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Coastal Douglas-fir Conservation Partnership (CDFCP) Carbon Project Feasibility Assessment

Project team

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Section 1 – Introduction

Nature-Based Solutions (NBS) are ways natural systems can be managed to mitigate carbon emissions and minimize negative impacts on ecosystem services. Forest carbon projects are one example of an NBS. When structured appropriately, a forest ecosystem can be managed such that it generates carbon credits. A carbon credit is a transferable instrument certified by government or independent bodies that represents an emission reduction (either from removals or avoided emissions) of one metric tonne of CO_2 or an equivalent amount of other greenhouse gases (GHGs). A carbon offset constitutes a carbon credit used to compensate for emissions that occur elsewhere, outside the project boundary. The terms carbon offset and carbon credit are often used interchangeably.

There are strong arguments for carbon credits as a tool for NBS[1]:

- The private sector pays for carbon offsets, which allows capital to flow directly to priority areas that have been traditionally underfunded.
- Robust carbon offset frameworks provide strong measuring, reporting and verification requirements to ensure projects result in genuine benefits.
- Carbon offsets can lower compliance costs for entities that must reduce their carbon footprint.
- Cost-effective mitigation options like offsets will help lower the overall costs of transitioning to a low-carbon economy.
- Carbon offsets broaden sources of revenue for the forest sector beyond timber extraction (conservation-based management, for example).

To ensure a carbon project delivers benefits to the atmosphere, credits must be:

- **Real:** They are derived from actual, real-world projects.
- **Additional:** Beyond GHG emission reductions or removals that would otherwise occur without revenue from sale of the carbon credits.
- **Verifiable:** Emissions reductions and removals that can be demonstrated to have occurred.
- **Permanent:** Emission reductions or removals are durable and protected over time.

On March 14, 2022, a representative of the Coastal Douglas-fir Conservation Partnership (CDFCP) engaged with 3GreenTree on work to inform the CDFCP of the potential for developing a grouped carbon offset project within its area of operations. In addition to the Coastal Douglas-fir Biogeoclimatic Zone, the CDFCP encompasses the very dry maritime variant (CWHxm) of the Coastal Western Hemlock Biogeoclimatic Zone in its working boundary, as well as components of watersheds and islands that are related to CDF and CWHxm ecosystems. This work

[1]After Monahan et al. 2020. NATURE-BASED SOLUTIONS: POLICY OPTIONS FOR CLIMATE AND BIODIVERSITY. Smart Prosperity Institute, University of Ottawa, Ottawa, ON. (institute.smartprosperity.ca).

encompassed two principal activities. The first activity was a mapping exercise to: (a) Delineate Private Managed Forested Land, Forest on Agricultural Land, Forest on First Nations Land, and Municipal Forests[2]; (b) Determine ownership of individual parcels within the private landbase, parcel size and carbon stock per ha; and (c) Assess how private land holdings might be assembled to form the nucleus of a grouped carbon offset project. The second activity was a review of potential carbon standards and methodologies as the basis for a grouped carbon offset project within the CDFCP operating area.

Section 2 – The Mapping Exercise

The project area consists of all private land holdings within the ~5000 km^2 CDFCP operating area.

GIS, Spatial Analysis, and Modeling

Forest cover and associated attribute data are required for the carbon modelling. The primary source of forest attribute data in BC, the Vegetation Resource Inventory (VRI), does not, however, contain data for the ~2000 km^2 (40% of the CDF zone) of private lands. A spatial database of basic forest cover information (vegetation type, broad age class, and aboveground biomass) was developed for lands within the study area using publicly available satellite imagery. The process involved the following steps: 1) Preparing a composite satellite image for the study area, 2) Classifying landcover types in the study area (and identifying forest area as either coniferous or deciduous), 3) Estimating broad age groups by forest type, and 4) Estimating aboveground biomass (AGB) in forested pixels. A detailed description of each step is provided below.

