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Geospatial Estimation of Forest Relative Density for Carbon Stewardship Decision Support across the Continental US

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The US Forest Services (USFS) under the Forest Inventory and Analysis (FIA) program estimates resource characteristics and statistics regarding forest attributes and ecosystem processes at various strategic scales with different levels of precision and refinement. A vital forest resource attribute is tree size-density, which informs regional and national policies and project-scale management. To enhance the development and distribution of key forest tree-size density metrics, a 30 × 30 m wall to wall spatial dataset for stand density index (SDI), maximum SDI (SDI_{MAX}) and relative density (RD), was developed using 54,925 FIA plots to produce estimates for ≈2,668,162,817 forested pixels across the continental US (CONUS) using a previously developed TREEMAP2016 raster. Summaries of SDI, SDI_{MAX}, and RD revealed key differences between FIA plot-based and TREEMAP raster estimates, attributed to spatial resolution, methodological assumptions, and spatio-temporal misalignments. The nationally consistent medium-resolution forest size-density raster and underlying data provide important and unique opportunities for quantification of tree competition levels, ecosystem vulnerability, carbon sequestration opportunities, and stand dynamics at different spatio-temporal scales.

Background & Summary

Numerous stand size-density metrics exist to guide forest monitoring, management, and modeling[1]. One of the most robust and comprehensive metrics is relative density (RD)[1,2], which is defined as the proportion of absolute number of trees per unit area compared to an empirically derived maximum size-density relationship (MSDR) estimate[3–8]. RD is specifically based on the stand's current stand density index (SDI) and its maximum SDI (SDI_{MAX}; $RD = SDI/SDI_{MAX}$). Due to its generality, robustness, and high interpretability, the predictions and quantification of RD imply that there is strong potential in anticipating current or future competition, growth and mortality, which can be useful for guiding forest management decisions[9–11]. RD objectively quantifies a forest's current size-density when compared against a maximum value with key biological objectivity from broad ecological and policy perspectives depending on spatial scale being evaluated, ranging from local to regional or even national-levels[10]. Therefore, the expression of RD is relevant for determining stand development stages, dynamic processes, and potential disturbance susceptibility at strategic spatial and temporal scales[3–8,11–13]. RD can be used for various management objectives such as fiber production and net carbon sequestration. RD can quantify key stand development processes that drive gross tree carbon accretion and depletion like canopy closure and mortality, disturbance re-growth, and the overall degree of tree-to-tree competition. These processes can significantly influence the future development of forest ecosystems and associated carbon pools. Density-dependent mortality from self-thinning plays a crucial role in the formation of snags and down woody material (DWM) which transfers carbon from the live to the dead pool. Therefore, metrics that assess size-density relationships, like SDI and RD, have the potential to contribute to a broader understanding of carbon dynamics, particularly DWM. In addition, scientists and policy makers dealing with carbon accounting

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programs may need to be informed by the best available science to address potential shortcomings of using potentially subjective ecological baselines such as minimum carbon stocks[14]. Data availability and analysis are important to recalibrate the current ecological thresholds for carbon offset project baselines, development stages of forests, biological potential for sequestration and emission and potential risk from climate change induced natural disturbances[11]. For example, the use of RD to optimize carbon sequestration in the context of adaptive silviculture has been suggested[1,11], because of the ability to better account for and minimize density-dependent mortality[15]. In order to meet the different applications of RD, a nationally consistent and spatially explicit yet a robust dataset of key size-density metrics is needed.

Globally, national forest inventories and monitoring databases assess key attributes and variables over large land areas[16]. The Forest Inventory and Analysis (FIA) program under the United States Department of Agriculture (USDA) Forest Service conducts national inventories. FIA determines the condition, extent, trends and status of forest resources across different land ownership classes in the United States (US)[17–19]. FIA inventories are annually sampled at a national base sample intensity of 1 plot per ~ 2,428 forested hectares with a specific remeasurement cycle of 5–10 years depending on states. This may limit the planning and management of forest resources based solely on FIA data when considering stand-level management needs in the context of error propagation[20]. To provide for key technological challenges of providing spatially contiguous estimates, there has been the development and application of varying statistical approaches that relate FIA plot data and environmental variables to cover forest areas not directly inventoried[21]. The availability of medium-resolution remotely sensed data from Landscape Fire and Resource Management Planning Tools (LANDFIRE) presents an opportunity for improved regular monitoring of size-density metrics when fused with conventional forest inventory datasets such as FIA. In particular, spatially-explicit imputation allows a few highly detailed observations to be assigned to unmeasured locations, which provides high-resolution and spatially contiguous information[21]. For example, Riley, Grenfell, Shaw, and Finney[20] modified a random forest approach together with LANDFIRE variables to impute FIA plot data to a 30 m gridded dataset TREEMAP2016 (hereafter referred to as "TREEMAP"). Similar methodology was used to develop subsequent generations of TREEMAP2020[22] and TREEMAP2022[23].TREEMAP provides the opportunity for the quantification and validation of ground-based size-density dynamics at spatial resolutions not achievable when using traditional methodologies alone[1]. The availability of gridded vegetation raster maps such as LANDFIRE and TREEMAP[20] provides a unique opportunity to produce landscape-level metrics of key forest attributes that drive forest planning and management (e.g. carbon, density, diversity, stand structure). Specifically, TREEMAP allows data collected from FIA plots to be presented at 30 m × 30 m pixel resolution. In this data description, we have linked SDI, SDI_{MAX} and RD attributes derived from FIA plot-level records to the publicly available TREEMAP raster attribute table to produce medium-resolution, wall to wall, and spatially contiguous maps for CONUS.

Importance of RD in policy/management decision making across spatial scales. Recently, there has been increased interests in the national scale quantification of size-density metrics like SDI and RD across CONUS[9,10] in the context of large-scale forest planning and management, potential fuel loading[24–26], and carbon stock analyses[11,27,28]. In particular, an estimation of the RD at the national scale allows for the prediction of future carbon stocks based on the identification of loss, gain or stagnation in forest growth[9] as well as disentangling the gross components of net forest carbon change[29].

Forest data produced by FIA is used by different partners for information, planning, and management purposes, especially in the context of biomass and carbon estimation, fire monitoring, and habitat utilization[20,30]. However, FIA data may be limited for certain infrequent forest types, species groups and ecoregions. This limits the general availability of high resolution size-density spatial products like RD, which would assist and allow for analyses at smaller scales not covered not adequately covered by -base national inventory sample intensity[20]. The potential of developing and refining size-density spatial products based on the available TREEMAP data is an interesting and potentially valuable leveraging of datasets, which could allow for the production of wall-to-wall coverage of size-density metrics like RD in space and time, while also supporting state- to national-level efforts for biomass/carbon estimation, fuel treatment, revision of forest plans and large-scale forest dynamics[20].

Size-density metrics like RD can be used for projecting future competition and stand dynamics, which is a key input into management decisions with some limited subjectivity in biological and management interpretations of the metrics[10]. Forest management treatments are premised on quantifying the observed stand density when compared to either an optimal, desired, or maximum density[7] for input into strategic-scale inventory assessments. At a stand-level, RD is used to inform silvicultural operations like pre-commercial or commercial thinning to improve growth and quality of trees. RD can also be used to assess the risk to potential disturbances like fire, drought or insect outbreak as high RD forest stands can have increased vulnerability and reduced resilience[2,3,11,29–32]. At a national-level, RD can be used to inform large-scale forest management and planning decisions in the view of climate change to restore ecological integrity and resiliency of forest landscapes. In short, RD is a useful metric that could be used during policy and management action development to increase resilience of forests at broad scales. Increased resilience can be done to maximize productivity and/or minimize the effects of disturbances, which will ultimately help forests to achieve multiple ecosystem services and persist during climate change.

Knowledge of the RD in a stand can be critical to guiding and optimizing management decisions, which has led to the development of decision-making tools such as size-density management charts (SDMCs)[2]. Incorporation of RD in SDMCs, allows visualization and anticipation of stand development through stages of competition in space and time[2]. Often SDMCs rely on regional size-density values, which may limit applicability in certain locations and applications. The use of more local size-density metrics could help refine and increase applicability of SDMCs, which could broaden their use beyond traditional forest management applications[33,34].

At a national-level, RD estimates may provide a useful baseline for assessing the potential long-term impacts of alternative disturbances or management regimes across contrasting forest types at meaningful spatial scales relevant for refining the understanding of current and future forest dynamics[9]. Stand-level data on size-density estimation is relevant for determining the biological capacity of a given species when determining site-specific management decision, whereas large scale data is generally needed for evaluating the underlying variability of density for certain management purposes[35]. At a national level, a robust and spatially-contiguous estimation of RD is useful for the development of policy-oriented frameworks for activities such as reforestation, optimizing density management for a variety of forest carbon management objectives. The carbon management activities may include avoided future catastrophic emissions and mitigation activities in service to a greater goal of enhanced forest carbon stewardship[10].

This article introduces 30 m resolution, spatially contiguous, and nationally consistent size-density metrics for CONUS. The article further presents the developed datasets and associated methods, evaluating key relationships across methods. Further the article summarizes the primary attributes across various metrics and spatial scales. In particular, two primary methods of estimating size-density metrics are evaluated across selected forest types, counties, and states across CONUS.

Methods

FIA Inventory data. Data used in the study was taken from the publicly available database of the Forest Inventory Analysis (FIA) program under the United States Department of Agriculture (USDA) Forest Service[36]. From around 2000, FIA conducted annual forest inventories in the US of forestland. Forestland is defined as an area with live trees occupying about 10% canopy cover or having capabilities of supporting 10% cover if having undergone harvesting or disturbances and having an area of ~0.4 ha and width of ~36.6 m[37]. The National Forest Inventory (NFI) design establishes a single plot in every 24 km^2 of forest[38]. Fixed area plots are nested within a cluster with large subplots with a radius of 17.95 m in which all trees 12.7 cm in diameter at breast height (dbh) and greater are measured. The small plots have a radius of 2.07 m and all trees >2.54 cm dbh are measured. A single inventory plot has a cluster of four subplots, specifically there is a central subplot and the other three subplots have an orientation of 0, 120, and 240° from the central subplot[37]. The subplots are 36.58 m away from the central subplot where live trees and snags are counted. In each plot, variables such as tree height, species, tree form, dbh, forest type, forest type group, stand age, ownership, slope, elevation, and aspect are recorded. For this particular analysis, SDI, were estimated at the subplot-level to provide multiple independent estimates for a given plot to ensure proper estimation of the plot-level random effects[10].

