.e., area estimates by fireshed) for portrayal in a bivariate choropleth map with break lines averaged for ease of display and non-forests masked using data from the classified National Land Cover Database (NLCD, 2021).

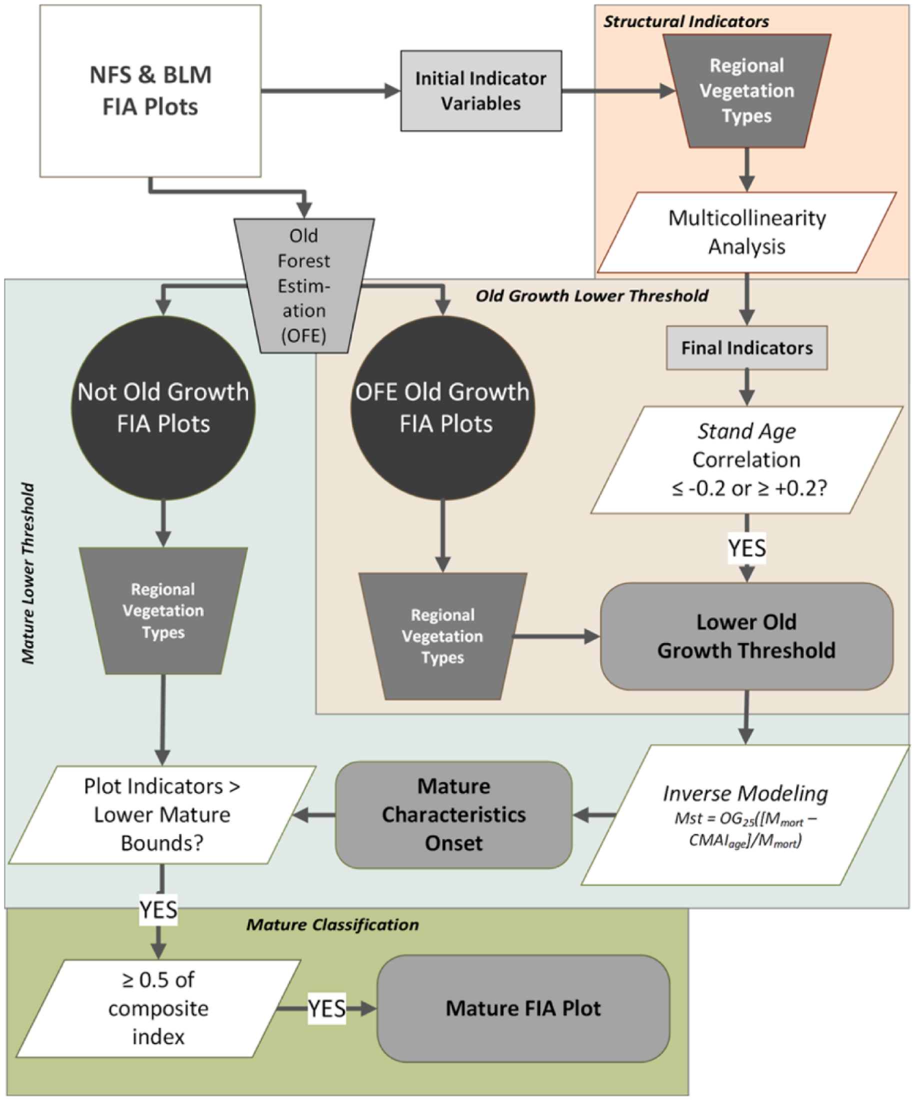

Fig. 4. Detailed schematic of FIGSS focusing on the workflow of FIA inventory data for estimating mature federal forest extent, US.

2.4. Identifying and evaluating FIGSS assumptions

Within the general FIGSS framework (Fig. 3), all the analytical components (Fig. 4) offer a variety of opportunities for subsequent improvement while being closely linked to the publicly available FIA inventory to enable transparency, repeatability, and verification.

Potential facets of FIGSS that could be considered initial assumptions at this stage of technique development include:

1. FIA plots identified as potential old-growth based on National Forest System definitions and old-growth surveys are an optimal “model development” dataset despite the inherent uncertainty and some inconsistency among US regions (see Pelz et al., same issue).
2. A variety of structural indicators (e.g., mean diameter of dominant trees) are correlated with stand age to identify a subset for use in inverse modeling mature attribute thresholds with the assumption that stand age is a reasonable independent variable for indicator selection using simple linear correlation and auto-correlation exercises.
3. The 25th percentile of selected old-growth structural indicators is the lower threshold of old-growth forest attributes.
4. The lower threshold of mature can be estimated using forest carbon accumulation (i.e., culmination of mean annual increment; Barnett et al., 2023) results in combination with basic assumptions regarding the maximum physiological age of common tree species recognizing the rarity of old-growth observations in eastern US forests (i.e., a censored observation).
5. The mature and old-growth stand development stages occur sequentially after a prior stand initiation/stem exclusion stage (i.e., young forest).
6. A correlation-weighted composite index is an appropriate method for compiling a variety of mature forest attributes into one metric with the initial requirement of at least a 0.5 index value correct for mature classification.