1. **Image preparation.** A Sentinel-2 satellite composite image of the CDF zone was developed in Google Earth Engine (GEE) using a cloud masking algorithm (Google, 2022a). Cloudy areas in the composite were filled using images captured between June 1st to September 29th, 2021, while prioritizing more recent imagery. A total of 217 images were used to build the composite. The image resolution was 20m*20m and includes 10 wavelength bands.

2. **Supervised landcover classification.** Supervised classification involves 4 general steps: 1) Collecting training samples representative of the different landcover classes; 2) Training a classifier algorithm to develop relationships between spectral signatures and landcover classes; 3) Implementing the classification algorithm on the target imagery; and 4) Performing an accuracy assessment of the classification[3]. Six landcover classes were differentiated using this approach: coniferous forest, deciduous forest, non-forest

[2] Although the CDFCP is keenly interested in incorporating FNs lands within the project boundary, this will introduce considerable complexity to the project development process and is not considered at this time.
[3] Stehman, S. V, & Foody, G. M. (2019). Key issues in rigorous accuracy assessment of land cover products. *Remote Sensing of Environment*, *231*, 111199. https://doi.org/https://doi.org/10.1016/j.rse.2019.05.018

vegetation (agriculture, grassland, greenspace, etc.), water, urban areas, and recently harvested areas (cutblocks)(Figure 1).

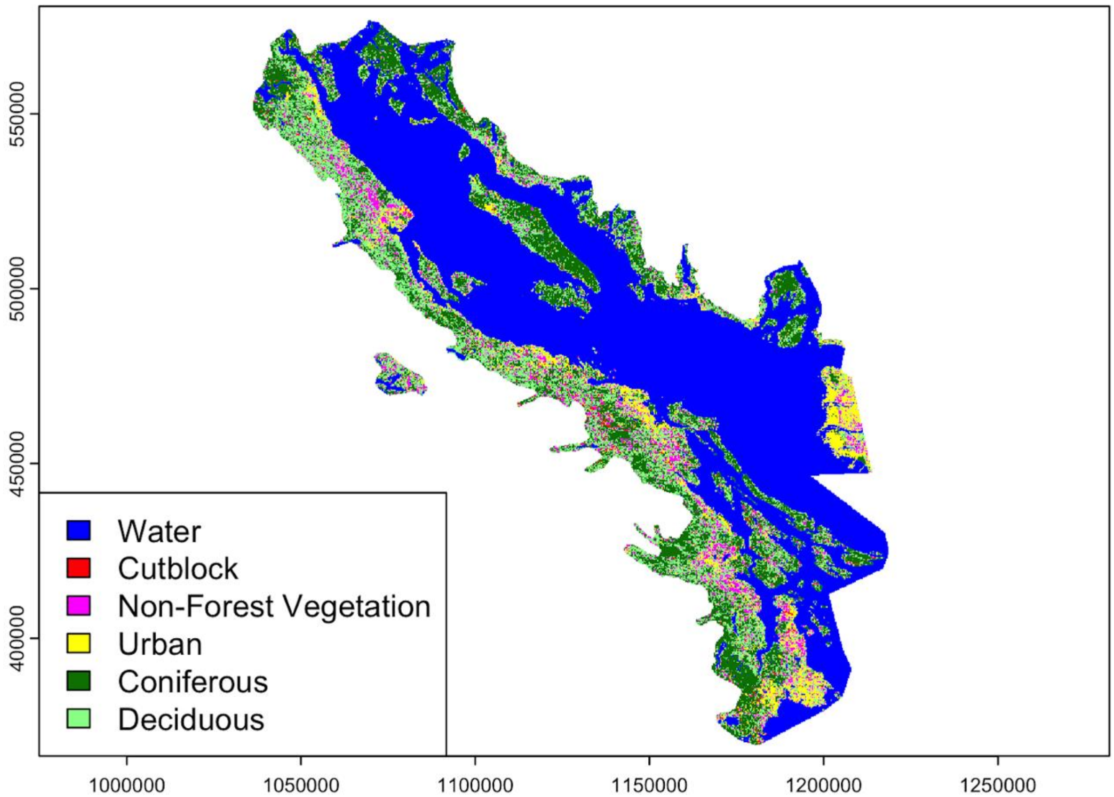


Figure 1: Random Forest (RF) classified Sentinel-2 image showing the distribution of the six predicted landcover classes. This classification had an overall accuracy of 0.79, with a Kappa coefficient of 0.74.

