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Deforestation Monitoring and Carbon Sequestration Remote Sensing Application

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Abstract

Management regimes and geographical variations in potential forest productivity significantly influence the dynamics of carbon sources and sinks. Spatially explicit data on land cover, stand age class, and harvesting practices can be effectively acquired through satellite remote sensing. When combined with regional climate records, carbon-cycle process models can estimate potential production rates and associated decomposition processes. This integration of remote sensing and modeling enables the generation of spatially explicit information on carbon storage and flux. Using this approach, carbon flow between 1992 and 1997 was analyzed across two 165 km² regions in western Oregon: the West Cascades and the Coast Range. The West Cascades study area, predominantly composed of less-productive public lands, experienced minimal harvesting during the 1990s, with only 1% of its land base harvested between 1991 and 2000. In contrast, the Coast Range study area, largely managed for timber production on private lands, saw 17% of its land base harvested during the same period. Despite hosting a substantial proportion of young, highly productive stands that acted as carbon sinks, the Coast Range's mean annual harvest removals exceeded its mean annual net ecosystem production. Conversely, the West Cascades region functioned as a net carbon sink. The spatially and temporally explicit nature of this integrated approach allows for detailed identification of the mechanisms driving carbon flux across forested landscapes.

Keywords: Remote Sensing; Deforestation Monitoring; Carbon Sequestration; Forest Management; Carbon Flux Modeling

Introduction

The process of removing, utilizing, and storing carbon dioxide from the atmosphere in order to lessen its impact on global warming is known as carbon sequestration (Qiu, Feng, Song, Zhang, 2020). Experts can use both natural and artificial methods, such afforestation and carbon capture technology, to promote carbon sequestration in the aftermath of climate change and its catastrophic effects on global temperatures and water supplies. Palit and Banerjee (2024). In order to assure sustainable mitigation of climate change and land resource management, researchers are drawn to the intriguing technique of quantifying carbon sequestration. Hammad et al. (2020) claim that by combining croplands and bushes for carbon absorption, agricultural landscapes effectively remove significant amounts of greenhouse gasses from the surrounding environment. Using drones and aerial photography, satellite imagery gathers data on vegetation, land cover, and other surface activities on Earth. Palit and Banerjee (2024). Therefore, Geographic Information System (GIS) technology is used to evaluate and understand the data in order to facilitate informed decision-making. Professionals assess and quantify carbon retention in agricultural settings using remote sensors and GIS due to their exceptional ecological study abilities. With satellite photography, plant types, nutritional status, and geographic distribution are all identified. Qiu and associates (2020).

When remote sensing is used with Geographic Information System (GIS) techniques, carbon sequestration estimations are more precise and effective (Banerjee and Palit, 2024). This method helps quantify biomass and estimate carbon stocks in soil and trees, and it allows researchers to compute and display the carbon dynamics within agroforestry systems (Lessmann, Ros, Young, & de Vries, 2022).

In order to understand the factors influencing carbon sequestration rates, GIS also takes ecological aspects like topography and climate into account. This integration also helps land managers and politicians make well-informed decisions about sustainable land use (Lessmann et al., 2022). Monitoring of temporal changes in carbon sequestration, deforestation, vegetation growth, and afforestation activities is made possible by the integration of remote sensing and Geographic Information System (GIS) approaches. GIS is crucial to climate change mitigation because it assesses the long-term feasibility of agroforestry practices and provides geographical data for optimal placements for carbon sequestration. Lessmann and associates (2022). This connection enhances real-time monitoring and adaptive environmental management solutions for climate change resilience and mitigation decisions. Some of the newest tools for assessing carbon in agricultural landscapes are presented in this review. The introduction emphasizes the importance of carbon sequestration in order to place the research within the framework of mitigating climate change. Additionally, it examines agroforestry landscapes as the main source of carbon sequestration using GIS and sensing techniques (Lessmann et al., 2022).

