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Contact Information:	Tyson Wepprich, Adaptive Management Specialist 503-945-7381, Tyson.M.Wepprich@Oregon.gov Michael Wilson, State Forests Division Chief 503-945-7374, Michael.Wilson@Oregon.gov

SUMMARY

The State Forests Division has overhauled its forest inventory program to improve its capacity to inform planning and operations following recommendations made by an internal Forest Inventory Needs Assessment (2017-2019). As part of the 2020 initiation of the Enhanced Forest Inventory (EFI), forest biometrics were concurrently monitored with systematically located ground plots and wall-to-wall aerial lidar collection. The Division is analyzing the results of the EFI and integrating it with the legacy Stand Level Inventory (SLI) to provide continuity for the data needs of core business while transitioning to a new system. A timeline is outlined for the remaining EFI rollout and anticipated products.

Because carbon in aboveground woody biomass is a direct linear function of tree volume, data improvements in inventory will aid in upcoming Performance Measures related to carbon. Questions about trends in carbon storage in live trees were raised at the November 3, 2021 Board of Forestry meeting and addressed in a follow-up memo included in the minutes for the June 8, 2022 Board of Forestry meeting. There is a mismatch between recent carbon trends on State Forests measured by ground plots and those in externally developed remote-sensing products. The differences are presented as well as potential reasons for the disagreement.

BACKGROUND AND ANALYSIS

Enhanced Forest Inventory

The EFI will contain metrics collected using different methodologies and different scales compared with those in the legacy SLI. Remotely sensed data including lidar and satellite imagery allow ODF to measure a comprehensive suite of forest inventory biometrics on every acre of State Forests land. These data provide reliable forest inventory estimates at the landscape scale and reasonable estimates at finer operational scales. The final products resulting from this effort will include overall estimates of current standing inventory across the ownership; local calibration for growth modeling, mortality functions, and yield table development; and an evaluation of statistical confidence for the inventory estimates. Furthermore, a series of core stand metrics (board volume, quadratic mean diameter, tree species composition, canopy closure, etc.) will be mapped across the ownership and summarized at multiple scales (e.g. management units, watersheds). The

Inventory Program is currently exploring the feasibility and reliability of predicting secondary biometrics such as snags and coarse woody debris using remotely-sensed data. The Inventory Program expects this suite of wall-to-wall inventory products to meet all of the Division's forest inventory needs for the purposes of strategic long-range landscape planning, including Forest Management Plans, Habitat Conservation Plans, and 10-Year Implementation Plans, as well as providing a robust basis for monitoring.

The wall-to-wall inventory is only one component of the forest inventory system, which also includes ground sampling, information management, decision support, adaptive management, and reporting (Figure 1). While lidar acquisition and ground plots in 2020 have been analyzed, there are many steps to make the EFI operational in the next year. This summer, the State Forest Division is sampling a network of 90 supplemental plots designed to improve the wall-to-wall model predictions. In addition, the Inventory Program is sampling stands delineated in the current revision of SLI this year to validate the EFI model accuracy and directly compare the legacy inventory with the nascent EFI. These results will be analyzed in winter 2022 so that the EFI can be used in the spring 2023 Implementation Plan development under the proposed Forest Management Plan.

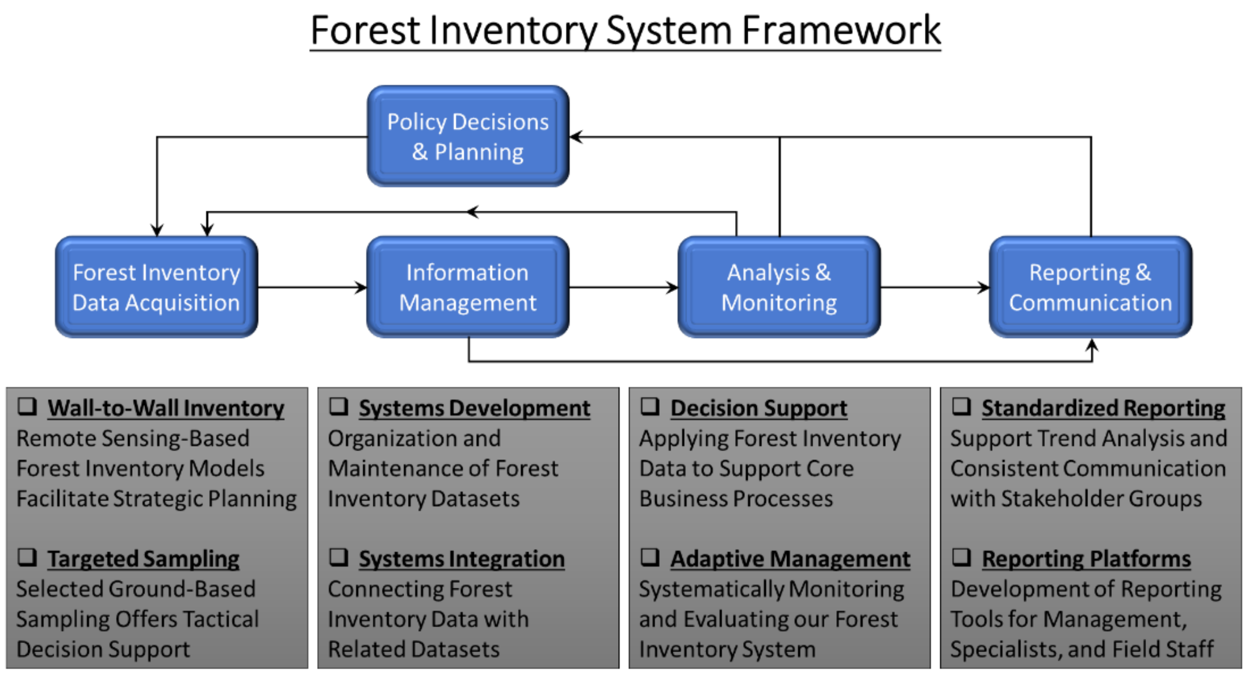

Figure 1: Framework developed by Forest Inventory Needs Assessment (2017-2019) showing how the State Forests Inventory Program interacts with other business needs and areas in which improvements are being made.