Estimating SDI_{MAX} and RD. FIA data is highly hierarchical and nested in structure, which poses a challenge in determining SDI_{MAX} estimates at various scales like the subplot-, plot-, county- and-/ or state-levels. In order to address and effectively leverage the nested nature of the data, a number of statistical methods have been used to estimate SDI_{MAX} across national levels[1]. Prior analyses have primarily used linear quantile mixed model (lqmm)[13] in the calculation of Reineke (1933)[39] relationship based on the number of trees per unit area and a given reference size metric like quadratic mean diameter (QMD):

$$ln(TPH) = (b_{10} + \upsilon_i) + (b_{11} + \gamma_i) * ln(QMD) + \varepsilon_i \quad (1)$$

where TPH is the number of trees per hectare (# ha^{-1}), QMD is the quadratic mean diameter (cm), b_i are the fixed effects parameters, ε_i is the residual for the *i*th plot and υ_i and γ_i are random effects for the *i*th plot. For this analysis, Bayesian hierarchical quantile regression methods were used to achieve more robust estimates and determine plot-level uncertainty in the derived values (Fig. 1). To do this, the Bayesian Multilevel Models using Stan (BRMS) package[40] in R v4.2.3 was used. A unique identifier for each FIA subplot was created and used as a hierarchical effect on both the slope and intercept. BRMS default values for the number of chains (4) and iterations (2,000) were used. Consistent with Woodall and Weiskittel (2021), a 95% quantile was specified, while normal priors based on their model fits were used. Based on the derived coefficients in Eq. (1), plot-level estimates of SDI_{MAX} were estimated from the FIA subplot data similar to Woodall and Weiskittel[10]. The SDI_{MAX} for each plot was estimated using a standard reference diameter (25.4 cm) in the following equation:

$$SDI_{MAX} = exp((b_{10} + \upsilon_i) + (b_{11} + \gamma_i) * ln(25.4)) \quad (2)$$

where all attributes are previously defined. RD is the proportion of absolute stem density in a stand relative to the maximum theoretical stem density achievable in a stand based on the maximum size-density relationship[3–8]. Plot-level estimates of RD were determined using estimates from both Eqs. (1, 2) as follows:

$$RD = \frac{SDI}{SDI_{MAX}} \quad (3)$$

Currently, generally accepted RD threshold values for critical stand developmental stages are available, namely crown closure and initiation of mortality (RD = 0.15–0.30), optimum growth (RD = 0.30–55), and zone of imminent mortality (RD = 0.55–1.0).

TREEMAP. The development of TREEMAP has been extensively described by the authors of TREEMAP[20,21,30,41], therefore, we will briefly describe it here. TREEMAP is a tree level model for forests in the US which is a product of two datasets from FIA and gridded data from LANDFIRE database[20]. TREEMAP uses machine learning algorithm such as random forest (RF) in the *yimpute* package in R software to impute plot data measured by FIA to landscape level gridded maps (disturbance, vegetation and biophysical parameters) in the

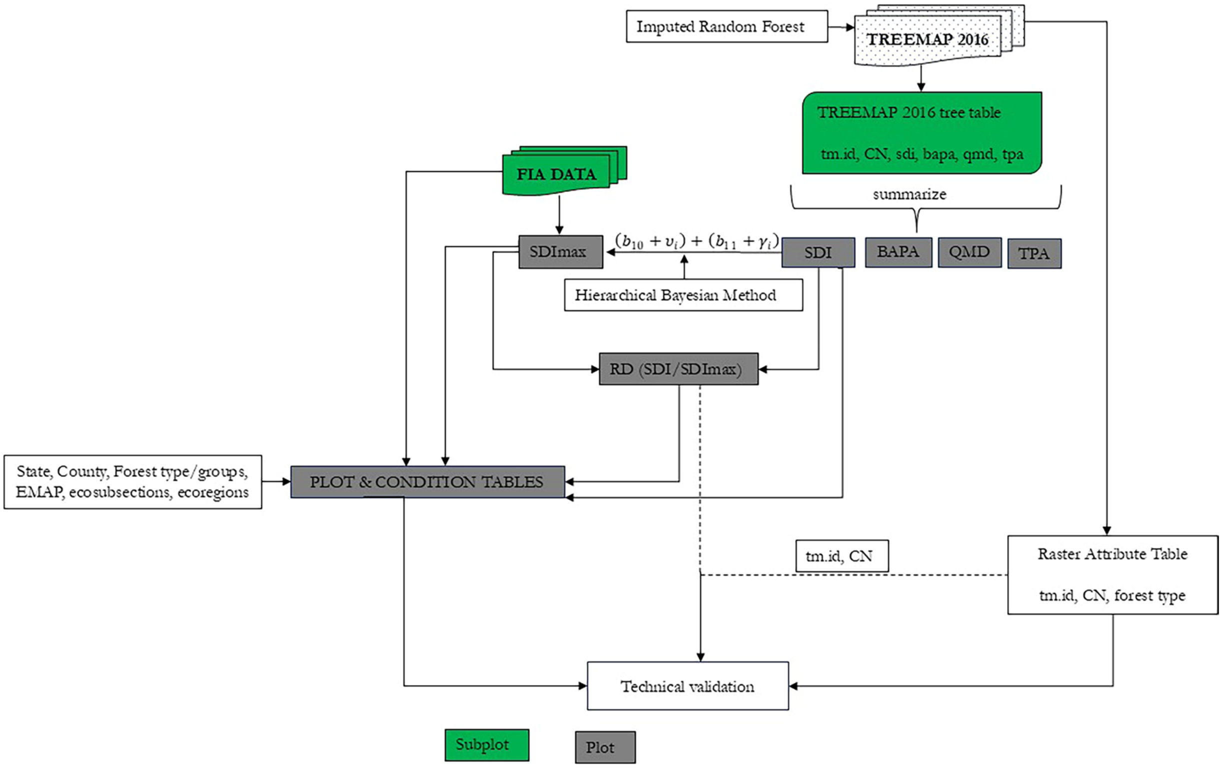

Fig. 1 The workflow used in this study. Plot and subplot represent the different scales of FIA data measurement. CN: sequence number; BAPA: Basal area per acre; QMD: quadratic mean diameter; TPA: trees per acre (see R code for the conversion from imperial to metric units).

LANDFIRE database[30]. Imputation is an estimation method where non-sampled measurements from the target dataset are replaced with observations with similar characteristics from the reference dataset[42]. In the context of TREEMAP, imputation was used to assign FIA plots (reference) to the target data (LANDFIRE database)[30]. A set of filters were applied to the reference data from FIA: measurements should come from single condition and accessible plots. The target data was from a LANDFIRE for a 2016 project and data included attributes predictor variables such as topography, latitude and longitude, vegetation, disturbance and biophysical characteristics which are needed to be available both in the reference and target dataset. Resultantly, the measured forest attributes available in raster format at a medium resolution of 30 × 30 m. Each forested FIA plot is assigned to the most similar forested pixels in the LANDFIRE database thereby producing a medium resolution data for forest characteristics[20]. The TREEMAP raster has an attribute table which allow for linkages between FIA data allowing users to make summarize of the variables and produce maps in a Geographic Information System (GIS)[20]. In this study we leveraged on the characteristics of the TREEMAP raster to link, summarize and produce maps of SDI, SDI_{MAX} and RD across CONUS.

The TREEMAP dataset has FIA tree level attributes measured at subplot level. In order to keep the observed variability and to produce robust estimates, tree level estimates of SDI were determined using the additive summation method and aggregated to plot level following[10] (Fig. 1). Plot-specific SDI_{MAX} estimates were derived using hierarchical Bayesian quantile modelling similar to the methods used by Woodall and Weiskittel[10] with RD derived from SDI and SDI_{MAX}. We leveraged on the common fields (TREEMAP record number (tm.id)), to join the TREEMAP raster and the FIA data. The joining of the two datasets allowed us to make summaries and comparisons between size-density estimates across forest types, Environmental Monitoring and Assessment Program (EMAP) hexagons, counties, and states (Fig. 1). Due to mismatch between the FIA and TREEMAP tm.id and RD > 1, (684 NULL observations were deleted), resulting in a total of 54,925 observations being used. In this study, SDI, SDI_{MAX} and RD were mapped at 30 × 30 m spatial resolution. We compared summaries of TREEMAP and FIA based size-density estimates across forest types, counties, state, and US EMAP 64.8 km^2 hexagons in CONUS. Several filters were applied to maintain national consistency and robustness, for example dealing with potential influential values, such as where RD exceeded 1 as this is not biologically feasible. In cases where FIA based estimates of RD exceeded 1, it was reset to 1 and this accounted for approximately 1,305 observations or 2.4% of the data. Preliminary analysis showed that this greatly skewed the overall distribution of RD and these observations were removed from subsequent analysis as most of the observations were located in uncommon forest types and/or ecoregions, which likely led to the initial imprecise estimate for the size-density metrics. For TREEMAP, 684 observations or approximately 1.2% of the data were removed as they had RD = 1 or had null observations, thus, we remained with 54,925 observations.

Summarizing RD across space/time. TREEMAP derived estimates of SDI, SDI_{MAX} and RD were centered on 2016 were compared with FIA estimates from 2013–2020. We graphically compared the distributions of SDI, SDI_{MAX}, and RD derived from TREEMAP and FIA plot-based estimates across multiple scales (Fig. 1). Primary scales of comparison were from specific FIA forest types, counties, states and EMAP hexagons to illustrate key similarities and differences across data products (Fig. 1). General trends and patterns are briefly highlighted and discussed below.

Data Records

The data records cited in this work are stored at FigShare, which is a public access repository for publishing research data[43]. This data set consists of 8 separate files. Descriptions of these data records are as follows:

FIA SDI_{MAX} plot file. This file provides the FIA SDI_{MAX} estimates determined using BRMS for plots across the CONUS[44].

FIA SDI subplot file. This file provides the subplot estimates of the stand density index (SDI) and the associated tm_id and the unique control number (CN) used to identify a survey record in the FIADB[45].

Treemap tree table. This file provides the TREEMAP tree table list with the CN, tm.id, trees per acre and diameter at subplot level[46].

TREEMAP SDI Raster. This file is the 30 m × 30 m resolution TREEMAP derived SDI estimates for forested areas of the CONUS in 2016[47].

TREEMAP SDI_{MAX} Raster. This file is the 30 m × 30 m resolution TREEMAP derived SDI_{MAX} estimates for forested areas of the CONUS in 2016[48].