To demonstrate the important effects of these initial assumptions on mature classification outcomes for further discussion and evaluation, the effect of varying percentiles of old-growth structural attributes on resulting mature classification were conducted. In addition, the effect of various minimum correlation-weighted composite indices for determination of the onset of mature characteristics was evaluated. All analyses were conducted in R (R Core Team, 2020) using base-R (Supplementary Code S5).

2.5. Results

FIGSS classified over 32.6 million ha of USFS and BLM forest land as being mature (45% of all forested land) which when combined with old-growth estimates derived from the OFE classification process (13.4 million ha; Pelz et al., same issue) resulted in approximately 64% of all USFS and BLM forest land as being MOG (Table 3a). As a total percentage of all USFS and BLM lands, forest stands with an age at 80 years or above resulted in an estimate of 63% but with a higher estimate of old-growth area and a lower estimate of mature area compared to FIGSS. Because area in this study includes areas of Alaska not included in recent, similar studies, FIGSS results were also determined with the exclusion of Alaska (Table 3b).

In terms of the spatial distribution of USFS MOG forest resources, the vast preponderance of eastern USFS forests is mature or younger with only potential occurrence of old-growth remnants comingled with mature forests along the Appalachian Mountains of the south/central US (Fig. 5). Eastern USFS forests have a much more pronounced occurrence of mature conditions widely distributed across most individual National Forests. In contrast, the western USFS forests exhibit the full array of potential MOG forest combinations/extents. Forests are dominated by MOG conditions over much of the western US with potentially fewer observations of mature-only firesheds compared to the eastern US in an absolute sense. The next most common western forest condition was non-MOG forest attributes across much of relatively xeric and/or fire/disturbance driven landscapes of eastern MT, central/eastern WY, and southern CA/AZ/NM. Nationally, there were 2,194 USFS firesheds (approximately 101,170 ha in size) with > 0 ha of old growth or mature forest. Mature estimates ranged from 0 to 100,455 ha; old growth ranged from 0 to 101,691 ha. On average, firesheds contained 14,896 and 6,099 ha of mature and old-growth forest, respectively.

Related to the coarse spatial distribution of mature/old-growth across USFS/BLM forest lands, area estimates by forest type group and among National Forest/BLM regions indicate that pinyon/juniper across the western US accounted for the plurality of MOG forest followed by fire/spruce/mountain hemlock, Douglas-fir, ponderosa pine and lodgepole pine (Fig. 6). For eastern US regions (8 and 9), oak/hickory, loblolly/shortleaf pine, aspen/birch, and white/red/jack pine were notable. In terms of ratios of non-MOG, mature, and old-growth extent across NFS/BLM lands (Fig. 7), the largest proportions of old-growth were for hemlock/sitka spruce and redwoods. In contrast, some of the highest proportions of mature forest were for eastern forest types such as maple/beech/birch and oak forest types while redwoods and California mixed-conifer types were notable in the western US.

Table 3
Forest land estimates (ha) from published methods and USFS methods (A) including Alaska and (B) excluding Alaska. FIA estimates that there are 72,230,000 ha of forested land on NFS and BLM lands.

(A)	Mature	Old Growth	Mature & Old Growth	% NFS/BLM Forested Land
Stand Age 80 & 150	28,889,000	16,712,000	45,601,000	63%
USFS FIGSS	32,682,000	NA	46,063,000	64%
USFS OFE	NA	13,381,000		
Barnett et al., 2023	15,807,000	6,537,000	22,344,000	31%
DellaSala et al., 2022	21,449,000	NA	21,449,000	30%
(B)	**Mature**	**Old Growth**	**Mature & Old Growth**	**% NFS/BLM Forested Land**
Stand Age 80 & 150	28,043,000	14,383,000	42,426,000	62%
USFS FIGSS	32,015,000	NA	42,705,000	59%
USFS OFE	NA	10,690,000		
Barnett et al., 2023	15,807,000	6,537,000	22,344,000	33%
DellaSala et al., 2022	21,449,000	NA	21,449,000	32%

The distribution of fundamental stand attributes used as structural indicators (see Table 1, Fig. 4) among FIGSS classifications (non-MOG, mature, and old-growth) (Fig. 8) suggests appropriate classification with important points of note. Non-MOG forests appropriately had distributions visibly different from MOG forests in terms of standard deviation of stand height, diameter diversity score, and the abundance/basal area of dominant trees. In contrast, non-MOG and MOG forests had similar right-skewed distributions of standing dead tree basal area but with an increasing preponderance of higher values from non-MOG to mature to old growth.