While a core concern is increasing the accuracy of the inventory, acknowledging its uncertainty appropriately will improve decision making that depends on inventory models. The preliminary lidar-based estimates for volume (Figure 2) have a prediction uncertainty associated with each 20x20-meter pixel, which is a resolution selected to match the ground monitoring plots. Staff are currently working to translate these results into estimates with confidence intervals for different spatial scales (e.g., stands, watersheds, districts). Uncertainty in the estimates is comprised of two types of statistical "error," or the difference between the predicted estimates and the observed values. Both the variability in ground measurements and variability in the model predictions are quantified to project the upper and lower bounds of the true value, whereas the legacy inventory relied on single estimates. It is critical that uncertainty in the inventory be quantified and acknowledged in planning and performance measures. For example, inventory scenarios higher and lower than the mean estimates could give alternative better- and worse-case harvest model results that could inform decision making by testing how sensitive harvest targets are to inventory uncertainty.

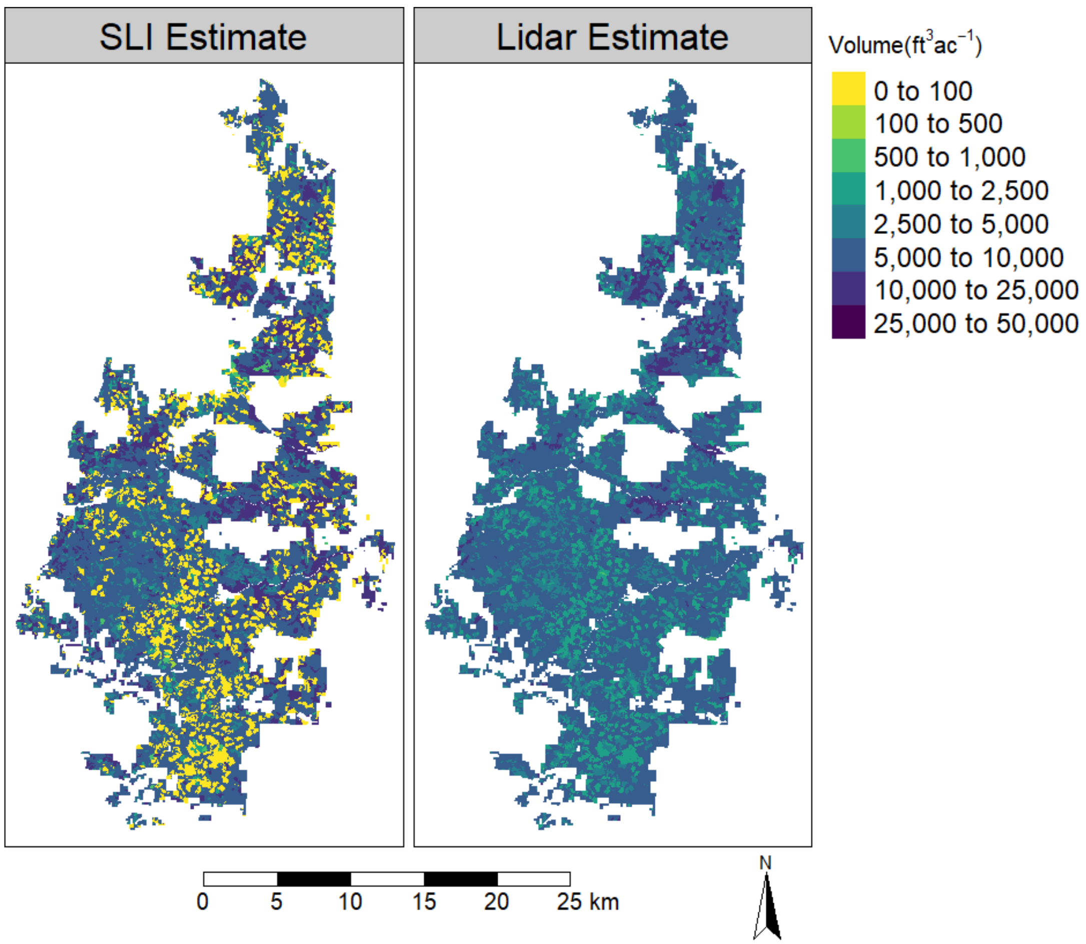

Figure 2: Spatial comparison of aboveground live tree volume (cubic feet per acre) estimated by stand in the legacy SLI (left) or with a lidar-based model in the new EFI (right). The mapped area covers most of the three North Coast districts. Note that SLI assigned clearcut stands a value of zero for years after harvest regardless of unharvested buffers or leave trees, while lidar-based models account for these.

Carbon trends

Division staff have analyzed multiple monitoring data sources and engaged outside experts to improve our understanding of inventory status and trends for both future harvest planning and carbon storage metrics. We present comparisons across datasets and analyze key questions about aboveground live tree carbon trends on State Forests.

Ground data: Forest Inventory and Analysis
The ground-truthing dataset comes from the Forest Inventory and Analysis (FIA) program, the USDA Forest Service's national forest inventory. The FIA "base grid" includes 124 permanent plots measured on a 10-year rotation since 2001 on ODF-managed lands. Volume can be measured as a 10-year stock (average of all plots sampled once) or as an increment/flux (average change in volume on plots remeasured 10 years apart). These data allow for estimates over large areas with a systematic sample. However, the 10-year sampling rotation makes it slow to detect changes in trends. For its EFI, State Forests contracted with the Forest Service to densify the plot network on ODF-managed lands, with 306 additional permanent plots measured in 2020 that will subsequently be added to the 10-year rotation. The densified FIA grid will reduce uncertainty in the estimates of aboveground live tree carbon on State Forests as the grid is remeasured.

The *Oregon Forest Ecosystem Carbon Inventory Report: 2001-2016* (FECIR) completed in 2019, for which the Board received an update at the June 8, 2022 meeting, uses the FIA base grid as its data for calculating carbon flux, or the change in carbon pools when plots are remeasured after 10 years. In the Coast Range, the reported change in aboveground live tree carbon was indistinguishable from zero on aggregated State and Local lands. For that report, ODF-managed lands were not analyzed separately. Here, we used FIA data through 2019 to give estimates of carbon stocks and carbon flux based on ground data on ODF-managed lands.