With an area of about 4 billion hectares, forests comprise one-third of the planet's landmass. The Boreal and Equatorial zones contain the biggest tracts of forest. This distribution is not static; rather, it has evolved over time as a result of human activity and environmental change. Forest classified as primary or intact accounts for one-third of present-day forested lands [FAO 2020]. Because of anthropogenic activities, the future of the remaining two thirds is questionable. Several million hectares of forest are lost annually, and others are degraded. The total loss of forest cover is known as deforestation. Deforestation is mostly caused by conversion to pastoral or agricultural land. Secondary forests can form when forest cover returns to some areas after they have been abandoned. Degradation, as opposed to deforestation, is the partial loss of forest cover. It is described as a reduction in the forest's ability to deliver ecosystemic services (forest products, carbon storage, etc.) as a result of human activities (Hammad, 2020). This degradation is characterized by the breaking up of forested areas following illegal land clearing, overexploitation of wood fires, etc. Degraded forests include a large diversity of forest types depending on the nature, intensity and frequency of the degradation. Forests provide a diversity of products and ecosystemic services. The living biomass of forests stores around 300 pg of carbon which means it plays an important role in the potential mitigation of climate change. Forests also represent a reservoir of biodiversity, especially tropical forests. Knowing the extent of forested areas, the state of forests and how they change over time is therefore particularly important with regard to current environmental concerns linked to climate change.

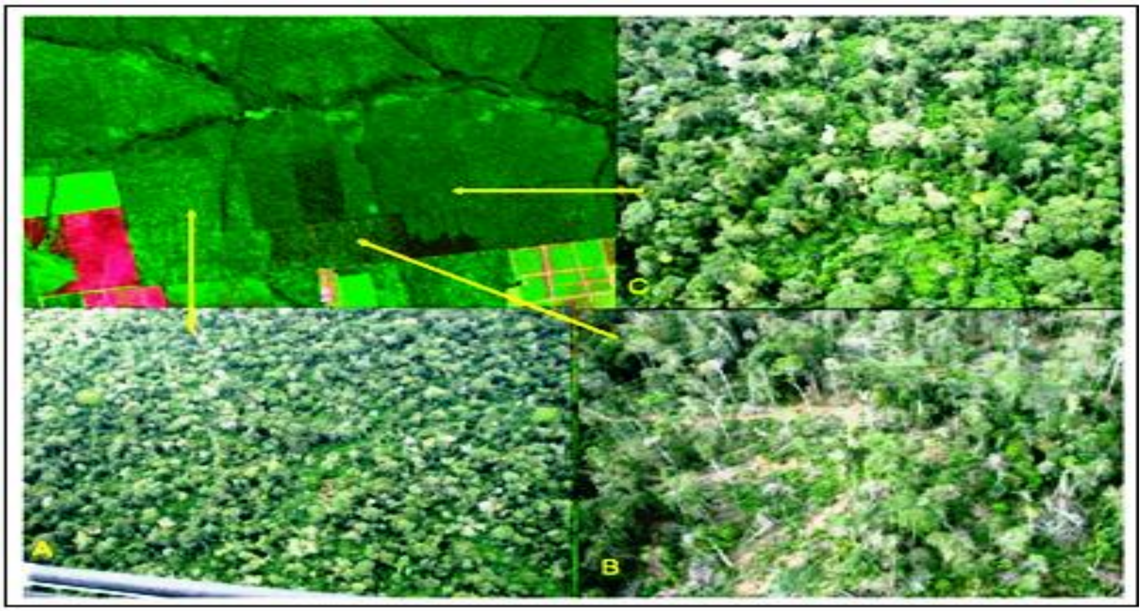


Figure 1: Information collected by remote sensing

Literature Review

Monitoring carbon sequestration in forests is crucial for global sustainability initiatives as climate change escalates. By absorbing atmospheric carbon dioxide (CO2) through photosynthesis and storing it as biomass in trees and soil, forests serve as important carbon sinks. To comprehend how forests help lower greenhouse gas concentrations, it is essential to accurately measure carbon sequestration. Song, Zhang, Feng, and Qiu (2022). Remote sensing (RS) and geographic information systems (GIS) offer an economical and effective way to manage huge forests by providing the instruments required for accurate monitoring and analysis. This article explores how GIS technology is revolutionizing carbon sequestration monitoring and the critical role it plays in sustainable forestry Qiu, Feng, Song, Zhang, (2022).