To evaluate the sensitivity of the FIGSS classification approach (Fig. 3) that enables refinement and incorporation of emerging data/science, an initial sensitivity analysis was conducted regarding the percentile used to identify the lower threshold of old-growth (FIGSS value: 25th percentile; Table 4) and minimum correlation-weighted index for onset of maturity (FIGSS value: 0.5; Table 5). Estimates of mature forests, both in terms of total area and percentage of FIA old-growth observations classified as at least mature (i.e., logic check on classification constructs), were highly sensitive to the selection of the percentile (Table 4). A selection of the 5th percentile resulted in over 80% of USFS/BLM land being classified as MOG. In contrast, a selection of the 95th percentile resulted in just 27.1% of USFS/BLM forests as being MOG but with only 26.3% of old-growth observations being classified as MOG via FIGSS.

The sensitivity analysis of the minimum requirement (≥0.5) for the correlation-weighted composite index for classification of the onset of mature conditions also indicated FIGSS sensitivity to this classification component (Table 5). If only a minimum value of 0.05 is required, then approximately 83% of all USFS/BLM forest land is classified as MOG. In contrast, if a minimum value of 0.95 is required then almost 40% of all USFS/BLM forest land is classified as MOG with similar estimates of mature and old-growth extent. Additionally, potential MOG classification results across the spectrum of composite index values may identify areas where conservation might be explored in the context of vulnerabilities to disturbance versus other areas with lower composite scores might suggest actions to increase MOG attributes (e.g., D'Amato and Palik, 2021).

3. Discussion

FIGSS estimated MOG area is nearly twice that of recent, comparable analyses (DellaSala et al., 2022; Barnett et al., 2023) in terms of absolute, total estimates of MOG extent on USFS/BLM lands. This difference is perhaps strongly related to estimates of old-growth extent/attributes because FIGSS uses old-growth attributes to inform the estimation of mature forest resources derived from decades of field inventories on USFS lands (Pelz et al., same issue). Pelz et al.'s (same issue) estimates of coterminous old-growth are ~ 13 million ha which translates into an estimate of ~ 32 million ha of mature when using the initial FIGSS walkdown calculations and composite indicator threshold. Consequently, the FIGSS ratio of mature to old-growth extent is 2.4. Barnett et al.'s (2023) estimates of mature have the same mature to old-growth ratio (e.g., 2.4) even though their analytical approach is forest ecosystem function-based (culmination of mean annual increment; Barnett et al., 2023) which is similar to recent carbon accumulation analyses conducted for a subset of National Forests (Birdsey et al., 2023) but maybe obfuscated in multi-cohort stands (e.g., Morgan et al., 2002). Such a difference in absolute MOG resource estimates is not surprising because all three classification approaches were chosen for different goals and used varying input data and associated assumptions. For example, Barnett et al. (2023) used biomass accumulation patterns and DellaSalla et al. (2022) used FIA data to calibrate remote-sensing derived data. Perhaps one important additional consideration in FIGSS is more inclusive assessments of forest conditions such as low-productivity systems expected of xeric sites (e.g., pinyon-juniper) or

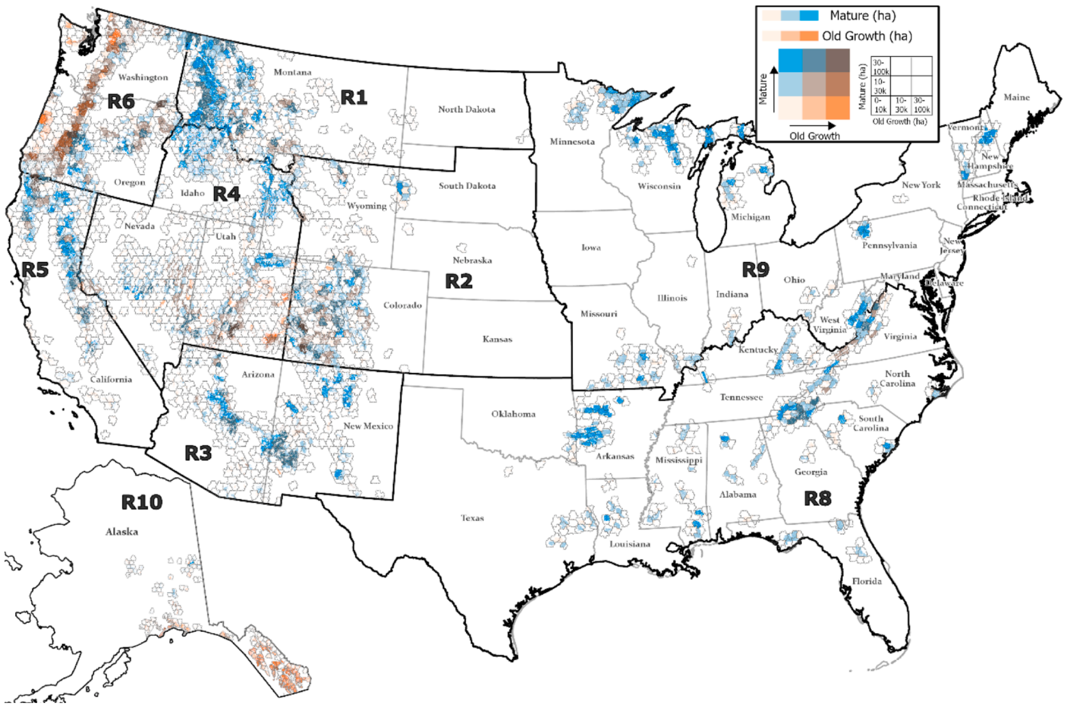

Fig. 5. Bivariate map of mature and old-growth proportion of area (low, medium, high) by fireshed for USFS/BLM forested land area, coterminous and coastal AK, US.