The FIA program evaluates its sample compared to the total forested landscape and adjusts the weighting of each site in a manner that makes 10-year stock estimates more accurate ("post-stratification"). Using the available post-stratified 10-year stock estimates, the FIA base grid estimates increasing carbon between 2010 and 2019 on Federal, ODF-managed land, and private forests in the Oregon Coast Range (Figure 3).

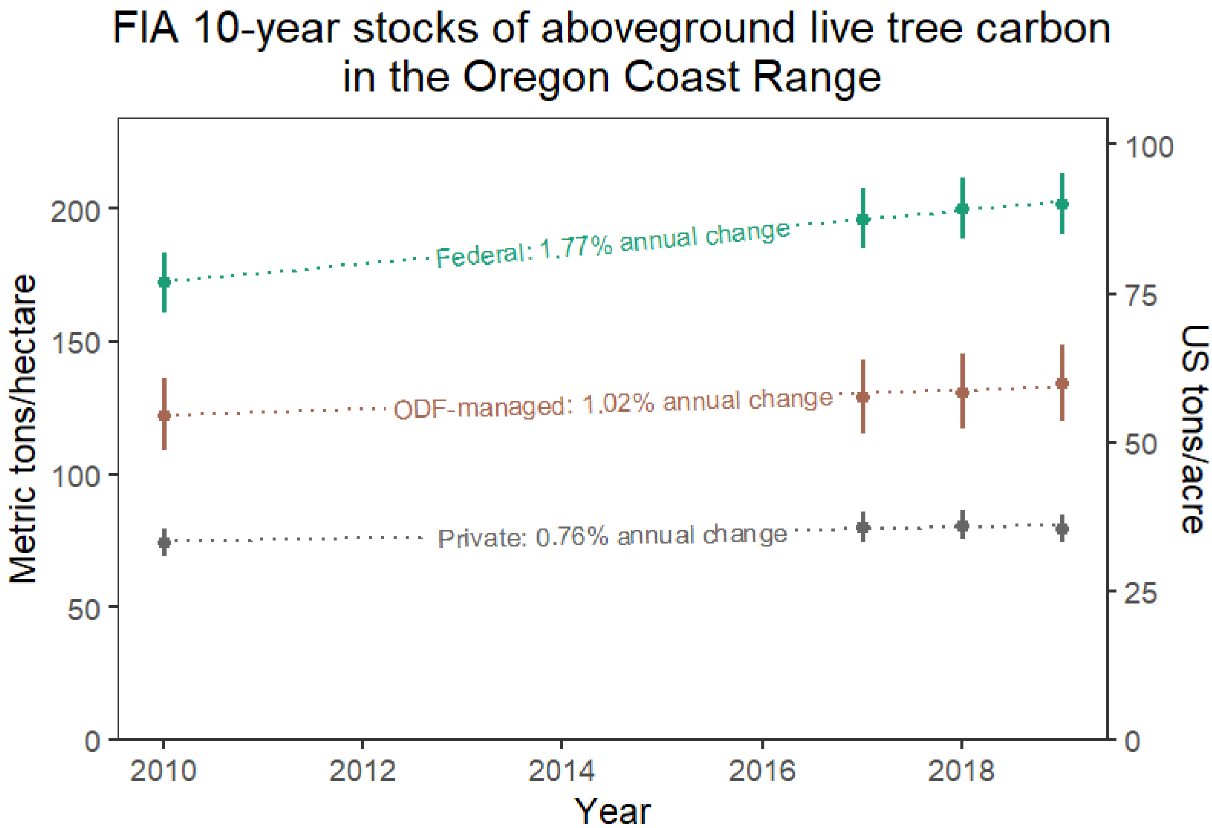

Figure 3: 10-year stocks estimated with 95% confidence intervals using the "Temporally Indifferent" estimator to match eVALIDator results using the *rFIA* R package (Stanke et al. 2020) with public FIA data within the Oregon Coast Range. We filtered the State/Local ownership to include only plots on ODF-managed lands. Annotated changes in aboveground carbon in live woody biomass represent the annual rate of change in the FIA estimate between 2010 and 2019.

Carbon flux from remeasured FIA base grid plots also is generally increasing as estimated by the Periodic Annual Increment (Figure 4). There is substantial variability between FIA plots due to management, stand age, and forest composition, which we summarize as an estimate for each district across plots. The estimates of Periodic Annual Increment are more precise on districts with more ground measurements.