The Need for Carbon Sequestration Monitoring

Forests, soils, and oceans are all vital parts of the carbon cycle on Earth. They store CO2 in the form of biomass after absorbing it from the atmosphere. A forest's ability to store carbon is influenced by a number of variables, including species mix, forest age, and land management techniques. To determine how much carbon a forest can store and comprehend its role in reducing climate change, accurate and timely monitoring of carbon sequestration is essential. Nelson Srubar Arehart (2020).

On-site biomass evaluation is one of the labor-intensive and frequently area-limited traditional ways of monitoring carbon sequestration. On the other hand, forestry managers can effectively monitor large forested regions because to the comprehensive and scalable solutions offered by GIS and RS. These technologies support the accurate estimation of forest biomass, detection of deforestation, and the assessment of potential carbon stock loss during forest degradation Arehart, Nelson Srubar (2020)

How GIS and Remote Sensing Aid Carbon Sequestration Monitoring

GIS and remote sensing technologies are capable of providing high-resolution spatial data, making it possible to monitor forest health, carbon stocks, and land use changes over time. Below are some key applications: Identifying Project Sites: GIS helps identify potential areas for carbon sequestration projects by analyzing forest cover, soil conditions, and climate data. This assists in locating areas with high carbon sequestration potential and minimal vulnerability Zhang, (2022).

Visualizing and Predicting Trends: GIS allows users to model how forest carbon stocks change over time and space. Using historical data and predictive models, GIS can forecast future carbon sequestration potential based on variables like climate change, land-use shifts, and forest management practices.

Estimating Biomass and Carbon Stocks: One of the core capabilities of GIS and RS is the estimation of above-ground and below-ground biomass. By using multispectral and LiDAR data, GIS systems can calculate the carbon stock and map forest areas with high sequestration potential Zhang, (2022).

Prioritizing Forest Conservation: With the help of GIS, forestry management can prioritize forest areas based on their carbon sequestration potential. This helps guide conservation efforts toward areas that can store the most carbon and are less prone to deforestation or other disturbances Srubar (2020).

Techniques for Carbon Sequestration Measurement

Several models and techniques are used to quantify carbon sequestration levels in forests. These include: Allometric Equations: These equations help estimate the biomass of trees based on their diameter, height, and species type.

Genetic Algorithm Models: This advanced modeling approach combines algorithms with environmental parameters to predict carbon sequestration.

Grey Correlation Analysis: This method analyzes the relationship between various environmental factors and carbon sequestration over time, helping improve predictive accuracy.

By integrating these models with GIS platforms, forest managers can simulate future scenarios, offering insights into how carbon stocks may change and where conservation efforts should be focused Srubar (2020).

Future Trends in Carbon Sequestration Monitoring

As we move toward a low-carbon future, there is increasing demand for more refined models to predict how forests will sequester carbon under various climate scenarios. New techniques like real-time visualization, temporal change modeling, and interactive GIS dashboards are emerging. These tools enable stakeholders to make data-driven decisions for carbon stock management, forest conservation, and compliance with global environmental standards.

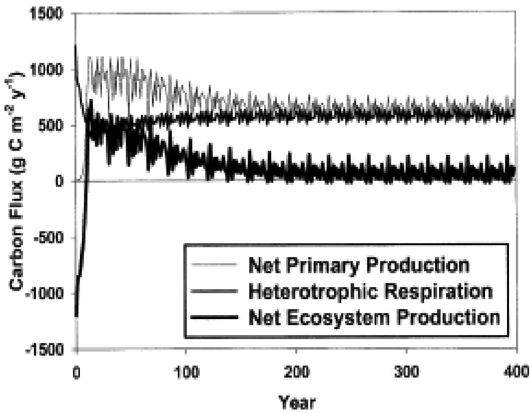


Figure 1. The trends in net primary production, heterotrophic respiration, and net ecosystem production over the course of succession. Values are from a simulation with the Biome-BGC model at a mid-elevation site in the Coast Range. The climate data are repeating loops of an 18-year daily climatology Zhang, (2022).