TREEMAP RD Raster. This file is the 30 m × 30 m TREEMAP derived RD estimates for forested areas of the CONUS in 2016[49].

TREEMAP 2016 raster. This is an updated version of the original TREEMAP 2016 raster and the associated files for CONUS. The new additions to the TREEMAP raster attribute table are the SDI, SDI_{MAX} and RD estimates[50].

R code. This file has the R code that was used to calculate SDI from the TREEMAP 2016 tree table. The code permanently merged the SDI, SDI_{MAX} and RD csv files to the original TREEMAP 2016 raster attribute table.

Data comparisons. *Forest type size-density comparisons.* TREEMAP and FIA SDI estimates were skewed towards fewer trees (≈500 tph) (Fig. 2a). The SDI distributions showed significant differences in the FIA (459 ± 272 tph) and TREEMAP based estimate (444 ± 234 tph; Fig. 2b also see Figure S1 for the comparison of SDI densities of all forest types according to TREEMAP and FIA datasets). There were no significant differences in the distributions of SDI_{MAX} across forest types based on the TREEMAP (844 ± 366 tph) and FIA datasets (845 ± 359 tph, Fig. 3b and also see Figure S2). For FIA, distributions of SDI were skewed towards lower values, which created distinct differences in the RD distributions across forest types (Fig. 4a, also see Figure S3). There were significant differences in RD between FIA and TREEMAP derived estimations (Fig. 4b). TREEMAP showed lower RD values (0.52 ± 0.14), while median FIA RD estimates were 0.54 ± 0.22. The variability of the estimates were consistent for both FIA and TREEMAP for most of the forest types. The variations in the shapes of the density metrics distributions arise from differences in the distinct estimation methods. For instance, the imputed Random Forest used in TREEMAP results in data being centered around mean estimates for all size-density estimates.

State-level comparison of size-density metrics. We summarized size-density metrics by states and a strong relationship between state-level FIA and TREEMAP size-density estimates was observed ($R^2 = 0.40$–0.88). Most of the FIA and TREEMAP estimates were within the bounds of the confidence intervals or around the regression line (Fig. 5a) (RMSE = 42). Divergence was observed in states such as Texas and Nevada (Fig. 5a), which are states associated with fewer pixels and low and sparse vegetation (Figure S4). Most of the state-level FIA and TREEMAP estimates for SDI_{MAX} were around the regression line yielding an $R^2 = 0.88$, RMSE = 40 (Fig. 5b). Similar to SDI, extreme cases of uncertainty in the estimates were for the same states, which were below the regression line for example Texas. The relationship between state-level mean RD derived from FIA and TREEMAP was high yet weaker in comparison to the other two size-density metrics ($R^2 = 0.40$, RMSE = 0.03). Most of the states were consistently scattered around from the regression line.

The scatterplots in Fig. 6 compare the plot derived size-density metrics between FIA and TREEMAP highlighting how the datasets align for different metrics. Weak to moderate relationships between county-level FIA and TREEMAP size-density estimates was observed ($R^2 = 0.25$–0.46). TREEMAP tends to have higher SDI at high levels when compared to FIA (Fig. 6a, RMSE = 93). Moderate relationships exist between FIA and TREEMAP for SDI_{MAX} at different counties (Fig. 6b) and the same pattern observed for SDI exists although there was a higher RMSE = 153. The weakest relationship for RD is where the models fail to capture much variability (Fig. 6c, RSME = 0.07). At finer spatial scales, the relationships between the density metrics derived from the two methods tend to get weaker.

Weak relationships existed between density metrics estimated at derived at plot level at Environmental Monitoring and Assessment Program (EMAP) hexagon level. The relationships ranged from ($R^2 = 0.18$–0.40). As the spatial level of estimation gets finer/higher, the relationships between the density metrics derived from

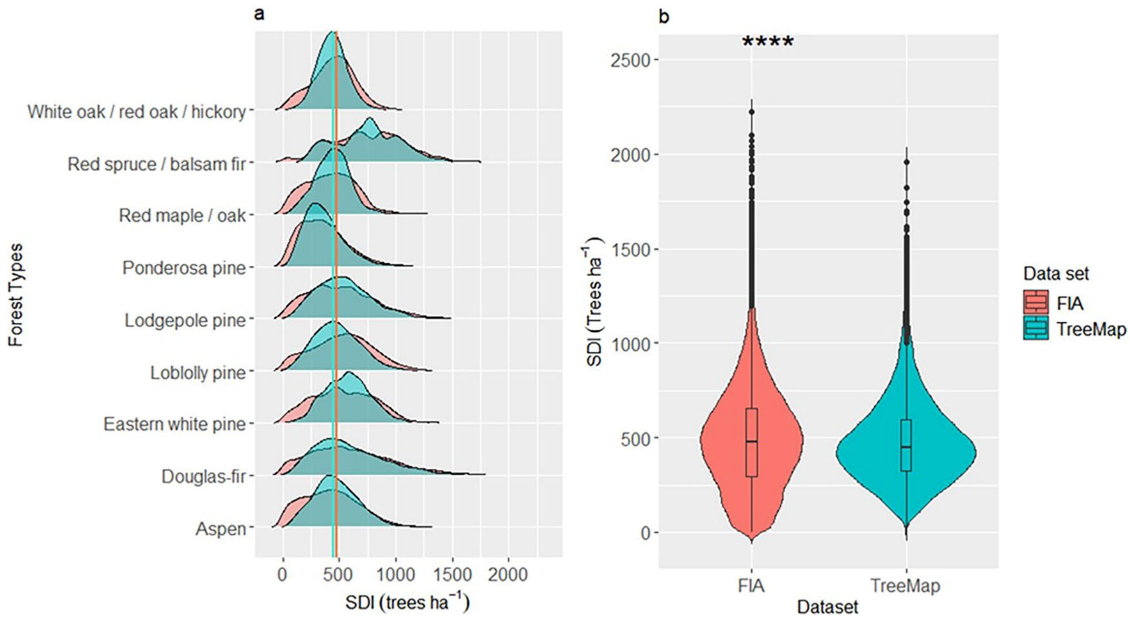

Fig. 2 Comparison of the size-density distributions of stand density index (SDI) for primary forest types in CONUS, including white oak (Quercus alba L.)/red oak (Quercus rubra L.)/hickory (Carya spp.); red spruce (Picea rubens Sarg.)/ balsam fir (Abies balsamea (L.) Mill.); red maple (Acer rubrum L.)/ oak (Quercus spp); ponderosa pine (Pinus ponderosa Dougl. Ex Laws); lodgepole pine (Pinus contorta Dougl. Ex. Loud.); loblolly pine (Pinus taeda L.); eastern white pine (Pinus strobus L.); Douglas-fir (Pseudotsuga menziesii (Mirb.) Franco) and aspen (Populus tremuloides Michx.). The forest types were generated using US Forest Service, Forest Inventory & Analysis (FIA) and TREEMAP data. (**a**) The brown line shows the FIA median value (459 tph), and the blue line shows the TREEMAP median value (444 tph) of SDI estimates. (**b**) *** show significant difference ($p < 0.05$) between FIA and TREEMAP based estimates across forest types.

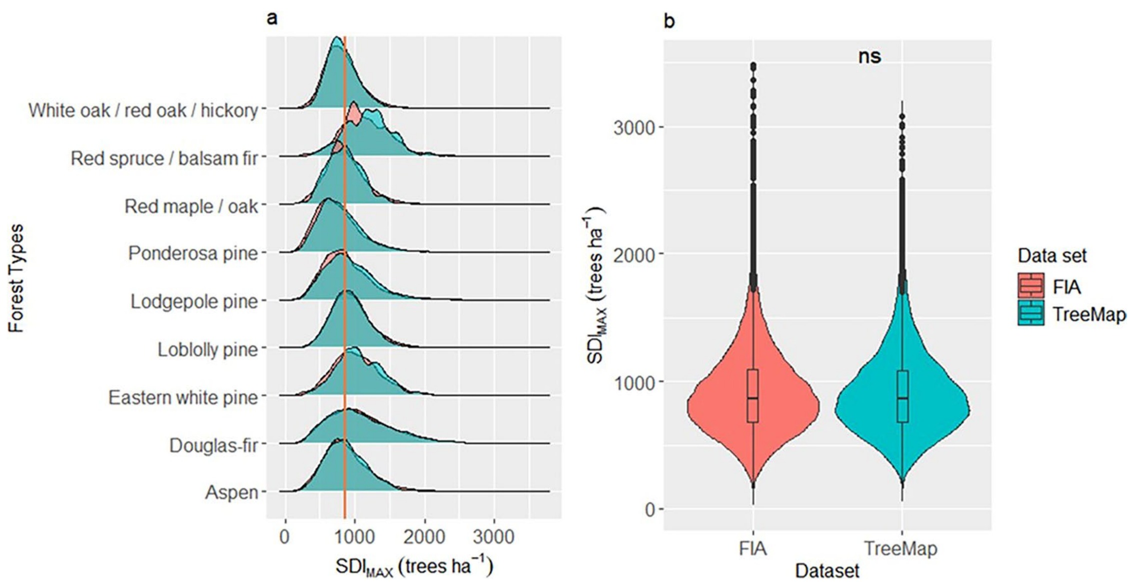

Fig. 3 (**a**) Comparison of the size-density distributions of maximum SDI (SDI_{MAX}) across primary forest types in CONUS. The brown line shows the FIA median value (845 tph), and the blue line shows the TREEMAP median value (844 tph) of SDI_{MAX} estimates. (**b**) ns = no significant differences between SDI based on FIA and TREEMAP estimates.

the two methods were weaker (Fig. 7a–c). The RMSE values for FIA and TREEMAP based models increased as the spatial scale became fine -from state to county levels and EMAP hexagons particularly for SDI and SDI_{MAX} (Figs. 5–7). FIA estimates become unstable at lower spatial scales such as county and hexagon levels whilst the TREEMAP estimates based on remotely sensed data also become biased and uncertain especially when the large-scale estimates are scaled down to small spatial scales. Additionally, downscaling further compounds bias