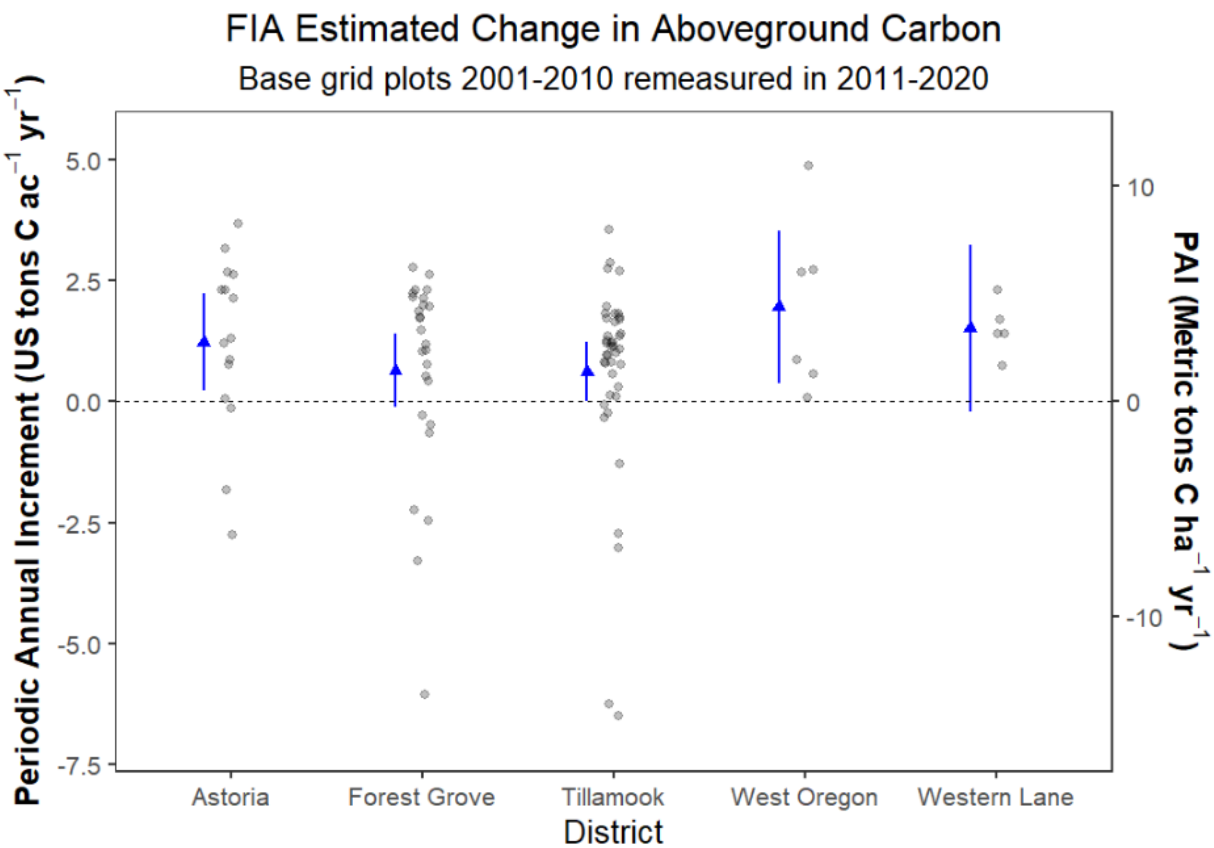

Figure 4: Remeasured FIA base grid plots show increasing carbon. Blue triangles and lines show the mean Periodic Annual Increments and 95% confidence intervals in live tree aboveground carbon estimated by district. Gray data points show the carbon flux over 10 years at each plot.

Remote sensing products

Three published datasets (Table 1) use the FIA network as training data for models of forest biometrics predicted with 30x30-meter resolution Landsat imagery. The Landsat program measures multiple spectra of visible and infrared light across the Earth at 16-day intervals. Models based on this satellite imagery can make wall-to-wall predictions across the landscape and enable rapid detection of temporal changes. While not as precise or accurate as lidar, these products use the decades of Landsat imagery for long-term model predictions of past forest change. However, they are generally better at detecting large disturbances such as clearcuts and may not adequately track growth in aboveground carbon after canopy closure.

Table 1: Remote-sensing data products with biomass models.

Product abbreviation (Years modeled)	**Reference <Data URL>**
LEMMA (1986-2017)	Landscape Ecology Modeling, Mapping, and Analysis (LEMMA) Team. 2020. Gradient Nearest Neighbor (GNN) raster dataset (version 2020.01). Modeled forest vegetation data using direct gradient analysis and nearest neighbor imputation. <https://lemma.forestry.oregonstate.edu/data>
eMapR (1990-2017)	Kennedy, R. E., J. Ohmann, M. Gregory, H. Roberts, Z. Yang, D. M. Bell, V. Kane, M. J. Hughes, W. B. Cohen, S. Powell, N. Neeti, T. Larrue, S. Hooper, J. Kane, D. L. Miller, J. Perkins, J. Braaten, and R. Seidl. 2018. An empirical, integrated forest biomass monitoring system. Environmental Research Letters 13:025004. < http://emapr.ceoas.oregonstate.edu/pages/data/viz/index.html>
CMS (2000-2016)	Hudak, A. T., P. A. Fekety, V. R. Kane, R. E. Kennedy, S. K. Filippelli, M. J. Falkowski, W. T. Tinkham, A. M. S. Smith, N. L. Crookston, G. M. Domke, M. V. Corrao, B. C. Bright, D. J. Churchill, P. J. Gould, R. J. McGaughey, J. T. Kane, and J. Dong. 2020. A carbon monitoring system for mapping regional, annual aboveground biomass across the northwestern USA. Environ. Res. Lett.:18. < https://doi.org/10.3334/ORNLDAAC/1719>

At the November 3, 2021 Board meeting, only LEMMA data were presented. Here, we compare trends across the three products by ownership, which show differences even though all are based on the same ground data (Figure 5). Different magnitudes of carbon estimated is in part due to choices of which land is mapped as forest or non-forest. One product (eMapR) notably includes more marginal forestland in its mapped estimates, which lowers its mean estimate compared to the other two products.

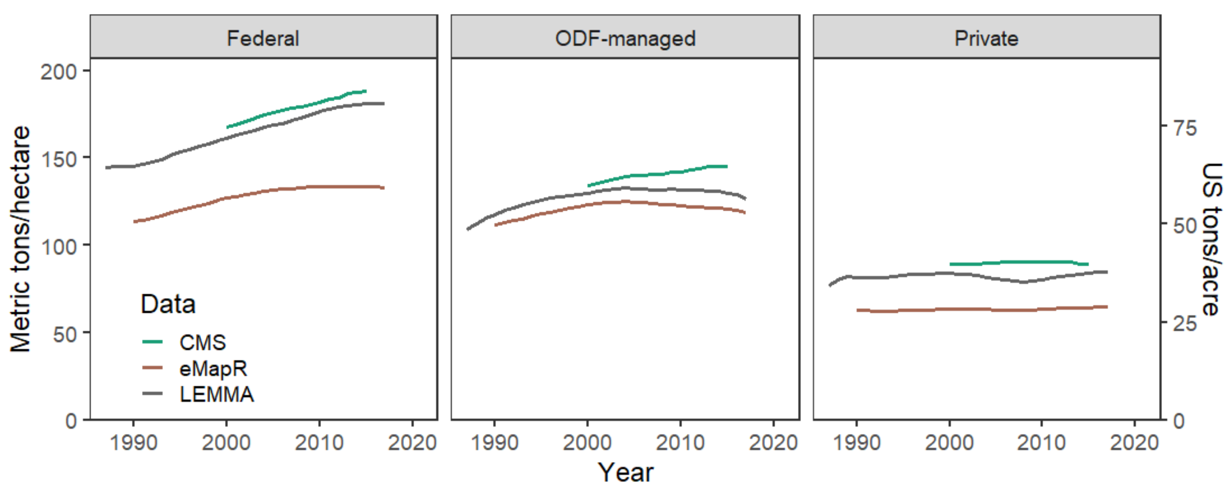

Figure 5: Remote-sensing estimates of average aboveground live tree carbon over time in the Oregon Coast Range by forest land ownership. The three remote-sensing products are detailed in Table 1.