The identification of regions with stand replacing disturbances (harvesting or burning) is made possible by repeated remote sensing coverage of the land area over a period of several years. This gives supplementary information on carbon transfers off the land base. In this work, two 165-km2 regions in the Pacific Northwest were monitored for forest carbon sequestration using a combination of remote sensing and modeling. Comparing the carbon flux in two wooded areas with different management histories and potential for production was the aim.

Methodology

The NEP scaling methods and initial validation results for their application in the Pacific Northwest have been reported previously (Turner and others 2023; Law and others in press) and are briefly reviewed here. The primary scaling tool in this approach is the Biome-BGC carbon-cycle process model (Law and others 2001; Thornton, 2022). To replicate primary and secondary succession, the model is run over a period of years using a daily time step. Photosynthesis, plant respiration, heterotrophic respiration, plant carbon allocation, and plant death are among the activities that are simulated. According to the models, NEP is negative immediately following harvest, remains constant or drops to almost zero in late succession, and is considerably positive in early to mid-succession (Figure 1). Numerous chronosequence investigations have noted this general tendency (Sprugel 2023; LaW 2021).

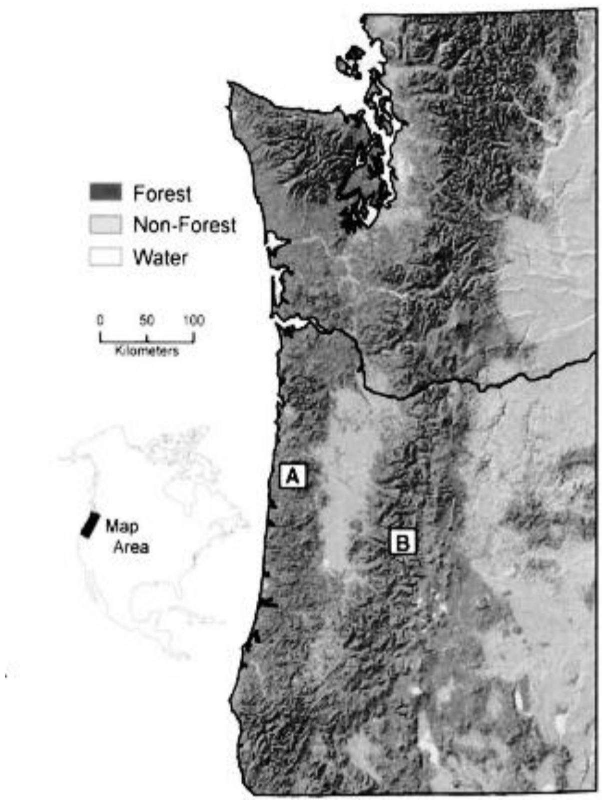
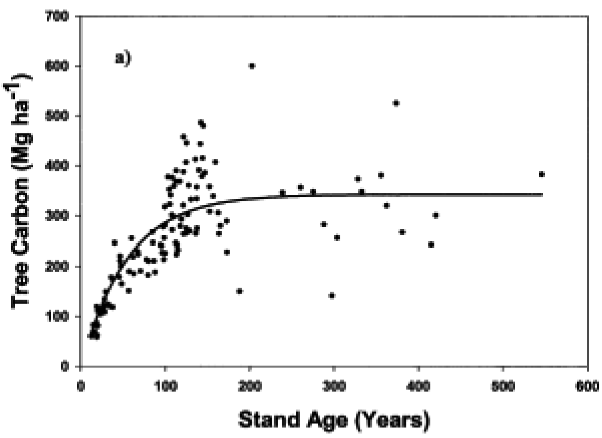
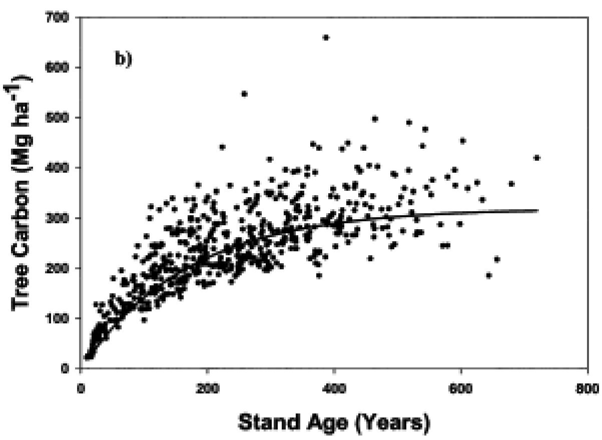