Landcover classes were well distributed and admixed throughout the study area (Figure 1). Aggregations of coniferous stands can be found in northern and southern regions, and on some of the Gulf islands. This probably indicates areas with relatively little disturbance since conifers are indicative of late seral stage conditions (see also below).

There are 6 principal owner types within the analysis area (Table 1). Collectively, they represent ownership of 76,135 properties. Private land is, by far, the most common ownership type, with municipal ownership a distant second. First Nations lands had the smallest ownership property count. Most properties are comprised of multiple parcels (Table 1). With respect to developing a grouped carbon project, many owners will have the option to enrol only selected parcels rather than being forced to make an all-or-none decision as to participation.

Total area reflects the ownership count in that there is more than 230,000 ha in private hands, with 53,000 ha and about 29,000 ha, in provincial and municipal ownership, respectively (Table 1). All lands have a relatively high percentage of their area as forest, ranging from 73% (private land) to 89% (First Nations)(Figure 2). Of the forested area, a clear majority was comprised of conifer-dominated stands (Figure 2). Private lands are a striking exception, which tend to contain more deciduous-leading stands (54%). The latter is indicative of prior disturbance, particularly harvesting, which would have removed the late seral conifer component and been replaced by regeneration of early seral deciduous species. This is a natural process of stand development within the CDF following disturbance. Given enough time, many of these are likely to revert to late seral coniferous-dominated stands if there is sufficient understory conifer regeneration. This deciduous feature of private lands would not necessarily have a material impact from the perspective of carbon credit potential. It does serve to highlight the degree of historical disturbance on private land, emphasizes the ongoing threat of forest removal, and thereby establishes a strong argument for a carbon-based conservation project.

Table 1. Ownership metrics within the analysis area.

Ownership type	*Count*	*Parcel multiplier*	*Total area (ha)*	*Biomass per ha*
Provincial	1,895	3.2	53,019	308.3
Federal	230	2.7	11,179	294.9
First Nations	53	16.7	5,210	323.0
Municipal	6,260	2.2	28,918	225.8
Private	49,281	5.7	230,461	232.1