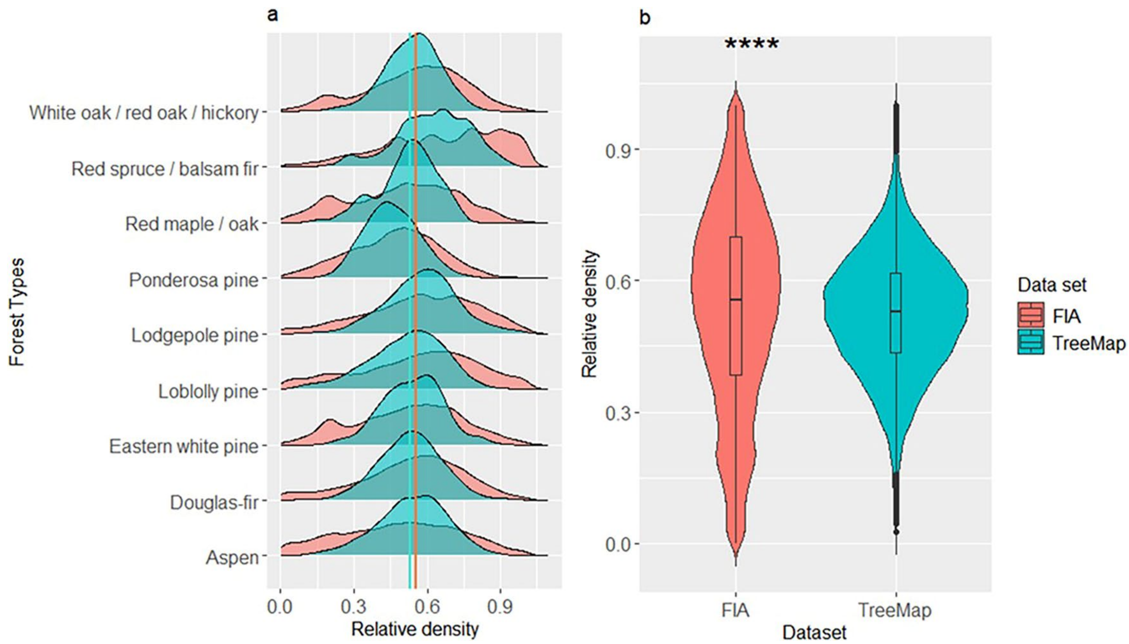

Fig. 4 Comparison of the size-density distributions of relative density (RD) across primary forest types in CONUS. The brown line shows the FIA median value (0.54), and the blue line shows the TREEMAP median value (0.52) of RD estimates. (**b**) *** show significant difference ($p < 0.05$) between FIA and TREEMAP based RD estimates across forest types.

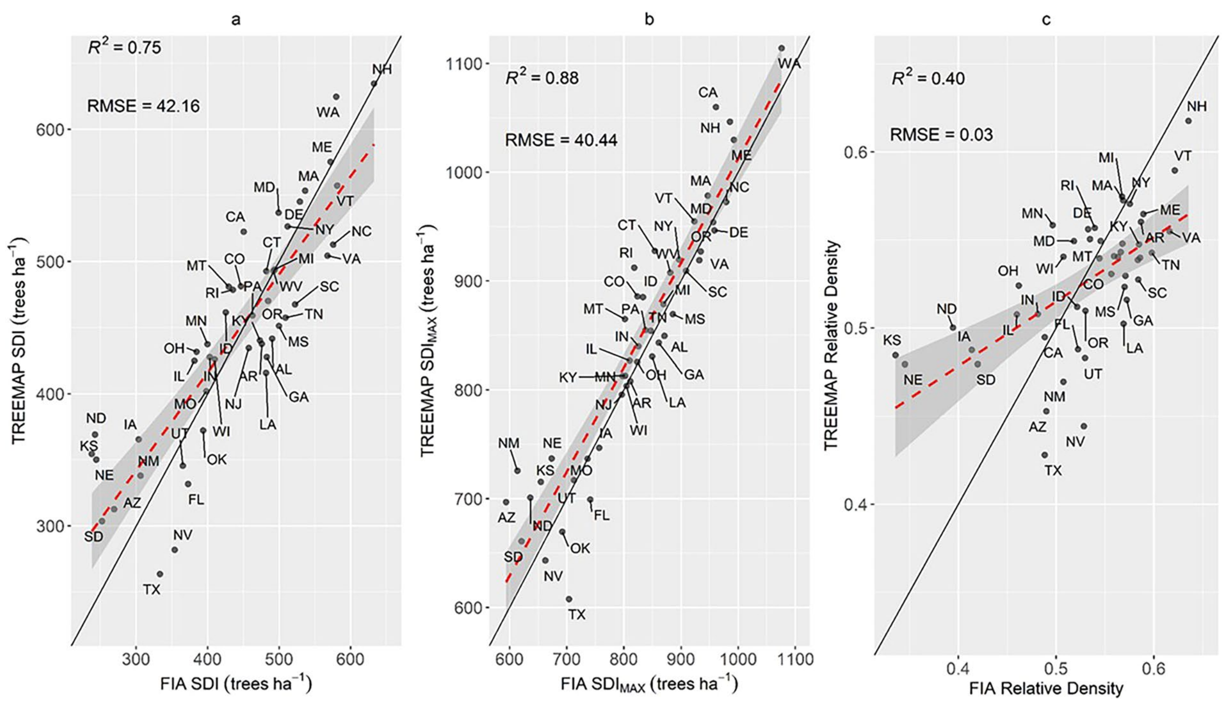

Fig. 5 Comparison of TREEMAP plot-based state level median for (**a**) stand density index (SDI); (**b**) maximum stand density index (SDI_{MAX}), and (**c**) relative density (RD) estimates and FIA based estimates in CONUS. The grey shaded area indicates the 95% confidence interval of the regression line.

as the level of uncertainty and map values are mostly meaningful considering them in their original resolutions (Duncanson *et al*., 2025).

TREEMAP derived summaries of SDI, SDI_{MAX} and RD. Spatially, SDI, SDI_{MAX} and RD were summarized based on the TREEMAP raster map across CONUS (Fig. 8). There was variability in the estimates of SDI across

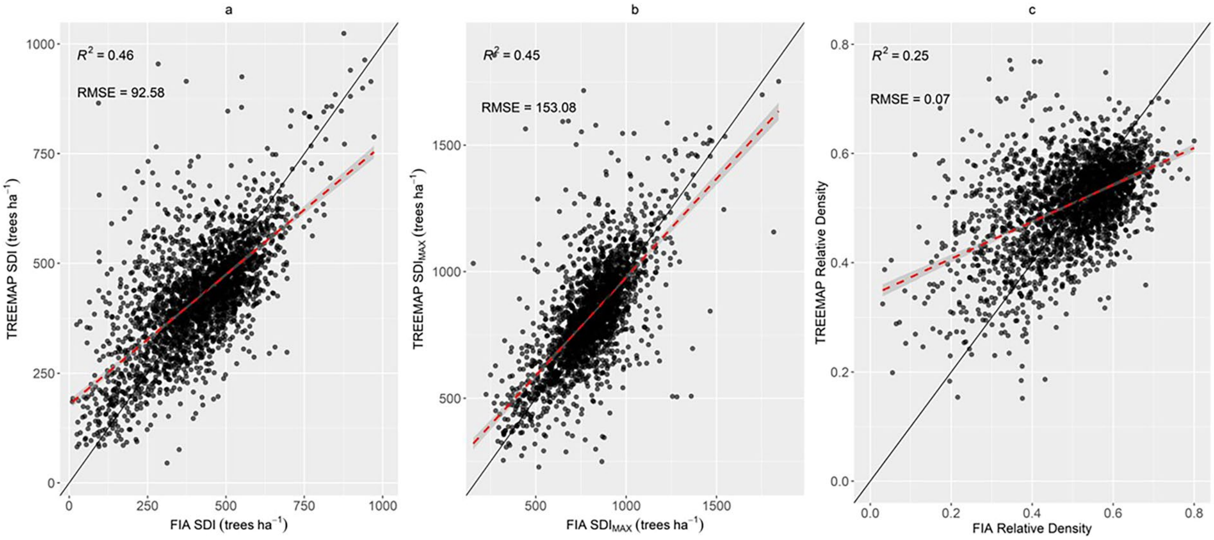

Fig. 6 Comparison of TREEMAP plot-based county level median for (**a**) stand density index (SDI), (**b**) maximum stand density index (SDI_{MAX}), and (**c**) relative density (RD) estimates and FIA based estimates in CONUS. The grey shaded area indicates the 95% confidence interval of the regression line.

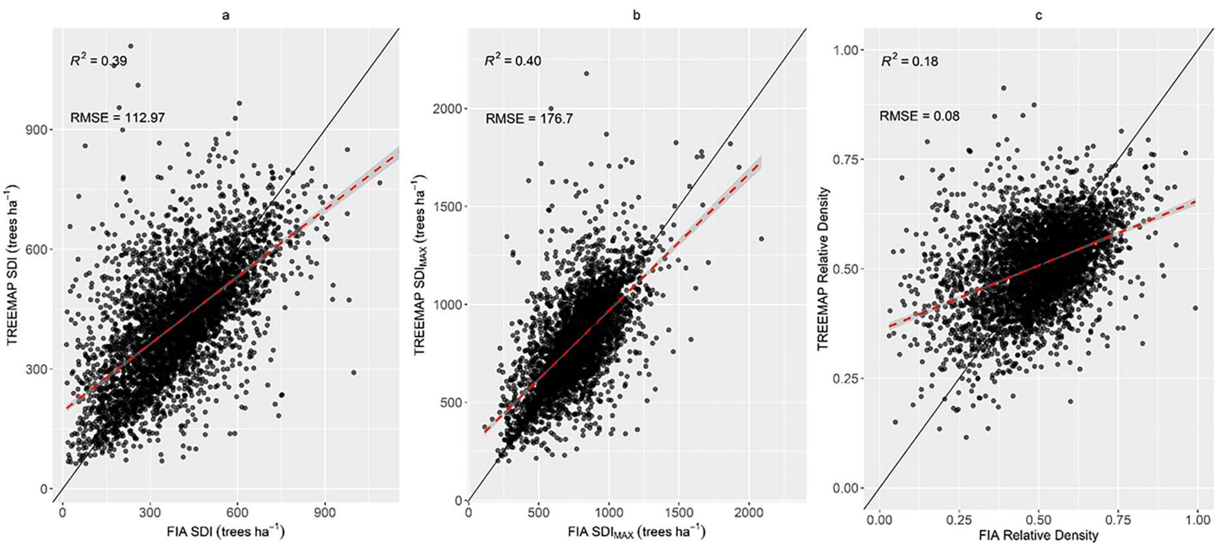

Fig. 7 Comparison of TREEMAP plot based Environmental Monitoring and Assessment Program (EMAP) 64.8 km^2 hexagon level median for (**a**) stand density index (SDI); (**b**) maximum stand density index (SDI_{MAX}); and (**c**) relative density (RD) estimates and FIA based estimates in CONUS. The grey shaded area indicates the 95% confidence interval of the regression line.

states (Fig. 8) for example 313 ± 190 tph for Arizona in the southwest, in the west (Oregon: 470 ± 323 tph) and southeast (Georgia 428 ± 192 tph), but highest in the northeast (Maine: 575 ± 249 tph). SDI_{MAX} showed the same trend as shown by SDI for example Arizona (697 ± 336 tph) and the highest in Maine (1030 ± 347 tph) (Fig. 9). As there was less variation in SDI_{MAX}, there were not many predicted variations in RD with the lowest (0.45 ± 0.11) in the southwest region (Arizona) and the maximum values were in Maine (0.57 ± 0.15) (Fig. 10). Using the RD thresholds for critical stand developmental stages available, example states Arizona, Georgia and Oregon are generally in the zone of optimum growth (RD = 0.40–55). Maine (RD = 0.57) is primarily on the boundary of the zone of imminent mortality (RD = 0.55–1.0).