One shortcoming in the November 3, 2021 Board of Forestry presentation was not showing uncertainty in the modeled estimates. With gridded products, an approach called small area estimation can account for the variability in the model predictions within a designated area, although it does not account for potential bias in the model itself (Bell et al. 2022). The LEMMA data reevaluated using small area estimation show that the trend presented in November underestimated the recent carbon estimates but fell within the 95% confidence intervals of the annual estimates (Figure 6).

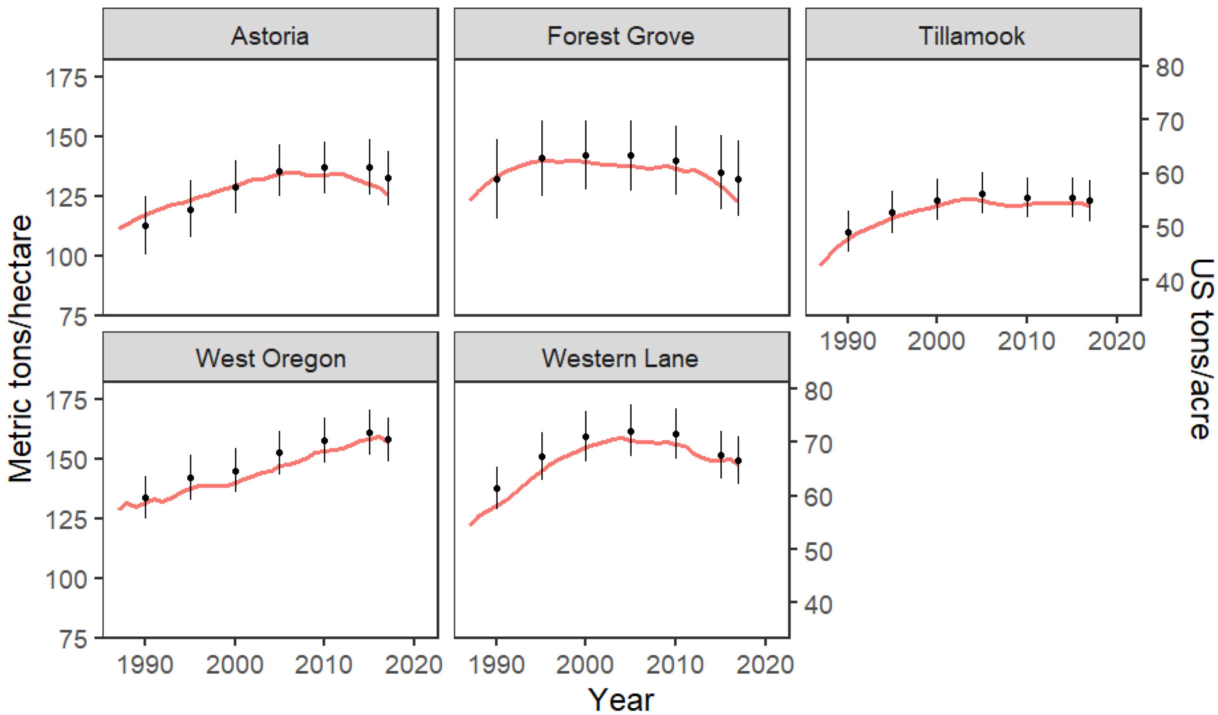

Figure 6: Small area estimation of live tree aboveground carbon by ODF District (black dots with 95% confidence intervals) and trend of LEMMA data averaged by year and district (red line). Note that the y-axis starts at 75 metric tons/hectare to highlight the differences between the trend and the confidence intervals of annual estimates.

Comparing FIA and remote-sensing products

The difference between the steady growth in carbon estimated by FIA and the apparent plateau or downturn presented by remote-sensing products warrants further analysis. Across datasets, it is apparent that State Forests fall between Federal lands and private lands in live tree carbon storage per unit area (Figure 7). Trends estimated by remote-sensing products generally fall within the confidence intervals for FIA base grid estimates at the scale of ownership group in the Coast Range, with the LEMMA product most closely representing the ground data (Figure 7). The densified FIA plots starting in 2020 through the EFI reduce the uncertainty of carbon estimates, even as the point estimates between the base grid and densified grid differ because they sample different plots that vary by chance (Figures 7 and 8). For the three North Coast districts, the LEMMA estimates with confidence intervals for 2017, the latest year available, are within the confidence intervals for FIA base grid estimates in 2017 and within the confidence intervals for the FIA densified grid estimates in 2020 (Figure 8).