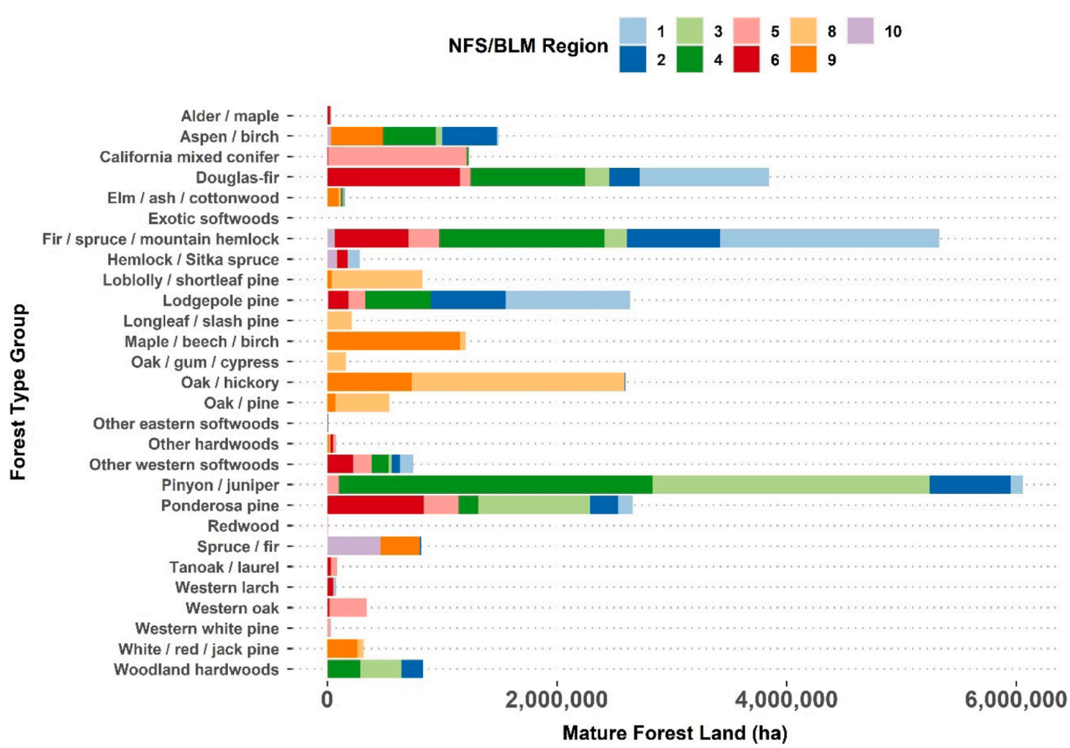

Fig. 6. Estimates of mature area by forest type group and National Forest System and BLM regions, US.

boreal systems (Kneeshaw et al., 2018). These forest ecosystems may be additional to Barnett et al. (2023) and DellaSalla et al. (2022) hence FIGSS produces larger MOG area estimates. Unlike many scientific pursuits, objective/unbiased estimates of MOG forests are not possible if one considers that related definitions are partially a social construct that may vary across communities. Considering this paradigm, FIGSS attempts to provide a system to tether decades of old-growth surveys, studies, and public dialogues including forest management plan development across USFS forests to the statistical framework of the FIA inventory program. As a result, regardless of any considered structural/development phase-based approach to MOG quantification, an unbiased estimate of the associated forest population attributes is possible (e.g., design-based estimators: Bechtold and Patterson, 2005; Barnett et al., 2023).