Due to the number of pixels and wide range in underlying estimates, we derived median values of SDI, SDI_{MAX} and RD from the TREEMAP raster using zonal statistics for forested EMAP 40 km^2 hexagons for CONUS (Fig. 11). The patterns in spatial variations in density metrics follow the same patterns as depicted by TREEMAP at 30 × 30 m resolution. High SDI values were estimated in the Pacific Northwest around Washington, Oregon, and California, Maine and Wisconsin. States like Arizona, New Mexico, and Texas showed low SDI estimates (Fig. 11a,b). However, FIA based estimates tend to be higher than those summarized from

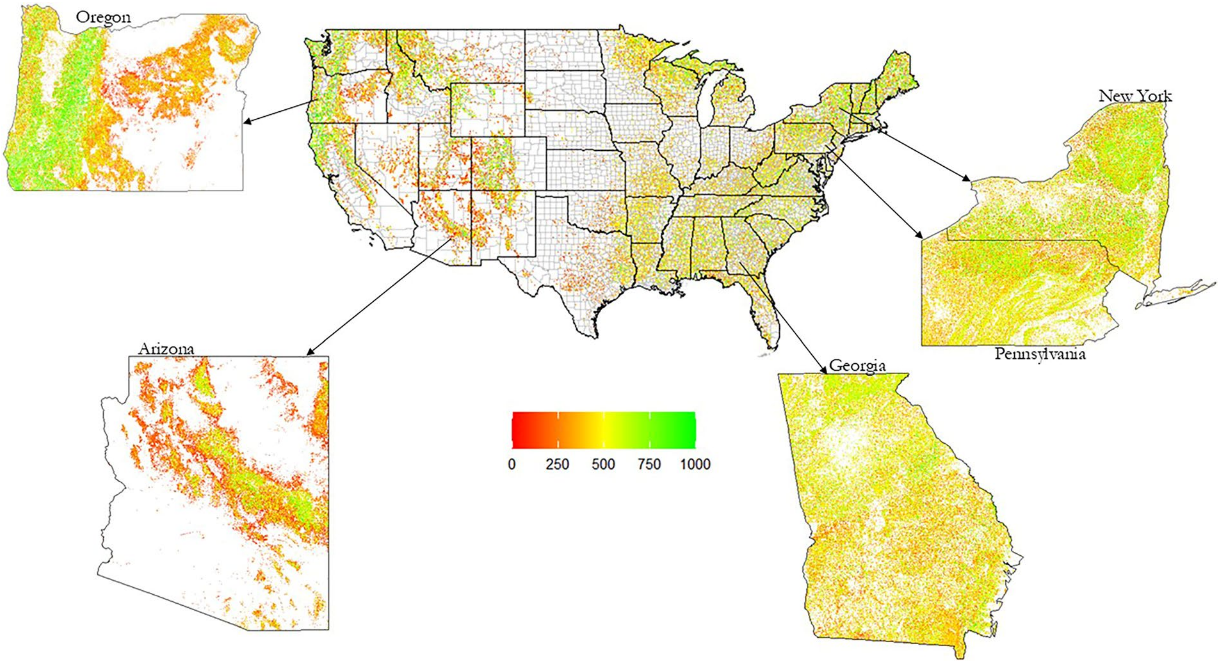

Fig. 8 A 30 × 30 m resolution raster map for stand density index (SDI; # ha^{-1}) estimates derived from TREEMAP for CONUS. Outlined black lines indicate the CONUS state boundaries and grey lines show CONUS county boundaries. Insets show how SDI estimates vary across selected states.

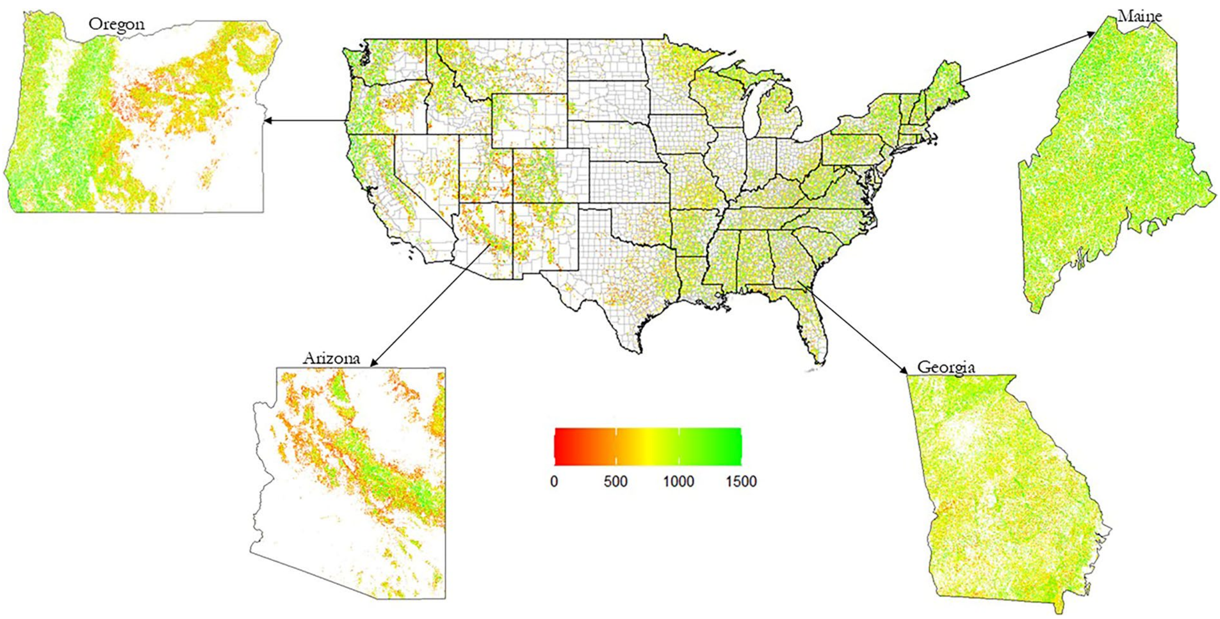

Fig. 9 A 30 × 30 m resolution raster map for maximum stand density index (SDI_{MAX}; # ha^{-1}) estimates derived from TREEMAP for CONUS. Outlined grey black lines indicate the CONUS state boundaries and grey lines show CONUS county boundaries. Insets show how SDI_{MAX} estimates vary across selected states.

TREEMAP. SDI_{MAX} variability followed patterns depicted by SDI especially for very dense areas of Washington, Oregon, and California with less dense states such Arizona, New Mexico, and Texas (Fig. 12a,b). Patterns in RD were different from what was observed for SDI and SDI_{MAX}. For TREEMAP (Fig. 13b), areas of high RD were observed in states such as Idaho, parts of Wisconsin, Minnesota, Kentucky, and Virginia. Low RD was estimated around states such as New Mexico, Texas, and parts of Nebraska (Fig. 13a,b).

To determine density metrics from the TREEMAP raster, we calculated zonal statistics by state, county and EMAP 64.8 km2 forested hexagons. Strong relationships were observed between summaries of median TREEMAP raster derived and FIA measured state level SDI estimates ($R^2 = 0.80$). Most of the states were along

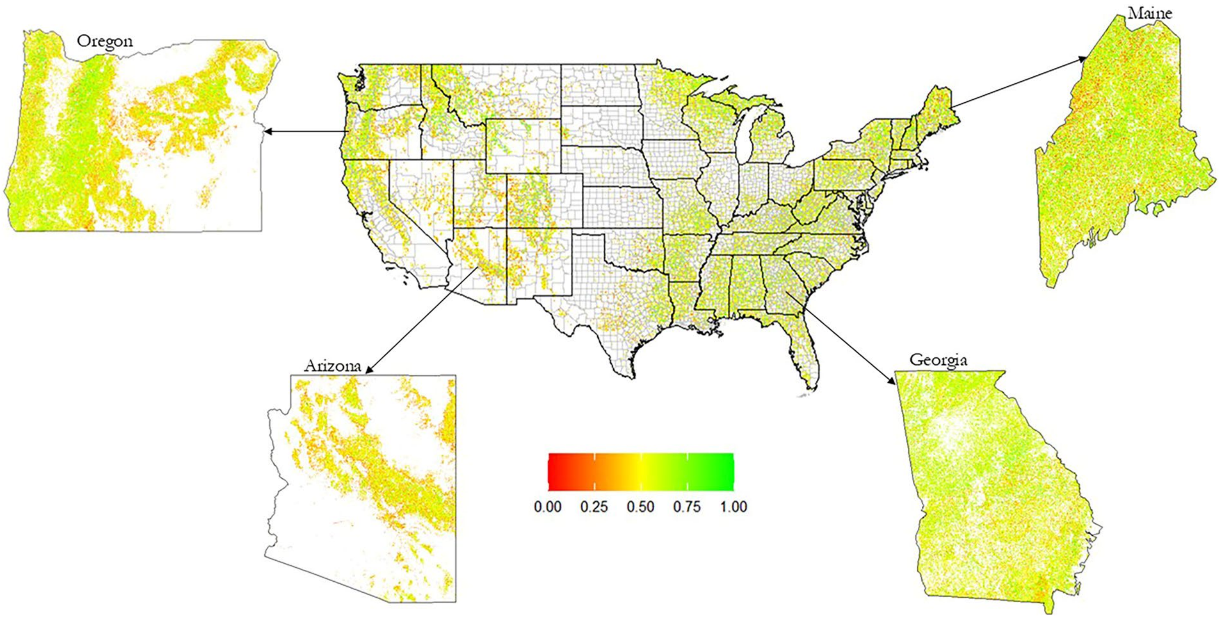

Fig. 10 A 30 × 30 m resolution raster map for relative density (RD) estimates derived from TREEMAP for CONUS. Outlined grey black lines indicate the CONUS state boundaries and grey lines show CONUS county boundaries. Insets show how RD estimates vary across selected states.

the confidence intervals of the fitted relationship. However, Nevada and Utah were found a distant from the diagonal line although these are states with sparse vegetation and were also assigned less pixels (Fig. 14) and see also Figure S6 a) and b). A strong relationship ($R^2 = 0.81$) between TREEMAP derived and FIA state level SDI_{MAX} with Utah below the diagonal line at low estimates and Washington at high estimates (Fig. 14b) and see also Figure S6 c) and d). Weak relationship between derived TREEMAP and FIA estimates of RD ($R^2 = 0.43$).