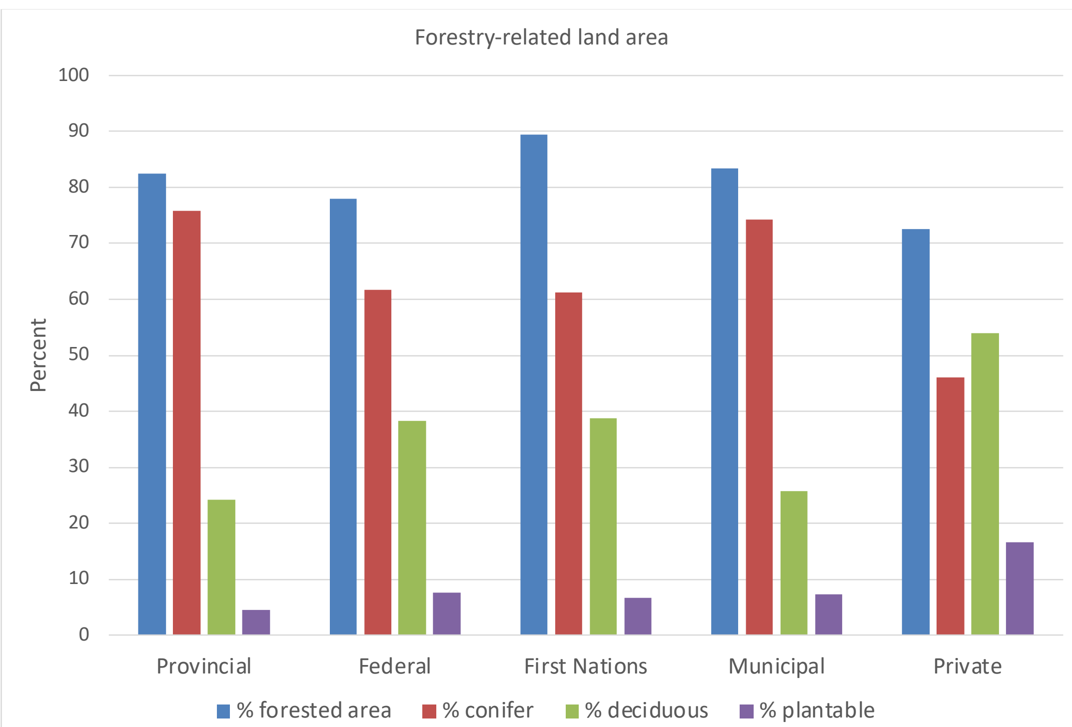
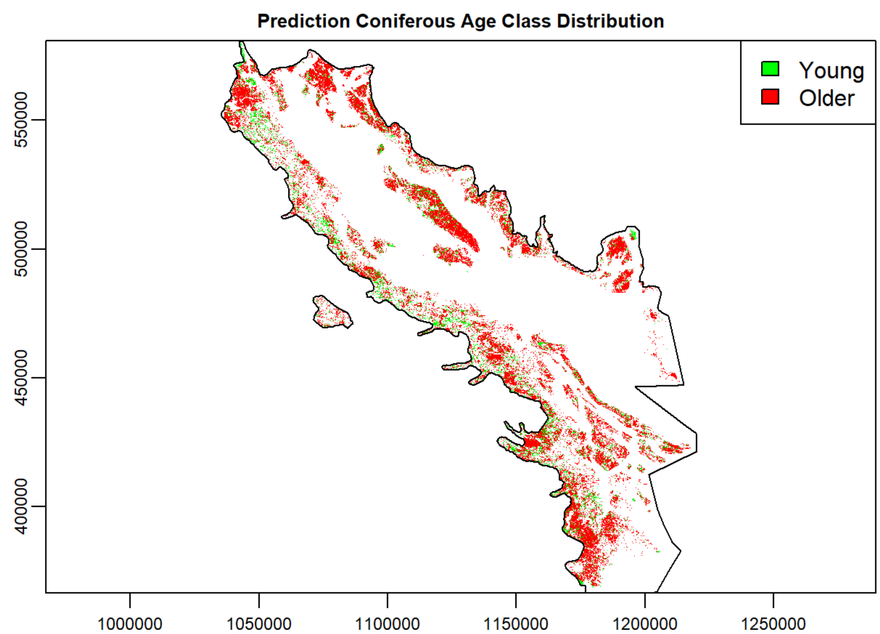


Figure 2. Forest-related metrics by low ownership category

3. **Forest Age classification.** Forest age is often well correlated with many forest attributes including carbon storage. Sentinel-2 imagery has been applied to estimate age class for temperate coniferous and deciduous stands[4]. While it is possible to estimate stand age using satellite imagery in conjunction with a statistical regression model, it was not practical for this landbase. Instead, broad stand age classes were estimated by analysing the spectral signatures of conifer and deciduous pixels with known ages from CDF areas with VRI data and using that information to parameterize a machine learning algorithm available in R. The parameterized algorithm was then used to predict age class on private land pixels (See Appendix 1 for details). Based on the spectral signatures for the conifer age classes, there are two spectrally distinct age groups: the "young" group, representing

Predicted Coniferous Age Class Distribution



[4] Grabska, E., & Socha, J. (2021). Evaluating the effect of stand properties and site conditions on the forest reflectance from Sentinel-2 time series. *PLOS ONE*, *16*(3), e0248459. https://doi.org/10.1371/journal.pone.0248459