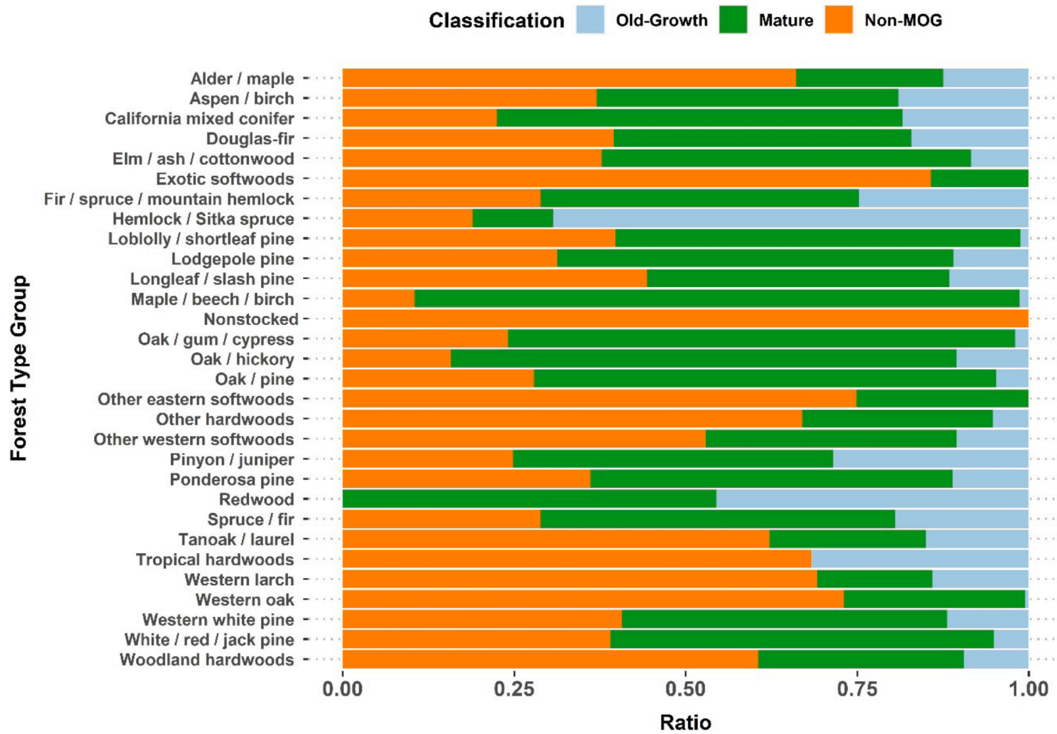

Fig. 7. Estimates of the ratios of non-MOG, mature, and old-growth extent of total forest area by forest type group for National Forest and BLM lands, US.

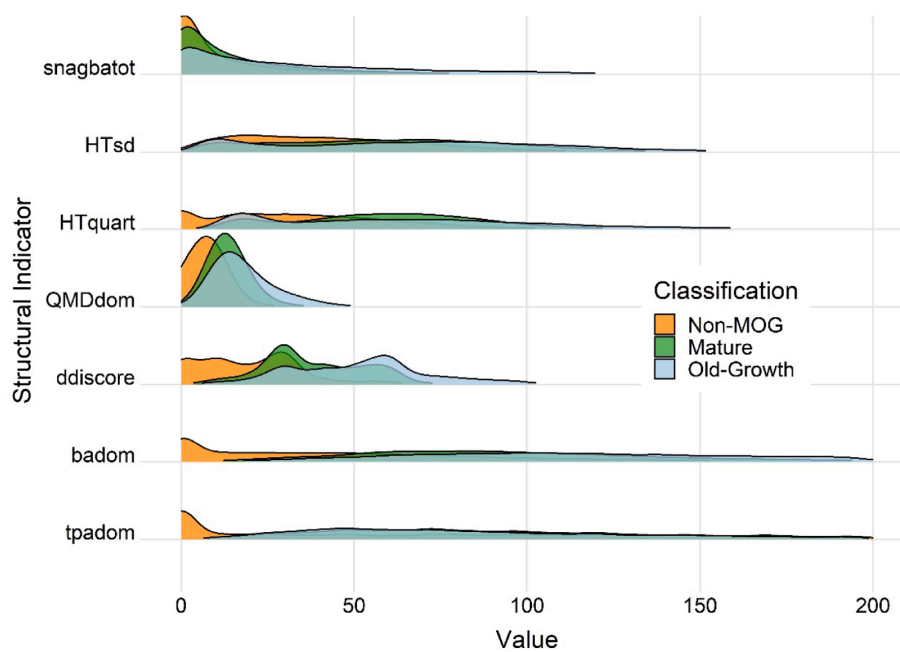

Fig. 8. Density distributions (value = standardized probability density function) of fundamental stand structural attributes used in mature classification among the final classifications of non-MOG, mature, and old growth in federal forests, US. Please refer to Table 1 for descriptions of structural attributes.

Numerous facets of FIGSS are designed to be intentionally sensitive to quantification approaches to empower future refinement such as where or when does the mature forest development progress into an old-growth phase (i.e., the 25th percentile of structural attributes is used as an initial value in FIGSS), how many mature structural attributes must a forest stand possess to reach an "onset of maturity" phase (i.e., >= 50% of the correlation composite index in this study), using structural indicators to define stages, structural indicator selection techniques, and the inverse-modeling paradigm for walking back old-growth indicators to onset of maturity (Fig. 9). To demonstrate the depth of research gaps associated with a few key FIGSS assumptions, we can first start with stand development classification itself. A major component of most stand development classification approaches, which is inferred to be a central part of EO14072 because the terms "mature" and "old growth" are explicitly stated, is the sequential development of a forest from a post-disturbance initiation (e.g., Oliver and Larson, 1996) towards an idealized, steady-state condition represented by advanced tree/stand ages. However, contemporary applied ecology offers more complex

Table 4
Sensitivity analysis results indicating how the percentile of old growth indicator values used in mature forest walkdown calculations affects total estimates of mature federal forests in FIGSS. FIA estimates that there are 72,230,000 ha of forested land on NFS and BLM lands.