Figure 2. The Pacific Northwest region. The studies areas are in the Coast Range (A) and the West Cascades Mountains (B).

For this study, Biome-BGC was run over a 25-m resolution grid for two areas of interest in western Oregon. Much of the forested portion of the Pacific Northwest is characterized by patches smaller than 1 km2 that originated from clearcut harvesting (Cohen, 2020), and stand age is a strong determinant of carbon flux (Sprugel 1985; Law and others in press). Thus, a 25-m resolution is essential to characterize spatial patterns in carbon flux (Cohen and; Turner, 2024). Two areas (each 165 km2) were selected (Figure 2) to provide a contrast in productivity and land use. The Coast Range study area is at relatively low elevations (mean of 383 m), has high soil nitrogen and potential productivity, and is intensively managed for wood production Zhang, (2022). The West Cascades area is at higher elevations (mean of 902 m) with colder winter temperatures, more snow, and seasonally dry summers. The West Cascades study area is largely public land that, for the most part, has not been harvested in the last 10 years. The requirements for model initialization include specification of land-cover type (e.g., conifer versus deciduous forest) and a stand age. Land cover determines the set of ecophysiological constants used in the model (the EPC file), and stand age determines the age to which the model simulation is run after a standinitiating disturbance to estimate current carbon pools and flux. The land-cover analysis resolved five primary vegetation classes (Table 1). The conifer, broadleaf, and mixed classes were all 85% cover, whereas the semiopen class was 31–84% cover and the open class was 30% cover. EPC files were created for each cover type based on White (2023) and recent field measurements (Law and others in press). For all stands 30 years of age, the year of stand origin was determined from remote sensing. These estimates were provided by analysis of current imagery from the Landsat Thematic Mapper sensor and change detection analysis using additional Landsat Thematic Mapper and Multispectral Scanner imagery from the last 30 years (Cohen 2022). These stands were aggregated into two classes: those 1–13 and those 14–29. For conifer stands 29 years, the remote sensing analysis was able to resolve three classes; young (30–99), mature (100–200), and old (200). For the other cover types, a reference age of 45 years was used that reflected the limited knowledge that they were 29 years old based on the change detection analysis. To drive the model, a daily climatology of minimum temperature, maximum temperature, precipitation, humidity, and solar radiation is needed. That data were provided by the DAYMET model, which performs spatial interpolation between meteorological stations using a Digital Elevation Model (DEM) and general climatological principles such as lapse rates (Thornton and others 1997; Thornton and Running 1999; Thornton 2020). DAYMET was run over a