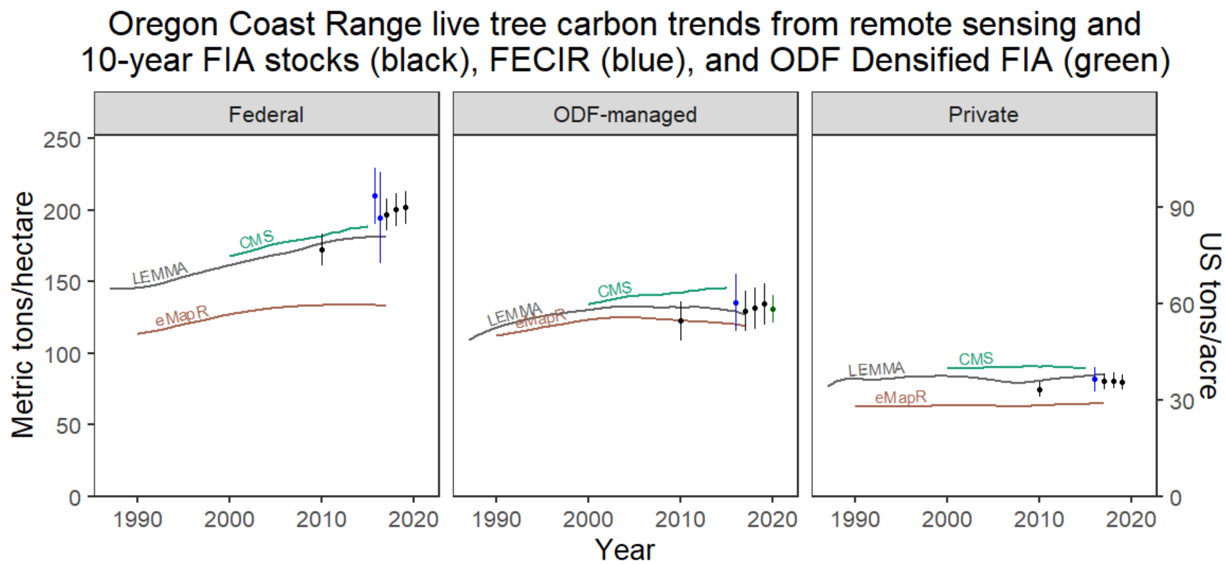

Figure 7: Comparison of aboveground live tree carbon from three remote-sensing products over time (labeled trend lines) and annual estimates with 95% confidence intervals from the FIA base grid (black for years 2010, 2017, 2018, 2019), Forest Ecosystem Carbon Inventory Report (blue for 2016, note the Federal land is divided into USFS and non-USFS estimates), and the FIA densified grid on ODF-managed lands (green for 2020 in center panel).

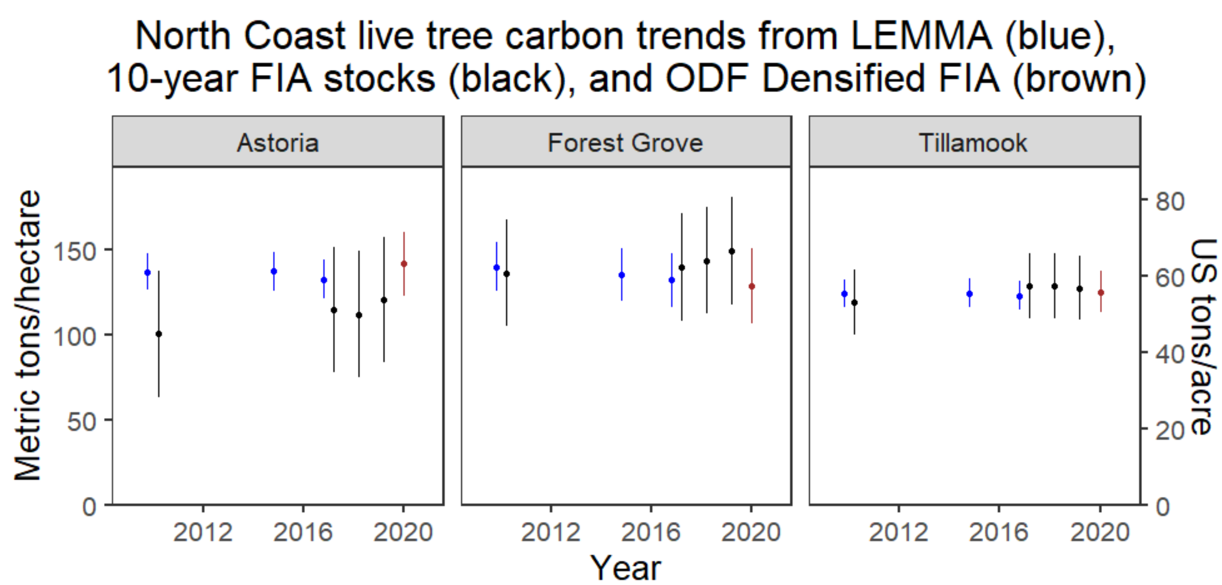

Figure 8: Comparison of aboveground live tree carbon estimates with 95% confidence intervals from the LEMMA product with small area estimation (blue for 2010, 2015, 2017), the FIA base grid (black for years 2010, 2017, 2018, 2019), and the FIA densified grid on ODF-managed lands (brown for 2020). The three North Coast districts are displayed in the panels. Estimates from different data sources in the same year are offset on the graph to prevent overlap.

Reasons for trend disagreement between datasets

Carbon trends are comprised of gains through tree growth and losses through mortality, natural disturbances, and harvest. With input from expert reviewers, the two following tests were performed to identify likely reasons for why trends were not aligning.

1. Unrepresentative sampling of losses

If FIA monitoring were less frequently located in harvested areas by chance, then they would be biased towards more positive carbon trends than wall-to-wall monitoring that tracks disturbance across all areas. We compared GIS data for past harvest operations across districts and selected the FIA base grid and densified plots contained within stands that were either clearcut, thinned, or unmanaged over the last 20 years (N.B.: data quality and the year these data started being recorded varies by district in the 2000s).

Generally, the proportion of the district in clearcuts differs between the base grid, densified plots, and GIS records (Figure 9). In some districts, the increase in number of plots in the densified grid improved the representativeness of the sample to align better with GIS records (Astoria, West Oregon). In other districts, the ground plots are underestimating areas of management (Western Lane). Tillamook GIS records are not available until 2007, which is why GIS underestimates management areas compared to FIA (top right panel in Figure 9).

The impact of the sampling variability is difficult to quantify in a dynamic landscape but could explain part of the reason why the FIA base grid for 2019 and densified carbon estimates for 2020 vary (Figure 8). When all Coast Range districts are combined, the percent of area in clearcuts in GIS records (16.0%) is less than the percent of FIA plots within clearcuts (base 17.2%, densified 19.8%). This would suggest that FIA is not underestimating harvest by their sampling locations.