Predicted Deciduous Age Class Distribution

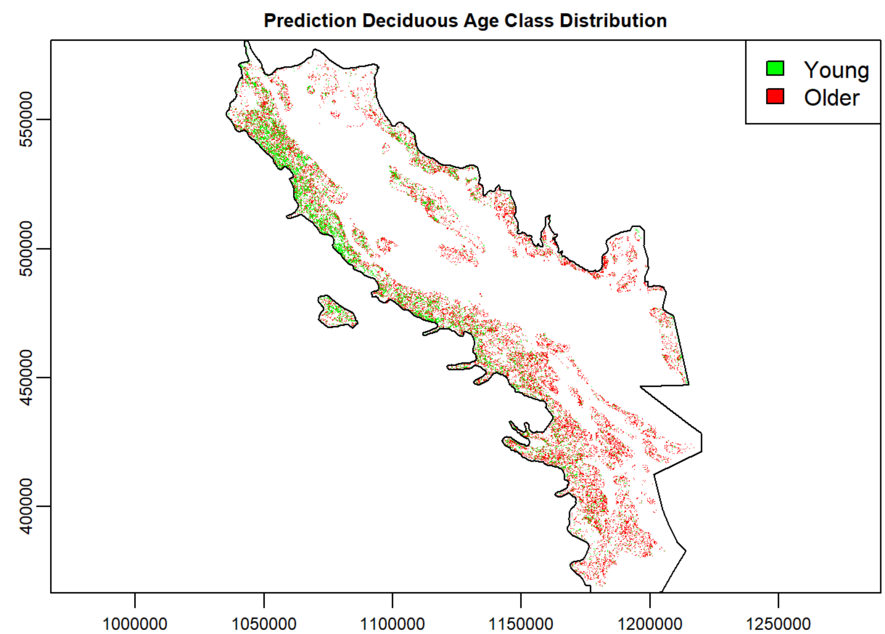


Figure 3: Predicted coniferous (upper panel) and deciduous (lower panel) age class distribution in the Coastal-Douglas-fir biogeoclimatic zone.

0 – 40 years and the "older", representing > 41 years (Figure 3). Younger age classes are located predominantly along the east side of Vancouver Island in both coniferous and deciduous forest types. This likely reflects the progressive urbanization of this region over the last several decades (see Figure 1). Older stands are predominant in northern and southern regions, and on the Gulf islands, indicating areas with little recent disturbance, and potentially good candidates for a carbon project.

There are differences among the ownership types in forest age classes (Figure 4). Young stands (≤ 40 years old), either coniferous or deciduous, are relatively uncommon (< 20% by area), regardless of ownership. Old coniferous stands occupy the greatest area, except on private land. Not only is the total area of older stands much lower on private land but there are more older deciduous stands than conifers – the only ownership class in which this is the case. This trend is consistent with higher disturbance rates on private land (Figure 4).