	Mature (ha)	Old Growth (ha)	Mature & Old Growth (ha)	% NFS/BLM Forested Land	Old Growth Plots Classified as Mature+
Old Growth 5th Percentile	44,790,000	13,381,000	58,171,000	80.5%	98.7%
Old Growth 25th Percentile	32,682,000	13,381,000	46,063,000	63.8%	92.6%
Old Growth 50th Percentile	22,133,000	13,381,000	35,514,000	49.2%	79.9%
Old Growth 75th Percentile	13,219,000	13,381,000	26,600,000	36.8%	59.7%
Old Growth 95th Percentile	6,194,000	13,381,000	19,575,000	27.1%	26.3%

Table 5
Sensitivity analysis results showing how adjusting the correlation-weighted composite index threshold needed for a FIA plot to be classified as mature in FIGSS (i.e., Old Growth 25th percentile in Table 4). FIA estimates that there are 72,230,000 ha of forests on NFS and BLM lands.

	Mature (ha)	Old Growth (ha)	Mature & Old Growth (ha)	% NFS/BLM Forested Land
Mature Composite Index >= 0.05	46,816,000	13,381,000	60,197,000	83.3%
Mature Composite Index >= 0.25	41,942,000	13,381,000	55,323,000	76.6%
Mature Composite Index >= 0.50	32,682,000	13,381,000	46,063,000	63.8%
Mature Composite Index >= 0.75	20,957,000	13,381,000	34,338,000	47.5%
Mature Composite Index >= 0.95	15,007,000	13,381,000	28,388,000	39.3%

concepts where a variety of endogenous and exogenous factors (e.g., disturbances, land-use change legacies, species functional traits, and/or self-thinning) interact across space and time resulting in complex systems (Franklin et al., 2020; Palik et al., 2020) that may defy discrete classification of one forest inventory plot but is reflected at landscape scales as a complex, shifting mosaic of forest ecosystem attributes/processes. We acknowledge that a model assuming a few discrete stages of forest development oversimplifies a complex and continuous process that is dynamic across space/time (see Gray et al., same issue) and may not apply consistently across all regions and ecosystem combinations occurring across the diverse landscapes of USFS/BLM lands (e.g., frequent-fire landscapes; Binkley et al., 2007). Furthermore, considering the drivers of global change and associated tree mortality (Yi et al., 2022) inclusive of climate change, insects/disease, urbanization/fragmentation, and/or economies/trade (e.g., beech bark disease in northeastern forest, Ducey et al., 2013) indicates that any contemporary forest stand development classification approach may need to be adaptable to novel climates and future conditions including social components (Frelich and Reich, 2003; Wirth et al., 2009) that could give rise to concomitant novel forest ecosystems within larger, evolving social/geopolitical contexts. Our experience developing FIGSS suggests that past data and research results (i.e., USFS old-growth surveys and studies) can serve to initially parameterize a classification approach but the approach itself should be able to ingest emerging data while being adaptable to environmental and social change. In this context, a number of FIGSS components have been intentionally designed to be sensitive to initial starting values (e.g., percentile of old-growth structural attributes). Key concepts involving disturbances and legacy creation (e.g., standing dead trees and/or residual live trees; Palik et al., 2020) which can increase the array of microclimates (De Frenne et al., 2013; Betts et al., 2018) against a backdrop of a shifting landscape mosaic of stand conditions (Frelich and Reich, 2003) suggest that the thresholds between discrete forest stages of development is uncertain across space and time (i.e., large standing dead tree in a post-disturbance initiating cohort of young trees). The pre-forest and/or stand initiation disturbances might not even be considered a discrete stage rather a stand/landscape process (Franklin et al., 2020) that is ubiquitous in natural systems across all stages that alters developmental trajectories with opportunities to confer resilience in complex systems (D'Amato and Palik, 2021) especially in the context of global change (e.g., Anderegg et al., 2022; Allen et al., 2015). The archetypes of cathedral-like old-growth west coast forests of the US (e.g., Spies and Franklin, 1988; Lutz et al., 2018) might need to have the same MOG classification probability as site-limited archetypes such as high-latitude boreal and/or moisture-limited western US coniferous forests (Morgan et al., 2002; Wirth et al., 2009; Binkley et al., 2007; Kneeshaw et al., 2018). An aspect of MOG-classification inclusivity across the diverse forest ecosystems of the US is not only incorporating uneven-aged and/or gap-phase dynamics but also including concepts of ecological legacies that transcend discrete classifications (i.e., standing dead trees).