County-level estimates showed the same trend with the plot level estimates of SDI, SDI_{MAX} and RD (Fig. 15). The relationships ranged from $R^2 = 0.27$ for RD and to $R^2 = 0.48$ for SDI. Figure S5a–f shows a comparison of the estimates at county level. Both TREEMAP and FIA identified counties in Oregon, Washington having highest SDI values although FIA maps show much variability than TREEMAP derived estimates (Figure S5a,b). Areas of higher SDI_{MAX} were estimated using FIA (Figure S5c) than by TREEMAP. Areas of high RD were estimated by TREEMAP and FIA (Figure S6c,d) though higher variability was in FIA than TREEMAP.

Integrating relative density into management guides. Forest managers can make management decisions by using RD derived from SDI and SDI_{MAX}, which can be used to link density management diagrams (DMDs) and stocking guides (SGs)[2]. For example, RD can be used in the timing and intensity of prescriptions which guide harvesting operations, determining stand density, optimum stocking levels and meeting different forestry management objectives such as the need to maximize carbon sequestration under climate change conditions[2,11,51]. Previously developed size-density relationship are primarily derived from older or inconsistent inventory data[52] whose reference point is based on past environmental conditions. The inconsistent inventory data may not be relevant in informing management and silvicultural decisions under current and future climate change scenarios[53,54]. Therefore, it is recommended that updated size-density metrics from this study can be used to inform density management practices under current global climate change conditions.

When viewing RD as a competition indicator, management guidelines can include additional factors like species composition, mean tree size, and spatial configuration of stems, which can help managers increase the resilience of forests towards insects, droughts and wildfires[10,51,55,56]. With greater interest in natural climate solutions, adaptive silviculture, and societal demands on forests, there is need for robust size-density measures that can reflect novel species combinations, unique stand structures, and evaluate climate change resilience. The size-density metrics and maps presented in this work effectively address this current need and can indicate areas that require silvicultural interventions such thinning treatments to minimize potential productivity losses[2,57], reduce vulnerability to climate stressors[58] and pests and disease[59,60].

Incorporation of RD in evaluating live above-ground carbon can provide increased capabilities of fostering additional carbon storage through species manipulation and stand structural changes[8,61]. This is especially the case for mixed species stands, as modifying stocking and species composition can help increase the potential optimization of carbon offset projects. When stands shift to high RDs, self-thinning mortality dominates stand development processes and effectively shifts carbon from live to deadwood pools[11,62]. Again, the derived sized-density metrics and maps from this work can help inform future efforts to improve carbon sequestration and minimize emissions.

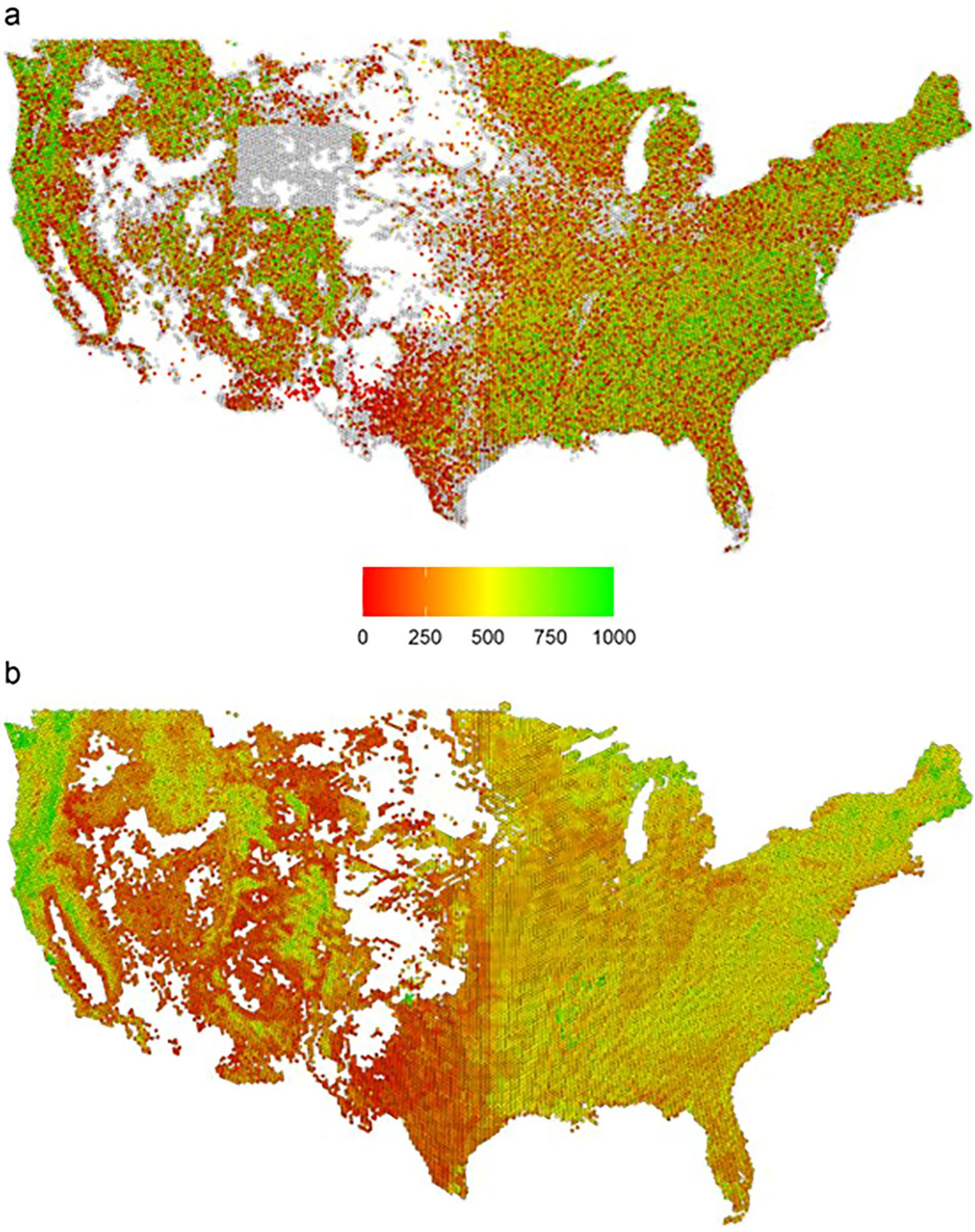

Fig. 11 Median for stand density index (SDI; # ha^{-1}) estimates summarized by EMAP 64.8 km^2 forested hexagons across CONUS based on (**a**) FIA plot level data and (**b**) TREEMAP raster derived estimates.

Data Records

The modified TREEMAP raster is stored as a 30 × 30 m raster in GeoTIFF (.tif) format and MS Excel files in.csv format with estimates for TREEMAP2016 tree table, SDI, SDI_{MAX}, RD, and tm.id can be accessed from through the FigShare data repository[43]. Plot level FIA data can be accessed from the https://research.fs.usda.gov/products/dataandtools/tools/fia-datamart.

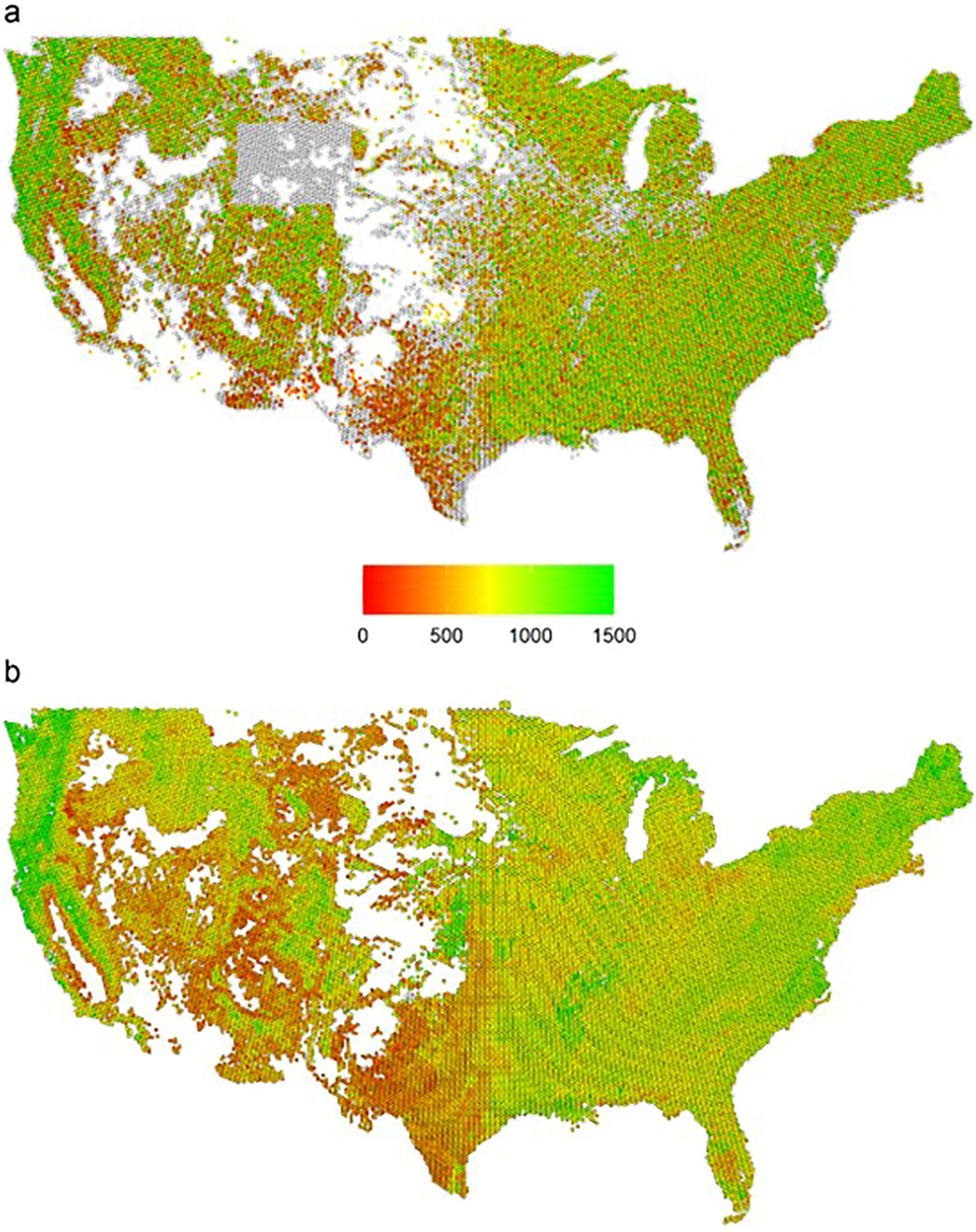

Fig. 12 Median for maximum stand density index (SDI; # ha^{-1}) estimates summarized by EMAP 64.8 km^2 forested hexagons across CONUS based on (**a**) FIA plot level data and (**b**) TREEMAP raster derived estimates.