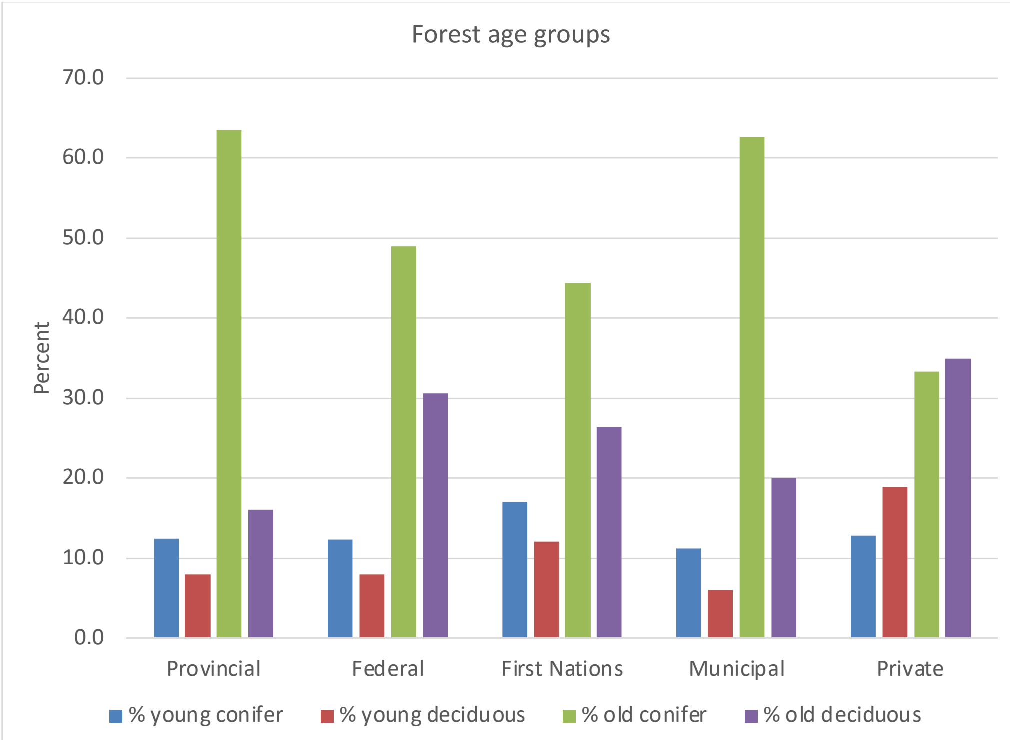


Figure 4. Percent of total forested area in one of two age classes, young ($\leq$ 40 years) and old (> 40 years), of coniferous and deciduous stands.

4. **Aboveground Biomass Modeling.** Aboveground biomass (AGB) is directly correlated with carbon storage in forests since biomass is comprised of 50% carbon. Accordingly, the Sentinel-2 data were used to predict AGB across the study site. Prior research has demonstrated the capacity of satellite imagery for forest AGB prediction in Canadian forests[5], including Sentinel-2 data[6]. As with forest age class prediction, AGB prediction was accomplished using the deciduous and coniferous VRI polygons as training data. A multiple linear regression model was developed using a built-in R modelling tool driven by the spectral data associated with VRI pixels with known ABG. The regression model (r^2 = 0.49) was applied to predict AGB in private land pixels. A detailed description of the approach is provided in Appendix 1. Figure 5 shows the total biomass per ha across the analysis area. Private lands had among the lowest biomass values (232.1 t/ha), slightly more than Municipal land (225.8 t/ha) but considerably less than Federal, Provincial, and

[5] Ahmed, O. S., Franklin, S. E., & Wulder, M. A. (2014). Integration of lidar and landsat data to estimate forest canopy cover in coastal British Columbia. *Photogrammetric Engineering & Remote Sensing*, *80*(10), 953–961. Matasci, G., Hermosilla, T., Wulder, M. A., White, J. C., Coops, N. C., Hobart, G. W., & Zald, H. S. J. (2018). Large-area mapping of Canadian boreal forest cover, height, biomass and other structural attributes using Landsat composites and lidar plots. *Remote Sensing of Environment*, *209*, 90–106. https://doi.org/https://doi.org/10.1016/j.rse.2017.12.020
[6] Pandit, S., Tsuyuki, S., & Dube, T. (2018). Estimating Above-Ground Biomass in Sub-Tropical Buffer Zone Community Forests, Nepal, Using Sentinel 2 Data. In *Remote Sensing* (Vol. 10, Issue 4). https://doi.org/10.3390/rs10040601

First Nations' lands (Table 1). These values indicate that, despite the variation among ownership classes, the landbase contains numerous parcels with substantial concentrations of carbon (Figure 5). Furthermore, mapped trends in biomass (Figure 5) reinforce the age class and species composition data presented above (Figure 3) – biomass values are highest in the oldest stands which tend to be coniferous-leading.