Another challenge for forest development classification is the spatial scale (Wiens, 1989; Schneider, 2001) and specificity of forest data itself. FIA data can be seen as a sample of current forest conditions in proportion to their abundance. For region-vegetation types where few field plots exist in older stages of stand development due to land use history, relationships built on correlation to stand age may be strengthened by adding additional data representing these rare elements. While the FIA dataset may not include the full range of potential old growth conditions in these vegetation types, old growth definitions did define old forest in them, and mature definitions are based on the sample as it currently exists. FIGSS, like the old growth definitions (Pelz et al., same issue), relies on the only available, nation-wide sample of forest conditions (FIA). The FIA sample measures forest conditions in a 0.07-ha plot. Scientists recognize that a larger spatial extent would capture with higher accuracy rare elements such as those present in mature and old-growth forest which is already a standard sampling approach for FIA plots in CA, WA, and OR (Davis et al., 2022). The complex forest characteristics that demonstrate mature and old-growth forest conditions are not expected to manifest on such a small area of ground. Consequently, structural indicator selection for FIGSS represents a careful balance among multiple indicators and spatial scaling limitations in ecology (Schneider, 2001). Hence, FIGSS may be revealing more about the current state of forest resource monitoring information and MOG science/assessments than answering western-science framed questions (i.e., how is old-growth defined in context of accelerating global change?) that may be better addressed by social constructs (traditional ecological knowledge; Kimmerer, 2000).

Perhaps one of the most nebulous but critical components of any forest stand classification system is incorporation of a variety of forest process/attribute constructs. FIGSS is an attempt to link an unbiased forest resource inventory and estimation system to an adaptable classification system that connects forest attributes of interest to society such that objective resource information can be produced for social consideration within an open-source development paradigm (See

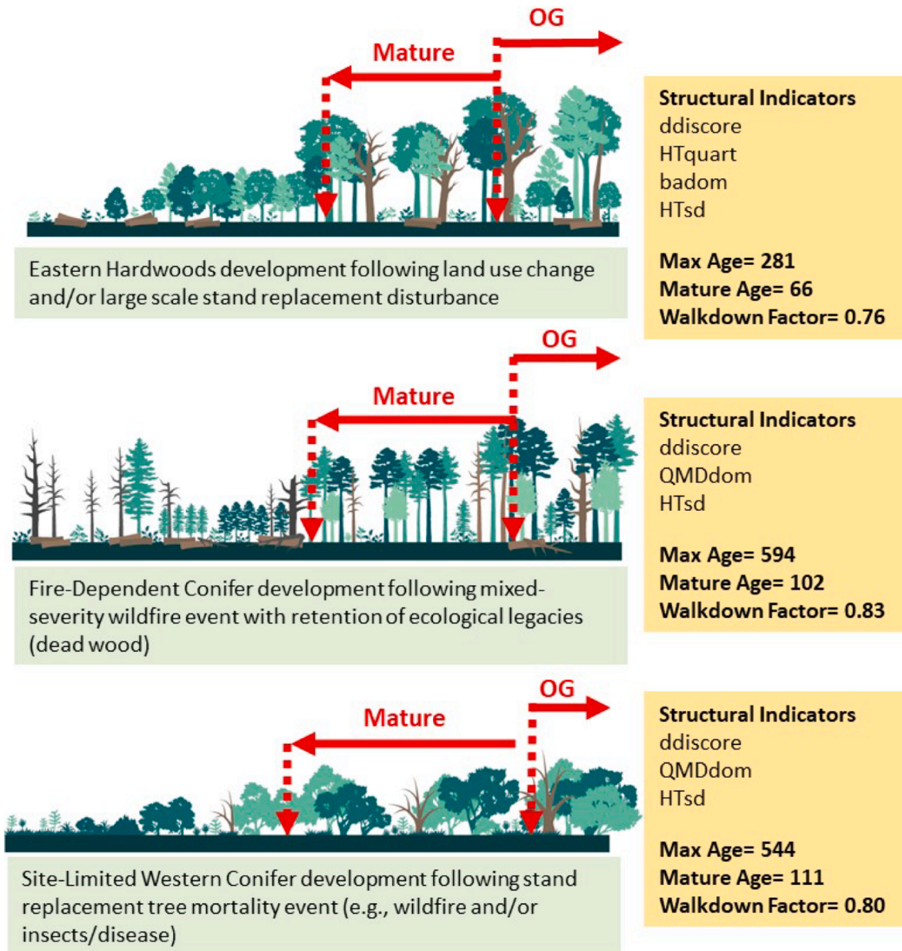

Fig. 9. Examples of applying components of FIGSS (structural indicator weights and thresholds plus walkdown factors) to classification of stages of stand development for a variety of ecosystem archetypes. Please refer to Supplementary Tables S3 and S4 for specific values for each region-vegetation type.