1-km grid for the conterminous United States and the climate database covered the 18 years from 1980 to 1997 (courtesy of P. Thornton, National Center for Atmospheric Research). The Biome-BGC model is sensitive to the leaf area index (LAI), which may also be derived from remote sensing (Spanner and others 1994; Turner and others 1999). However, the LAI cannot by directly prescribed because it is self-regulating within the model. The relatively dry summers in the Pacific Northwest mean that the water storage capacity associated with soil depth strongly influences the maximum LAI that can be supported on a site (Grier and Running 1977). Therefore, an initial set of model runs was made for each cover class within each 1-km grid cell using different soil depths to determine the soil depth that resulted in an LAI closely matching the corresponding LAI from remote sensing. Note that soil depth also impacts NPP and, hence, pools of aboveground and belowground carbon, so uncertainties in the remote-sensing-based LAI (Law, 2020) tend to be propagated into the carbon flux estimates. Once the input datasets were assembled, a model "spin-up" was conducted for 1000 years to generate the slow turnover soil carbon pools and bring them into near-steady-state. The magnitude of the soil carbon pools is important because these pools continue to support heterotrophic respiration after a disturbance and, thus, must be correctly estimated to accurately simulate NEP in early succession. For the spin-up, the 18-year climate record was repeated as needed. To account for the effects of wood residues from previous disturbances on NEP, a disturbance regime was imposed in the model runs after the spin-up such that two clearcut harvests preceded the final secondary succession. In these disturbances, a specified proportion of tree carbon (70%) was transferred off site and the remainder was assumed to stay on site to decompose. After the spin-up and the disturbances, the model was run forward to the age associated with the remote sensing classification. For the conifer cover type, the reference age was the midpoint of the age range for the remote-sensing-based classes. In the model runs, yearly meteorological files were arranged as needed such that for all runs, the last 18 years were 1980–1997. Outputs were saved as surfaces for each year from 1980 to 1997 and included NPP, stemwood production, NEP, and live carbon mass. The resulting map of NEP accounted for all biologically driven carbon fluxes. A mean value for the last 5 years of the simulation was used in reporting the results to minimize effects of interannual variation in climate. Carbon is also transferred off the land base by harvesting and fire. To account for harvests, a flux was estimated based on the change detection analysis (Cohen, 2022). Surfaces for land cover in 2000 and 1991 were compared and all forested area that had been harvested was identified. The amount of aboveground tree carbon at the time of harvest was based on an ecoregion-specific relationship of stand age to aboveground tree carbon (Figure 3). A stand age of 90 was assumed (Spies 2023). After adding an estimate of carbon in coarse roots to the aboveground tree carbon estimate, the proportion of tree carbon removed from the land base at harvest was derived from the relationship of merchantable to total tree carbon in Turner, (2023). Burned areas should be treated differently because a larger proportion of tree carbon is usually left after disturbance, but fire was not a significant factor in these areas during the study period.