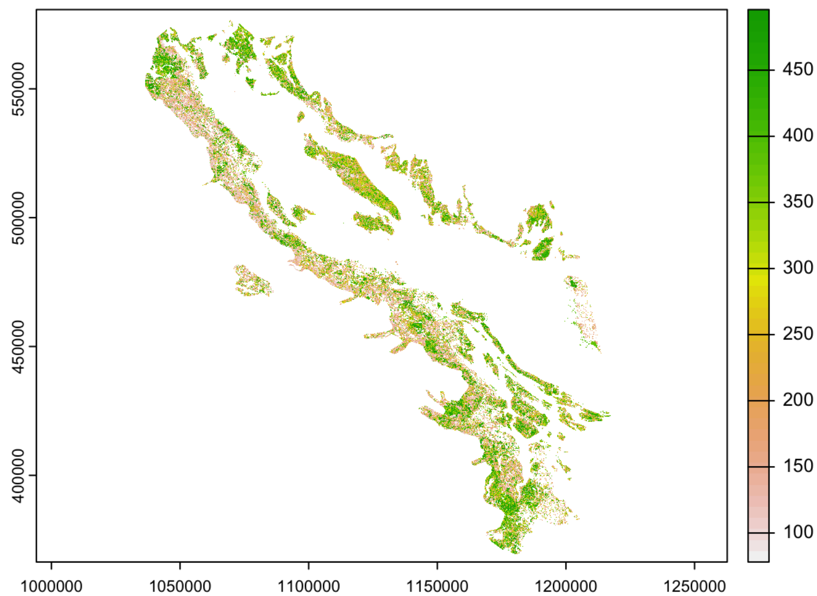


Figure 5: Biomass values (tons/ha) predicted in areas within the forested portions of the Coastal Douglas-Fir zone.

Section 3 - Evaluating Opportunities for Carbon Projects

Based on the range of metrics evaluated to this point, any of the five ownership types are amenable to developing a forest carbon project. A key feature of any carbon project, however, is the principal of 'Proof of Right' (PoR). PoR can take a variety of forms, depending on the carbon standard, but in essence it constitutes the right to all and any GHG emission reductions or removals generated by the project. Typically, PoR resides with the landowner or any entity for which the latter has granted the carbon rights. This can be problematic for First Nations who, because of the complexities associated with aboriginal land interests, may have difficulty establishing an outright PoR claim. In British Columbia, a small number of First Nations who possess Reconciliation Agreements with the provincial government have negotiated Atmospheric Benefits Sharing Agreements (ABSAs). An ABSA defines how the carbon revenue from a project is shared between the parties. While provinces and the federal government have indicated interest and support in First Nations participating in the carbon offset market, PoR is an ongoing issue that is not easily resolved. For the same reasons, government land outside of First Nation's interests is not a practical option for developing forest carbon projects by the CDFCP. PoR is not problematic for fee simple private lands, however. This option is considered the most viable for developing carbon projects supported by the CDFCP, and its potential was evaluated, as follows[7].

1. The distribution of available land was classified by all of the ownership types (private, municipal, First Nations, etc.) and associated metrics, including total area and parcel size.
2. Parcels were classified as to basic cover type, either forested or non-forested, and included all the stand attributes derived from the mapping exercises, as reported above.
3. Unsuitable areas (e.g riparian setbacks, buildings, roads, etc.) were removed.
4. Based on cover type, parcels were classified as to their suitability for harvesting versus reforestation.
5. In one of the baseline scenarios, any harvesting was assumed to remove a total of 40% of the existing forest, over a 3-year period. To simplify calculations, carbon stored in harvested wood products was not included, nor were fossil fuel emissions from harvesting and processing. Hence, carbon emissions were the direct result of harvest removals.
6. A second baseline was developed for non-forested land. In this case, carbon stocks were assumed to remain constant year over year. This assumption is not unrealistic where, for example, parcels are cropped annually, or used for grazing cattle.
7. Parcels suitable for reforestation were planted with conifer species at a density of 1,000 stems per ha. Growth rates were applied using locally appropriate yield curves for sites of 'average' productivity, from which carbon accrual rates (removals) were then calculated.
8. The PlanID field in the Parcel Map database was used to aggregate parcels within a single ownership, when appropriate. This means that any frequency data for 'properties' reported below reflect the number of owners, not the number of underlying parcels.