Technical Validation

The tm.id was used to link the 54,925 FIA plots with the TREEMAP raster attribute table, which translates to ≈2,668,162,817 forested pixels in CONUS. We compared estimates of SDI, SDI_{MAX} and RD between FIA and TREEMAP at different spatial scales. Firstly, we compared plot-level SDI, SDI_{MAX}, and RD across forest types, CONUS counties, states and forested EMAP hexagons. We also summarized SDI, SDI_{MAX}, and RD from the TREEMAP 30 × 30 m raster using zonal statistics across counties, states and EMAP hexagons. However,

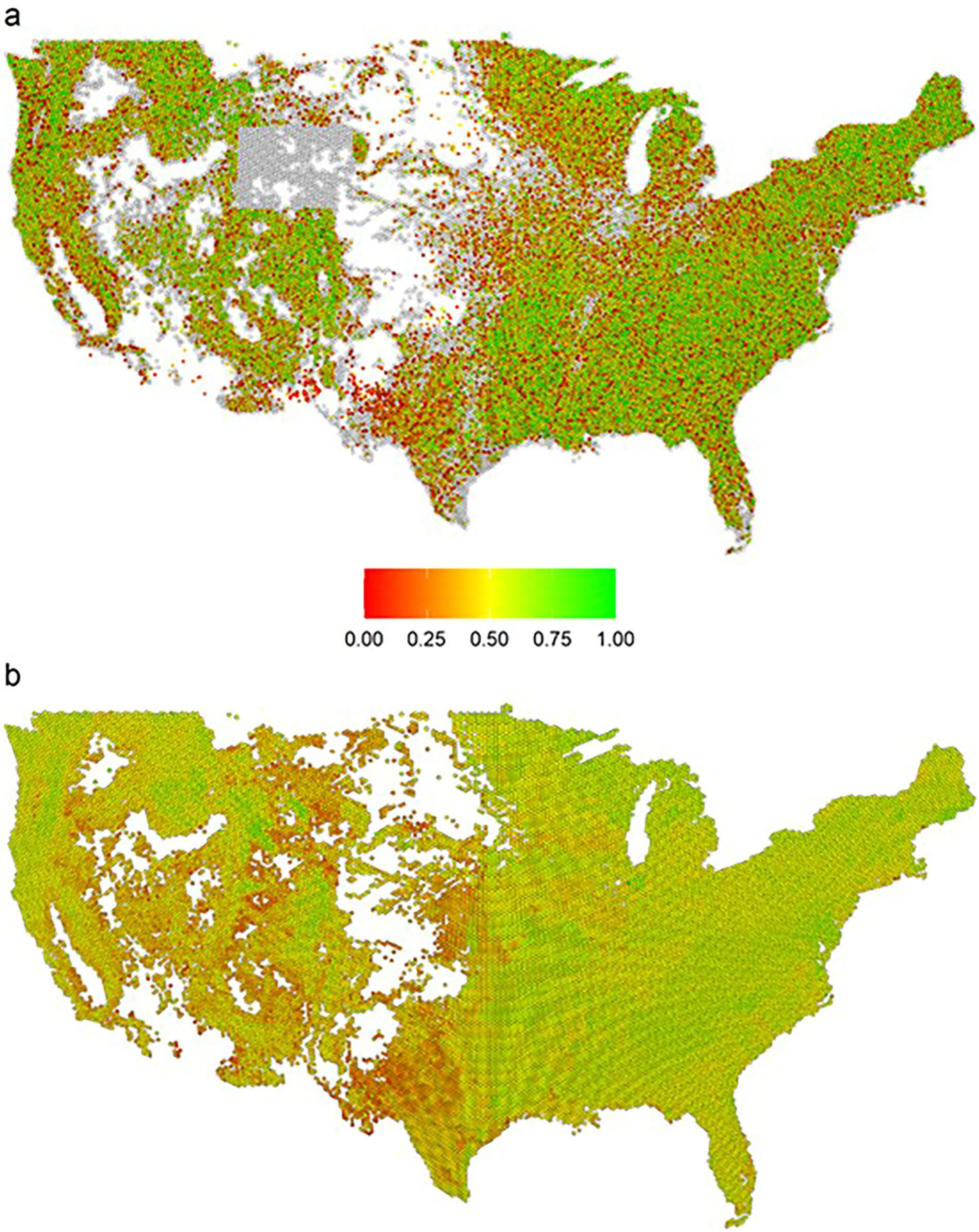

Fig. 13 Median for forest relative density (RD) estimates summarized by EMAP 64.8 km^2 forested hexagons across CONUS based on (**a**) FIA plot level data and (**b**) TREEMAP raster derived estimates.

the weaker relationship between FIA and TREEMAP estimates of RD can be attributed to a variety of factors, particularly the different assumptions and variables used to generate the estimates (Table 1). For example, the predictor variables for linking FIA plots to the LANDFIRE database to create TREEMAP were variables such as longitude and latitude, topography and vegetation and biophysical variables and disturbances, which could create potential spatial misalignment.

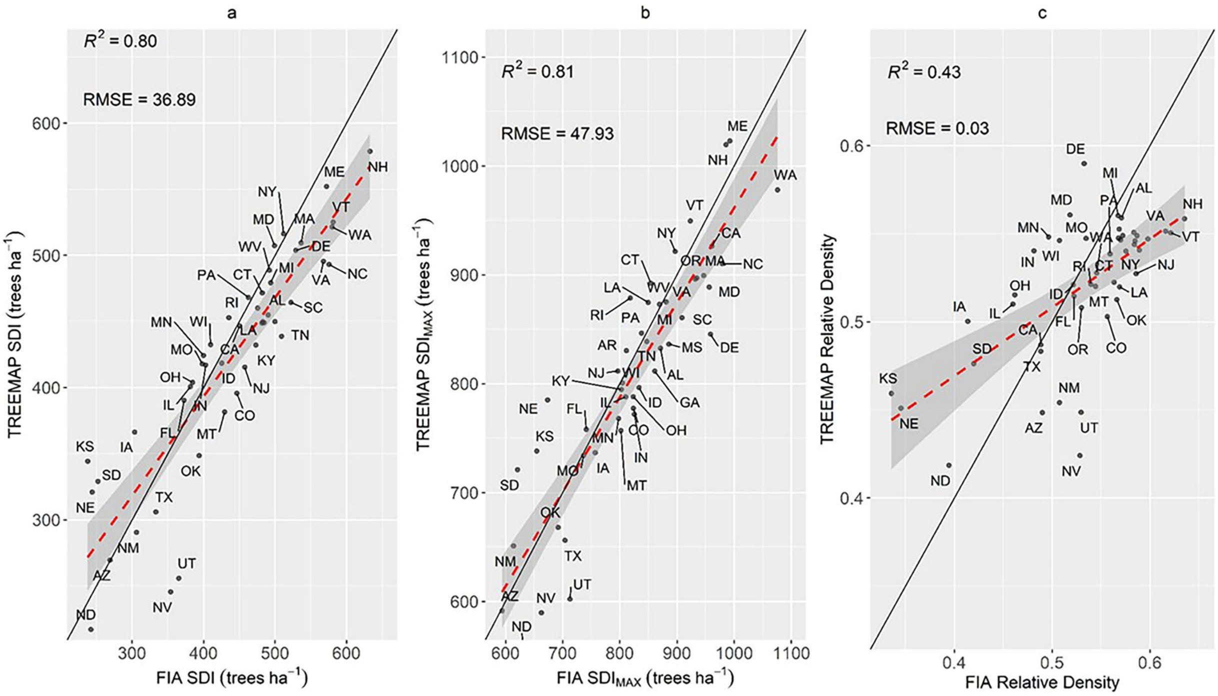

Fig. 14 Comparison of TREEMAP raster derived state level median for (**a**) SDI (**b**) SDI_{MAX} and (**c**) RD estimates and FIA based estimates in CONUS. The grey shaded area indicates the 95% confidence interval of the regression line.