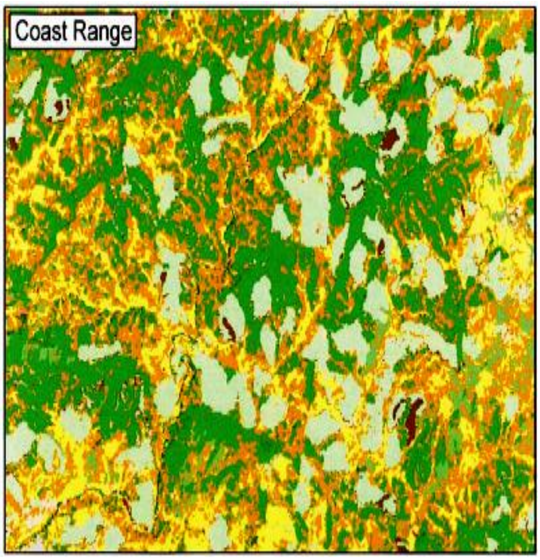


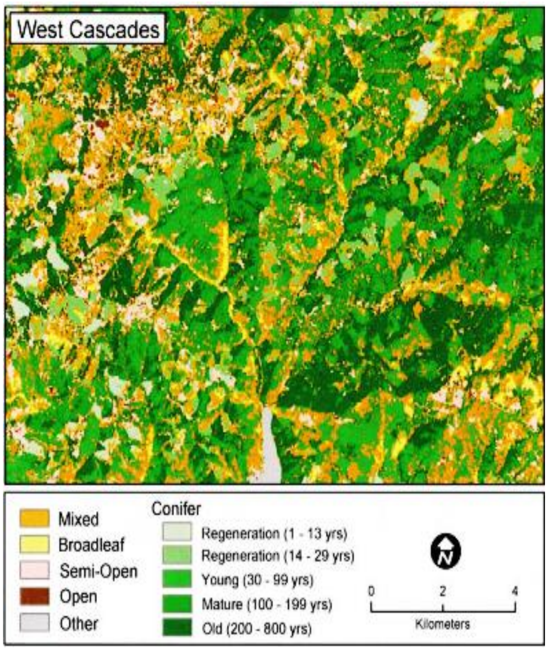


Results and Discussion

Land-Cover and Stand-Age Class Distribution The land cover in both study areas was predominantly conifer forest (Figure 4, Table 1). In the more mesic Coast Range, red alder (Alnus rubra) competes with conifer species across much of the landscape, resulting in a relatively large proportion of the area as mixed conifer/hardwood (21%) or hardwood

(11%). Overall accuracy of the remote sensing classification for a large area in western Oregon was on the order of 80% based on validation with aerial photography (Cohen 2024). The stand-age class distribution within the conifer class was dominated by relatively young stands in the Coast Range study area but relatively old stands in the West Cascades area (Table 1). Less than 4% of the Coast Range area was classified as mature or old conifer compared with 21% in the West Cascades area. Much of the Coast Range was heavily logged or burned in the early part of the 20th century, leaving little area in the oldest age classes. The area continues to be logged with a dispersed clearcutting approach (Figure 4). The cutting in the West Cascades was largely delayed until after 1950 (Harris 2023). The harvest rate reached a peak in 1985 and has subsequently fallen dramatically to accommodate the conditions of the Northwest Forest Plan (Garman, 2020). NPP/NEP Analysis The mean NPP was higher in the West Cascades (684 g C/m2 /year) than in the Coast Range (571 g C/m2 /year). This difference was primarily a reflection of differences in age class distribution rather than differences in the productive potential of the forests in the two geographical areas (Law and others in press). A much larger proportion of the Coast Range area was in the early regeneration phase (age 14) compared to the West Cascades. The simulated NPP is relatively low in this class; hence, the overall mean NPP is lower. There was more area in the mature and old classes in the West Cascades, but the NPP remains relatively high in those stands, so the impact on mean NPP was not large (Acker, 2022). Differences in the productive potential were indicated in the conifer age sequence by a more rapid recovery of the maximum NPP in the Coast Range. The older regeneration class (age 14–29) had a mean NPP





of 824 g C/m^2 /year in the Coast Range compared to 601 g C/m^2 /year in the West Cascades. The faster recovery of NPP in the Coast Range may be due to more favorable climatic conditions (Runyon, 2023) as well as higher nitrogen availability. Foliar nitrogen concentrations for conifers are generally higher in the Coast Range than in the West Cascades (Law and others in press). In the Old class, mean NPP values were only marginally higher in the Coast Range. Law and others (in press) found good agreement between the NPP modeled by Biome-BGC and the measured NPP at 36 sites in a set of 3 chronosequences in western Oregon (slope of 1 to 1 line = 1.1, R^2 = 0.73). The mean NPP in nonconifer-cover classes was lower in the Coast Range (Table 2) despite generally more favorable growing conditions, and the presence of thenitrogen-fixing alder. This pattern was driven primarily by lower LAIs as indicated by remote sensing. There has been relatively little validation of the LAI and NPP differences for the nonconifer-cover classes in these study areas and this uncertainty should be addressed in future studies (Zhang, 2022). The mean NEP (Table 3, Figure 5) was 199 g C/m2 / year for the Coast Range area compared to 177 g C/m2 /year for the West Cascades area. The most negative NEPs were in the early regeneration class (ages 1–13) of conifers in the West Cascades, where a slow recovery of NPP did not provide a strong enough carbon sink to overcome the carbon source associated with decomposing harvest residues. The maximum NEP was in the Coast Range in the older conifer regeneration class (ages 14–29), where the LAI had fully recovered and the carbon source from decomposing residues had significantly declined.