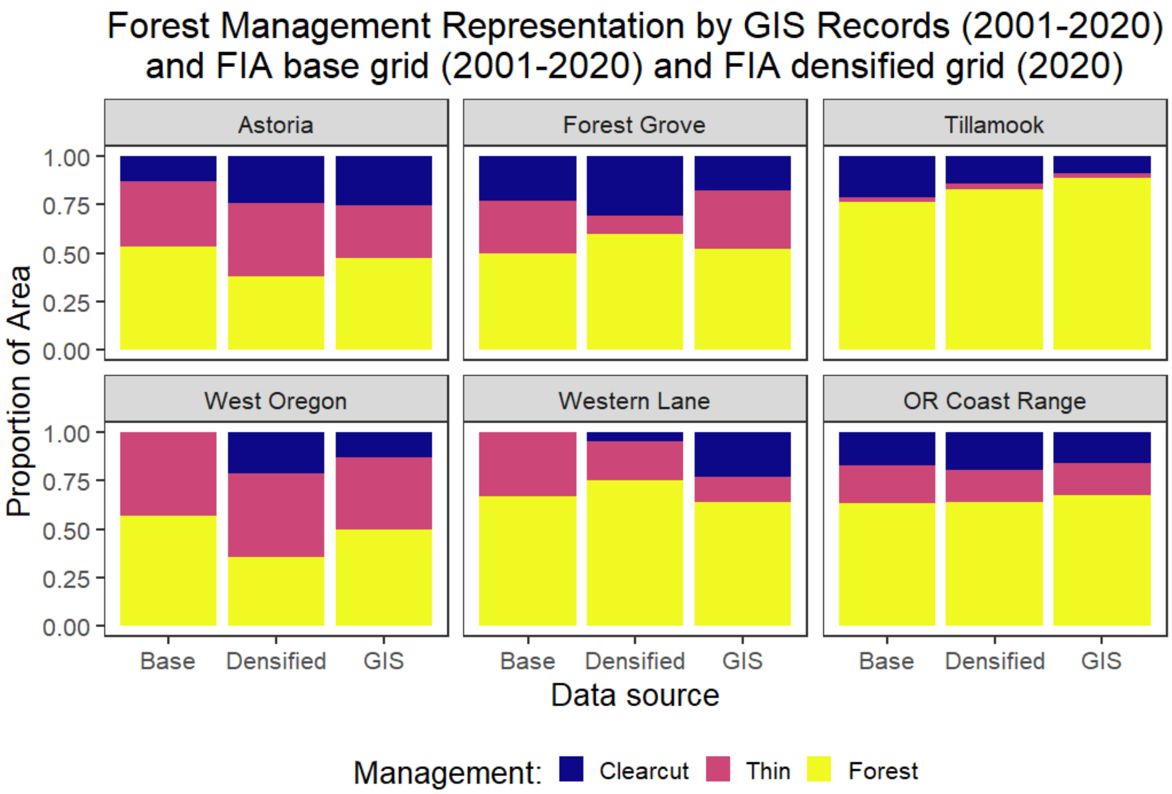

Figure 9: The proportion of district area with different management in the last 20 years represented by internal GIS records and FIA base grid and densified grid sampling. Management categories aggregate different types of management for simplicity (e.g., "Clearcut" includes modified clearcuts and salvage harvests and "Forest" includes no-harvest buffers within sale areas).

2. <u>Remote-sensing imagery saturation minimizing growth</u>

If remote-sensing products cannot track growth accurately once the canopy closes, then unmanaged areas would show greater growth in the FIA remeasurements than in the remote-sensing products. In an analysis similar to the Periodic Annual Increment (Figure 4), we calculated the 10-year change in LEMMA estimates (2007-2017) and FIA remeasured plots (2001-2020) within areas receiving no management according to internal GIS data. Growth estimated by LEMMA consistently underestimated growth compared with FIA mean growth estimates, although it was within the 95% confidence intervals of the FIA estimates (Figure 10). For the three North Coast districts, ground-measured growth was two to three times that of LEMMA modeled growth. It is likely that remote-sensing products systematically underestimate growth in mature forests and the total amount of carbon in larger biomass stands.