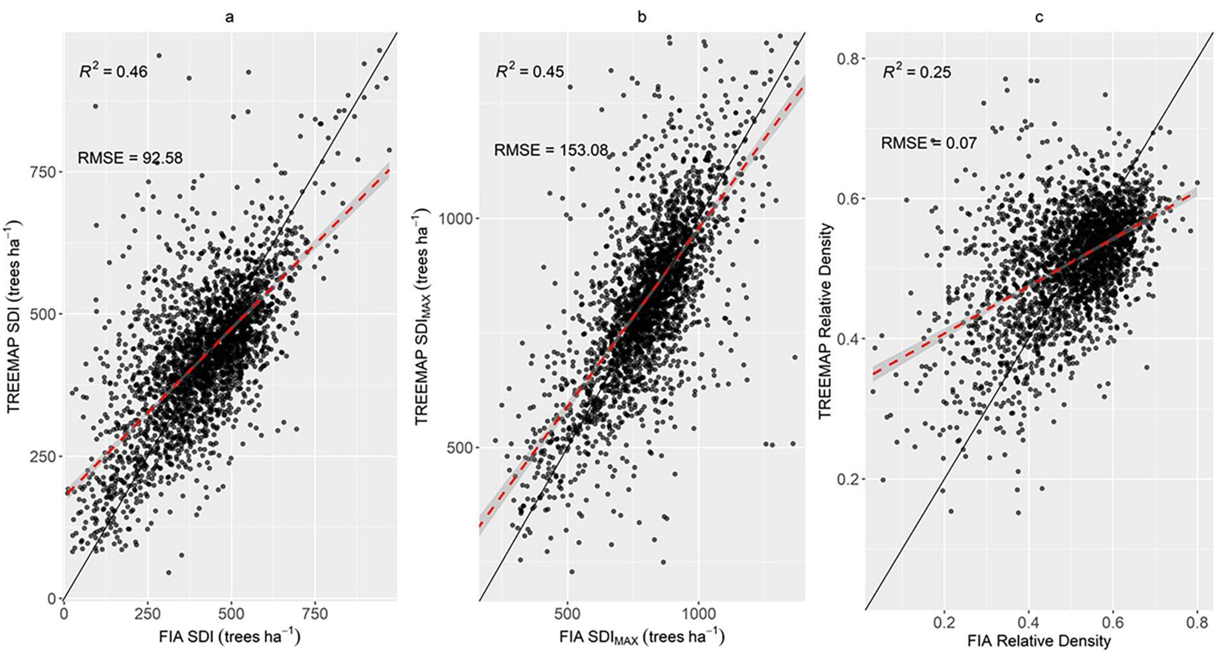

Fig. 15 Comparison of TREEMAP raster derived county level median for (**a**) stand density index (SDI # ha^{-1}); (**b**) maximum stand density index (SDI_{MAX}; # ha^{-1}); and (**c**) relative density (RD) estimates and FIA based estimates in CONUS. The grey shaded area indicates the 95% confidence interval of the regression line.

The FIA size-density metrics can be affected by field measurements, the unexplained variability between plots, and sampling error[63,64]. Consequently, there is need to better understand the various factors that influence potential uncertainty and the overall level of confidence in these derived values. The uncertainty in FIA data can ultimately influence the interpretation of this data[65]. Since FIA plots are used as reference data for random forest imputation, this implies that a certain degree of additional uncertainty is also extended into the TREEMAP

Data Element	Dataset	
	TREEMAP2016	FIA
Data sources	Remote sensing and FIA data	Field measurements
Model fit	Imputed random forest	Bayesian hierarchical modeling
Spatial resolution	30×30 m	1 plot per 24 km^2
Temporal resolution	Single year centered on a reference year for example 2016	5–7 years eastern and southern states and ≈15–20% remeasured annually. 10 years western states and ≈10% remeasured annually.
Plot design	—	Clustered/nested fixed area
Forest definition	At least 10% live tree cover for reference year for example 2016, severely disturbed areas excluded.	Land with minimum 10% live tree cover at some given point in the past, disturbed plots included
Application	Snag hazard mapping, forest vegetation mapping, habitat distribution, wildland fire effects, carbon estimation and fuel assessment, revision of forest plans	Volume/growth estimation, wildland fire risk assessment, disturbance assessment, biomass/carbon estimation, wildlife habitat assessment, forest health monitoring
Strengths	Easy data integration, nationally consistent medium-resolution data which covers where FIA is inadequate, rapid mapping of forest attributes, product applicability varies by spatial location and usage, adjustability of their products, suitable for locally based estimates of forest attributes	Coarse resolution for national assessments of forest attributes, long term repeated measurements (trends and changes in forest conditions), standardized protocols allow spatio-temporal comparisons, integration with remotely sensed data, easily integrated with other databases,
Limitations	Computationally complex and extensive, easily introduces uncertainty if imputation is based on estimates, under/overestimation of the true variability, cannot extrapolate outside the range of modeling data, model accuracy assessed through LANDFIRE	FIA plots do to cover the spatial heterogeneity of US forest types, different remeasurement periods between states are sources of uncertainty, spatial underrepresentation based on systematic sampling, rapid forest changes not captured during sampling cycles, within plot variability cause uncertainties.

Table 1. Comparison between TREEMAP 2016 and FIA datasets based on a number of key elements, which may affect their estimates.

estimates. Similarly, the uncertainties in the target data will also be extended to the imputed data making direct or even robust comparisons of the different datasets difficult.

In some cases, even though the same statistical methods were used on the same species, the SDI_{MAX} estimates can be quite different, with the variation being attributed to the sample size, inventory plot size and type, species composition, climate, and topography[1]. In this analysis, TREEMAP used random forest imputation and the FIA estimates of SDI matched to the tm.id were derived using a hierarchical Bayesian model (HBM) which used 'priors' from Woodall and Weiskittel[10]. In addition, the variability in the estimates can be due to the measurement protocols, which exist between FIA and TREEMAP. For example, FIA has 4–7 years of inventory in eastern states and 10 years in the western states. At the same time, TREEMAP estimates are derived using remotely sensed data for a single year. Further, the remeasurement periods also vary between the eastern and western states, which means that they may fail to capture the changes captured from remote sensing in the measurement year making the FIA measurements to be lower than TREEMAP based estimates. In areas of rapid change, for example, fire prone states such as California, Texas, North Carolina, Montana, and Oregon where tree mortality is high, this may influence the derived size-density metrics. The mismatch in measurement times between FIA states and TREEMAP, is another factor why the estimates cannot be precisely compared[20]. However, the integration of RD measures into TREEMAP can be regarded as suggestive rather than prescriptive and also viewed as a conceptual development at national level rather than at specific locations[66].

There are also differences in the definitions of forested land between FIA and TREEMAP. For example, TREEMAP includes pixels with 10% of live tree cover and this excludes disturbed plots and for FIA, a forested plot must have a minimum of 10% live tree cover. TREEMAP will not assign an tm.id to a disturbed plot yet FIA takes measurements from such plots. Thus, the assignment of plot between FIA and TREEMAP will lead to differences in estimates of SDI, SDI_{MAX}, and RD between the two datasets.

Usage Notes

The modified TREEMAP raster datasets provide the opportunity to have updated estimates of SDI, SD_{MAX}, and RD across different forest types, county state and EMAP boundaries across CONUS. RD raster maps can be used for tracking the level of competition in stands in space and time and when to initiate silvicultural operations like pre- and commercial thinning to improve growth and quality of trees in a forest stand. Silvicultural treatments are premised on quantifying the observed size-density metrics compared to a predetermined or optimal desired density[7] for input into strategic-scale density assessments. Medium resolution RD raster maps can be used to assess the risk from disturbances such as forest stand to fire, drought or insect outbreak. At a national level, RD can be used to inform forest management decisions in determining forest types that can persist during global climate change.

SDI and forest type/group data are freely downloadable in different formats from the FIA Datamart and additional calculations are needed for making plot estimates in metric or imperial systems. More detailed information on plot, county and state level estimates for the measured tree are accessible from the FIA DataMart in different forms. The major outputs of this paper are a modified TREEMAP 30×30 m raster, where we linked FIA plot-based SDI, SDI_{MAX} and RD estimates across the continental US. The modified raster and supporting MS Excel tables are available in the FigShare data repository. Users can link their own datasets with the modified TREEMAP raster attribute table using the tm.id and summarize at different spatial scales (Table 2). Alternatively, the user tables can be joined to the TREEMAP raster attribute table using the FIA sequence number ("CN") number which is for forested plots only.

Column name	Description	Source	Usage notes
tm_id	TREEMAP record number; corresponds to "Value" field in the TreeMap raster ("TreeMap2016.tif")	TREEMAP2016 raster attribute table	This column name can be used to link/join the TREEMAP raster with SDI, SDI_{MAX} and RD table in ArcGISPro/R
CN	Control number is a unique sequence number used to identify a survey record.	See Burrill *et al.*, (2021) subsection 2.1.1	FIA sequence number which users can join their forested plots to the TreeMap raster attribute table
FORTYPCD	Field forest type code from FIA algorithm	See Burrill *et al.*, (2021) subsection 2.5.16	Forest type code to translate the code into forest description by FIA for reporting purposes
ForTypeName	Description of the forest type derived using FIA algorithm		Derived from the FIA code (FORTYPCD)
FLDTYPCD	Forest type code, given by FIA inventory field crews	See Burrill *et al.*, (2021) subsection 2.5.17	A forest type code from FIA field measurement crews
FldTypeName	Forest type description given by FIA inventory field crews	—	Relates the SDI, SDI_{MAX} and RD estimates based on the tm_id
SDI	Stand density index (trees per hectare)	Derived in this analysis	TPH per forest type based on FIA and TREEMAP estimates
SDI_{MAX}	Maximum stand density index (trees per hectare	Derived in this analysis	TPH per forest type based on FIA and TREEMAP2016 estimates
RD	Relative density	Derived in this analysis, calculated as SDI/SDI_{MAX}	Relative density per forest type based on FIA and TREEMAP2016 estimates

Table 2. Definition of attributes and sources of data and how they were used in TREEMAP2016 raster for continental US.

Code availability

The original size-density metrics were derived from tree-level measurements based on plot-level evaluations across the US conducted by the USFS FIA, which are hosted online as Oracle databases on government servers. This inventory data is publicly available in different file formats from https://research.fs.usda.gov/products/dataandtools/tools/fia-datamart. R software was used to join the TREEMAP attribute raster and FIA datasheet using the tm.id. From the joined raster attribute table. The Lookup tool in the Spatial Analyst extension in ArcGIS Pro was used to create new raster for SDI, SDI_{MAX} and RD. Specifically, the Lookup tool uses the Lookup table to extract values of the specified field from the raster attribute table (RAT) of the input raster and assigns these values to the respective pixels of the new raster. R code for the analytical steps and creation of SDI, SDI_{MAX}, and RD rasters for the CONUS, is available at the FigShare data repository.

Data availability

The original TREEMAP 2016 raster and the associated files is available at https://www.fs.usda.gov/rds/archive/catalog/RDS-2021-0074. FIA data is available at https://research.fs.usda.gov/products/dataandtools/tools/fia-datamart. The updated TREEMAP 2016 raster, individual rasters for SDI, SDI_{MAX}, RD, the R code and associated files are available at https://figshare.com/projects/Geospatial_Estimation_of_Forest_Relative_Density_across_the_Continental_US/222516.

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Author contributions

Conceptualization and methodology, Aaron Weiskittel and Christopher Woodall; formal analysis, visualization, original draft preparation; Emmerson Chivhenge; supervision, Aaron Weiskittel; review and editing, Aaron Weiskittel, Christopher Woodall, Anthony D'Amato and Adam Daigneault; funding acquisition, Aaron Weiskittel.

Competing interests

The authors declare no competing interests.

Additional information

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