Supplementary Code S5). At the outset, structural indicators are used to identify forest inventory plot observations as old growth leading towards production of mature forest population estimates. Wirth et al. (2009) found that the most common criteria across several old-growth studies were structural in nature. From an ecological perspective, FIGSS is currently centered on the development of structural characteristics of standing live trees with some aspects of carbon accumulation (Barnett et al., 2023), physiological tree age (Loehle, 1988), site/vegetation type, and dead wood resources (Morgan et al., 2002; Woodall et al., 2021) influencing classification. A variety of additional ecological perspectives could be brought to bear because a focus on live tree development is just one perspective: stages of development could be focused on other ecosystem attributes such as carbon sequestration, water provisioning, wildlife habitat (Betts et al., 2018), or carbon emission risks (Birdsey et al., 2023). From a social perspective, often our cultural/personal relationships to the natural environment can influence our perception as to what we see when we view any forest condition (Frelich and Reich, 2003; Moore and Nelson, 2023). The current FIGSS classification follows a western science centric paradigm where MOG forests may be assumed to be places where no humans exist (e.g., Table 5.1 in Palik et al., 2020) whereas supplementary paradigms associated with decolonization might be brought to bear where humans are intrinsically part of earth's ecosystems (Kimmerer, 2000). As postulated by Moore and Nelson (2023), how would a mature forest define itself? As a means to move beyond the initial configurations of FIGSS, future versions might consider replacing the stages of development with other classifications across alternate spectrums of ecosystem response such as adaptive silviculture to climate change (D'Amato and Palik, 2021; Millar et al., 2007; e.g., resistance to transition), carbon risk profiles (avoided catastrophic emissions to carbon additionality), or social integration via co-production opportunities presented by Traditional Ecological Knowledge (TEK) (e.g., Two-Eyed Seeing frameworks, Reid et al., 2021). In particular, TEK fundamentally acknowledges that our human cultures/ecosystems are inherently entwined with our natural ecosystems whereby we collectively change together with indigenous communities possessing a millennium of knowledge that can empower adaptation and resilience (Kimmerer, 2000; Reid et al., 2021). Whereas western science dominated classification approaches may inadvertently separate individuals/communities from the natural ecosystems (Burow et al., 2018) in which they reside and who possess the knowledge and proximity to affect local resilience in response to global change, TEK may offer opportunities to restore natural ecosystem function inclusive of human culture/activity (Kimmerer, 2000) as opposed to excluding it.

Finally, FIGSS is proposed as a system for society to explore how forest resources (e.g., forest area) may be sorted into discrete classes to empower decisions regarding their future with opportunities to be dynamically refined with additional data/science. FIGSS provides a framework to start conversations with stakeholders regarding forest development processes and indicators (structural or otherwise) that help to define them. As such, conversations and coproduction of science are anticipated to help improve the classification over time which is a tenet suggested by Frelich and Reich (2003). We suggest it could be useful research to explore the refinement of the following components of FIGSS: 1) exploration of the impact of spatial scale of monitoring (i.e., FIA plot extent) on classification, 2) benefits of expanded old-growth field surveys on development of structural indicators, 3) machine learning approaches for selection of structural indicators (e.g., Liaw and Wiener, 2002), 4) refinement of the composite index in terms of identifying the onset of maturity, 5) incorporation of emerging ancillary information such as LiDAR or SAR, and 6) adoption of paradigms of forest classification that can be seen as complimentary to those of western science such as TEK. Although FIGSS or any other MOG assessment approaches would benefit from continued/expanded forest inventories and advances in remote-sensing (e.g., GEDI; Dubayah et al., 2022), it is increased social co-production with such forest classification initiatives that may yield the most effect in terms of technical refinement and forest resource impacts. For example, citizen science initiatives to identify rare older forests or to continue development of old tree lists (e.g., Pederson, 2023) may help refine FIGSS approaches such as the determination of walkdown procedures and identification of older forest attributes beyond the most studied archetypes (e.g., Fig. 9).

4. Conclusions

Recognizing the lack of scientific consensus regarding the definition of a mature forest across the diverse federal forests of the US and multitude of stakeholder perspectives, this study proposes a mature classification system inclusive of old-growth forests that is adaptable to future data, science, and public/stakeholder co-production. This study's FIGSS system relies on decades of old-growth assessments across USFS lands to identify key structural indicators of old-growth in FIA, the U.S. official forest inventory, that may be used to estimate preceding thresholds of mature forest attributes. Using this general approach with numerous initial assumptions, approximately 45 percent of USFS and BLM forest lands were initially estimated as potentially being mature. As this estimate cannot be easily verified against any truth, numerous opportunities are highlighted for future refinement including expanded old-growth surveys/studies, evaluation of the multi-stage stand development paradigms and TEK when classifying complex forest ecosystems into discrete classes, refining the inverse modeling of the onset of mature forest structural thresholds, and the selection of structural indicators via refined techniques such as machine learning. Perhaps the most important FIGSS developmental paradigm is transparency via open-source code using publicly available data. Given the social aspects of mature forest classification, one of the most vital next steps might include you the reader who can participate in future refinements to forest classification that perhaps can be based on science, contemporary data streams, and inclusive of social constructs/economies/communities as we collectively seek to understand the truth about the future of our forests against a backdrop of continuous global change.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foreco.2023.121361.

FIA data that are used in conjunction with this supplementary data are available via the publicly available FIA database (FIADB) https://apps.fs.usda.gov/fia/datamart/datamart.html. The associated R code used in FIGSS as a text file is included in the supplementary material (Supplementary Code S5) while the associated data file (i.e., distillations of FIADB queries) are posted at Figshare https://figshare.com/articles/dataset/FIGSS_Input_Data/23864268.

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