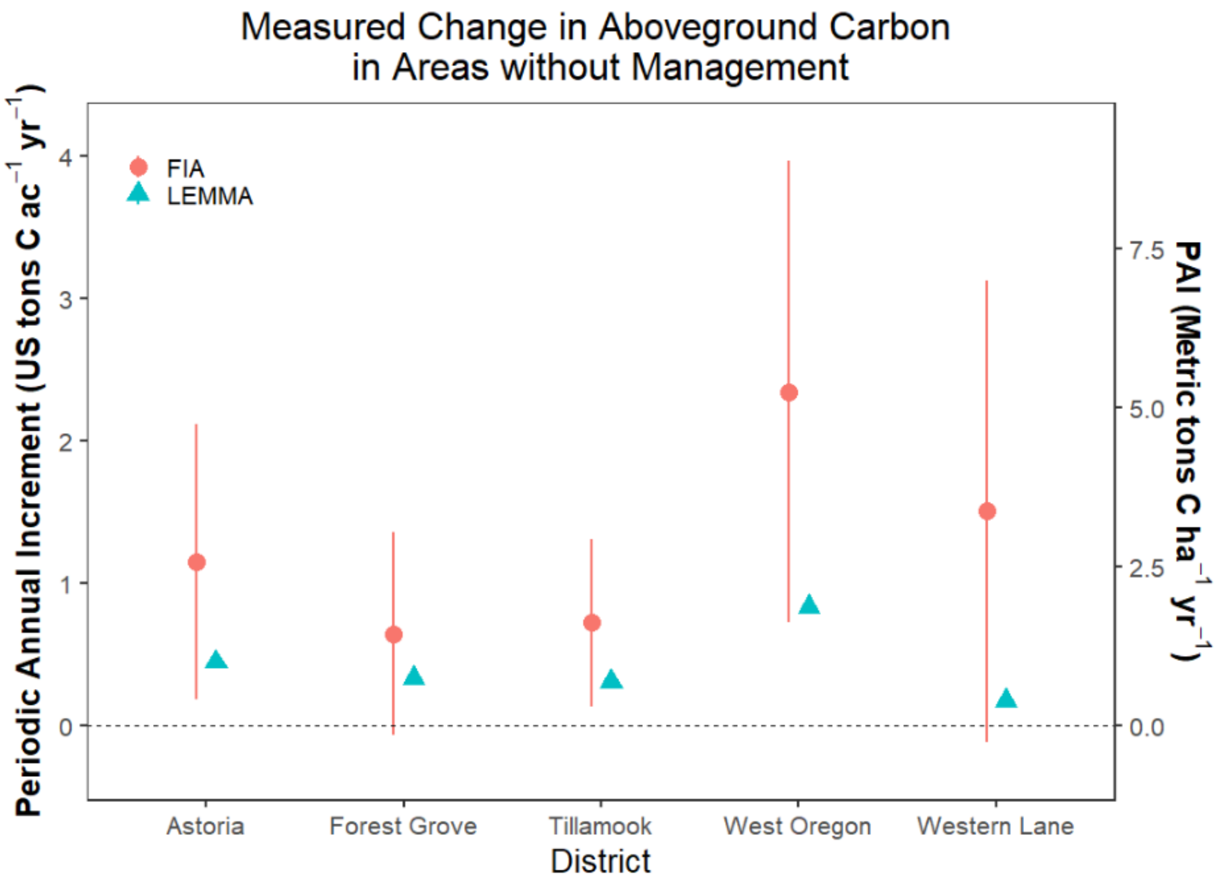

Figure 10: In areas without recent management, 10-year changes in LEMMA carbon estimates (blue triangles) underestimate the FIA plot estimates for remeasured plots (red circles and 95% confidence intervals) by district.

Underestimating high-biomass stands is not a problem unique to LEMMA. The remote sensing literature documents radiometric saturation[1] of Landsat band 3, corresponding to the green region of the electromagnetic spectrum (530 – 590 nm), upon canopy closure. We demonstrate the effect of saturation by comparing carbon estimates at the stand level (mean 86 acres) from SLI cruises from 2014-2018 and the three remote-sensing products. If radiometric saturation were not a source of bias, then the predicted aboveground carbon from a remotely-sensed dataset should match those from SLI ground measurements (visualized as data points following the diagonal black line in Figure 11). However, these remotely-sensed products generally overestimate carbon in low-biomass stands and underestimate carbon in high-biomass stands (blue line in Figure 11). We have not analyzed how underestimation of aboveground carbon, in stands above approximately 50-60 US tons/acre, could change the reported historical carbon trends in remote-sensing products (Figures 5 and 6).

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[1] Radiometric saturation occurs when a radiometric detection instruments' maximum measurable signal is exceeded by the input signal.

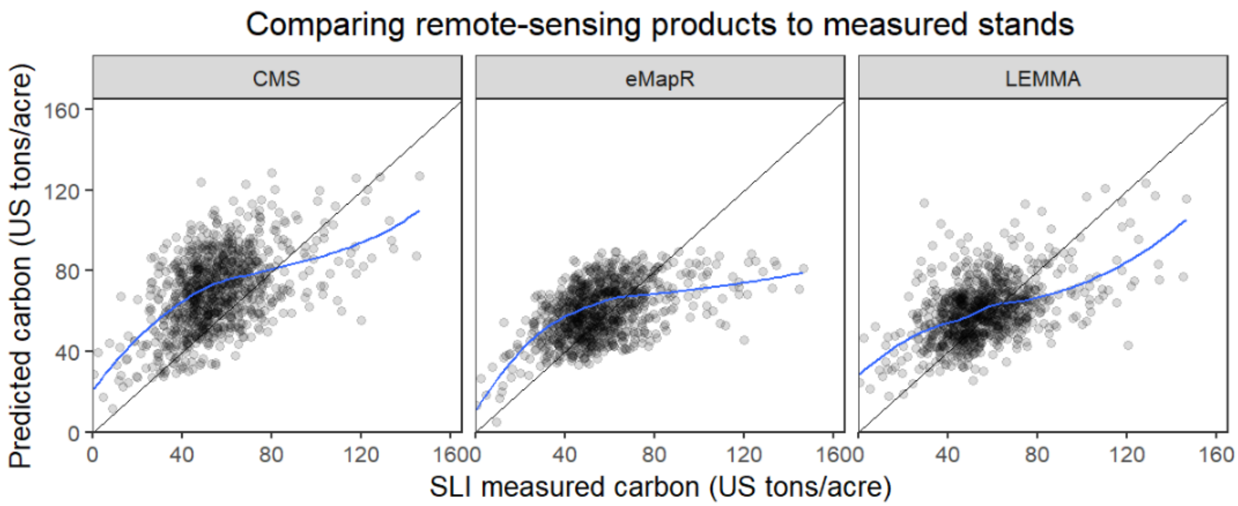

Figure 11: Three remote-sensing products overestimate carbon in low biomass stands and underestimate carbon in high biomass stands when compared to SLI ground measurements from the legacy inventory. Each data point is a stand measured between 2014-2018 (mean: 86 acres, range: 9-529 acres). Blue lines track the observed versus predicted carbon relationship with a locally weighted scatter plot smooth.

Carbon conclusions

Even though FIA monitoring and remote-sensing products have indicated different carbon trends, there is close alignment on the recent estimates of aboveground carbon on ODF-managed lands at the scale of management districts among LEMMA, base FIA, and densified FIA data (Figure 8). The differences among data sources for carbon estimates on ODF-managed lands are relatively minor compared to the differences noted across ownerships in the Coast Range (Figure 7). It is plausible that Landsat-based products do not adequately capture growth on higher-biomass stands, but we have not tested how this would shift carbon trends on ODF-managed lands compared to trends on other ownerships. External data sources will play an important role in verifying carbon trends reported by the EFI, especially as model products improve with technology such as spaceborne lidar. Rather than relying on a single data source for carbon or inventory trends, we will improve precision in estimates on ODF-managed lands by integrating the densified FIA monitoring with periodic lidar and other remote sensing products ("model-assisted estimation"). Ongoing work on the EFI ground data and modeling this year will improve our confidence in inventory data and will be used to forecast carbon and volume trends under different management scenarios.

RECOMMENDATIONS

Information only.

NEXT STEPS

The Inventory Program continues to integrate the EFI into Division needs and improve it through new ground monitoring, model development, and integration with external data sources. Volume and carbon status and trends will have improved estimates with quantified uncertainty once the EFI is fully operational. We have identified areas in which remotely-sensed biomass models align with FIA-based estimates and reasons why they may show different long-term trends. This analysis will inform Board-adopted Performance Measures for inventory or carbon and how to structure the reporting of Performance Measures with acceptable ranges and thresholds for action given their associated uncertainty.