Estimates of the NEP are more difficult to evaluate than the NPP because of the greater uncertainty about the measured NEP. Quantifying the NEP requires estimates of carbon budget components that each have associated errors (Law and others in press). For the modeled values, one of the greatest uncertainties is the amount of wood debris left after the harvest. Annual NEP estimates are increasingly being made at eddy covariance flux tower sites and these values will provide additional opportunities for model validation (Law, 2022). As with the NPP, the age class distribution of the stands strongly influences the mean NEP estimates. The large areas of low NEP mature and old conifer in the West Cascades area tended to reduce the area wide mean NEP value. There was also about three times as much area in the highest NEP class (young) in the Coast Range, which tended to give it a higher NEP. Land-Base Carbon Flux The area harvested between 1991 and 2000 in the Coast Range study area was a significant proportion of the total area (16.9%). That pattern is consistent with the transition to predominantly short-rotation plantation forestry in the Coast Range (Rasmussen and Ripple 2020; Garman, 2023). Virtually no harvesting (1% of the area) occurred during that period in the West Cascades. Most of the West Cascades area is in the Willamette National Forest and was subject to a legally mandated reduction in harvest in the 1990s. Thus, the average rate of removal over the study area was 364 g C/m2 /year in the Coast Range and 7 g.

Table 2. Modeled NPP by cover class.

Cover type	Coast Range Mean (g C/ m^2/year)	Coast Range SD	Coast Range Total (g C × 10^6)	West Cascades Mean (g C/ m^2/year)	West Cascades SD	West Cascades Total (g C × 10^6)
Conifer						
Regeneration (1–13)	160	35	4,752	439	164	1,097
Regeneration (14–29)	824	201	6,510	601	238	4,748
Young (30–99)	897	70	40,634	1,017	151	22,781
Mature (100–200)	845	54	3,126	802	56	29,273
Old (+200)	784	72	627	715	44	24,238
Broadleaf	491	97	11,195	752	86	1,221
Mixed	546	49	25,061	622	61	17,108
Semiopen	262	52	1,729	455	84	11,134
Open	239	10	526	313	86	1,278
Other	—	—	—	—	—	—
Total			94,160			112,878

Note: Ranges for stand age are given for conifer classes. The total NPP is the product of the area and the mean value.

Table 3. Modeled NEP by cover class

Cover type	Coast Range Mean (g C/ m^2/year)	SD	Total (g C × 10^6)	West Cascades Mean (g C/ m^2/year)	SD	Total (g C × 10^6)
Conifer						
Regeneration (1–13)	−6	14	−178	−142	47	−355
Regeneration (14–29)	389	92	3,073	254	98	2,007
Young (30–99)	299	22	13,545	354	69	7,930
Mature (100–200)	84	6	311	82	14	2,993
Old (+200)	47	4	38	49	8	1,661
Broadleaf	202	42	4,606	320	72	1,248
Mixed	230	21	10,557	265	27	9,964
Open	99	4	218	134	35	228
Semiopen	109	22	719	193	35	3,455
Other	—	—	0	—	—	0
Total			32,889			29,171

Note: Ranges for stand age are given for conifer classes. The total NPP is the product of the area and the mean value.

Conclusion

Satellite remote sensing in combination with spatially distributed carbon-cycle modeling shows promise for monitoring of land-base carbon flux at high spatial (30 m) and temporal (3–5 years) resolutions. Both the NEP and harvest removal components of a land-base carbon budget are treated. In western Oregon, this approach revealed areas of intensively managed forest that tended to lose carbon or be near the carbon steady state with respect to the land base (however, they were carbon sinks in terms of storage of long-lived forest products). Areas with relatively little harvesting in the last 10 years had an older stand-age class distribution and were significant carbon sinks.

The monitoring of carbon sequestration in forestry is a crucial part of global climate mitigation efforts. With the aid of GIS and remote sensing technologies, we now have the tools to track and predict carbon stocks on a global scale, enabling better forest management and environmental decision-making. As more companies, governments, and organizations look to reduce their carbon footprints, technologies like those offered by SPARC will play an essential role in supporting sustainable development and protecting our planet's natural carbon sinks. In the era of climate change, utilizing advanced geospatial tools for carbon sequestration monitoring is not just an option but a necessity for a low-carbon future.

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