Carbon credits are generated from the difference in removals and avoided emissions between the baseline condition (the counterfactual scenarios in steps 5 and 6 above) and the project activities, either avoided harvest, or reforestation (as per step 7). Figure 6 shows generalized carbon accrual curves for avoided harvest and reforestation, over a 30-year time horizon. For avoided harvest, there is large tranche of credits that would be generated on a parcel in the first 3 years, corresponding to the emissions from harvesting that would have occurred in the baseline, but which would no longer occur in the project activities. Thereafter, a lesser number of credits are generated reflecting the small relative difference in emission reductions between the baseline and project activities.

In the case of reforestation, carbon credits accrue only very slowly initially when trees a small and slow growing. Once established, stands develop quickly as do their carbon stocks.

[7] For simplicity, the analysis excludes any municipal or other lands that may possess fee simple title. This does not, however, preclude the latter as eligible for inclusion in a grouped carbon project since the principles highlighted in this report are still applicable.

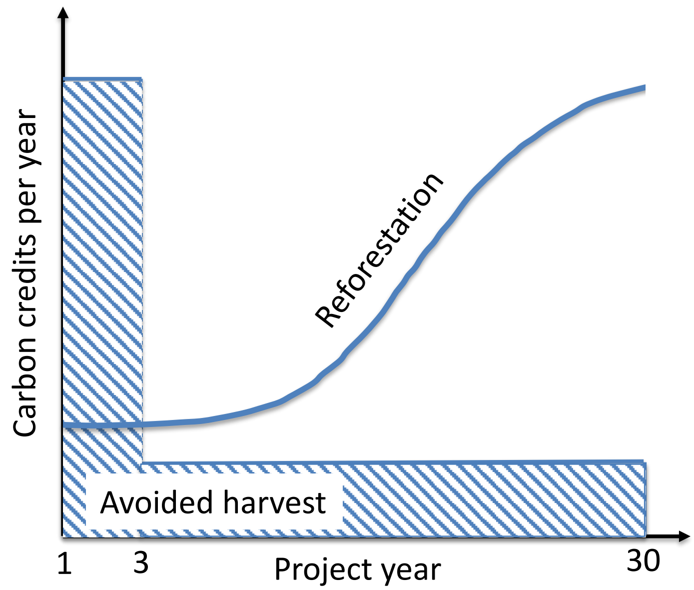


Figure 6. The annual flow of carbon credits over a 30-year period from a reforestation project and avoided harvest. Axes are not to scale. See text for details.

Avoided harvest offers considerable opportunities for developing a grouped carbon project within the CDF. A total of 1139 properties[8] were identified as having the potential generate at least 5000 carbon credits[9] over a 30-year project length (Figure 7). Many more properties generated a smaller number of credits than this minimum (data not shown), but these would have to be considered as uneconomical to include within the grouped carbon project. 82 properties (7.2%) had credits in excess of 50,000 t CO_2e, and there are 215 (18.8%) that could generate 20,000 t CO_2e, or more. Credit potential is linearly related to property size (data not shown) and so one caveat concerns the assumption that 40% of the land area is cleared within a 3-year period (see above). For very large properties, this assumption may not be achievable, which would act to delay the credit flow into subsequent years.

There were 614 properties available for reforestation credits greater than 1000 t CO_2e over a 30-year project length (Figure 7). Only 9 properties generated offsets of 19,000 t CO_2e, or greater. Hence, not only is there a smaller number of properties available for reforestation, but their credit potential is much reduced versus avoided harvesting. In addition, to generate credits in larger amounts requires at least a decade after initial planting (Figure 6), which renders the economics of reforestation a challenge.

[8] As noted previously, frequency data for 'properties' reflect the number of owners, not the number of underlying parcels.
[9] 1 carbon credit is the equivalent of removing 1 tonne CO_2e.

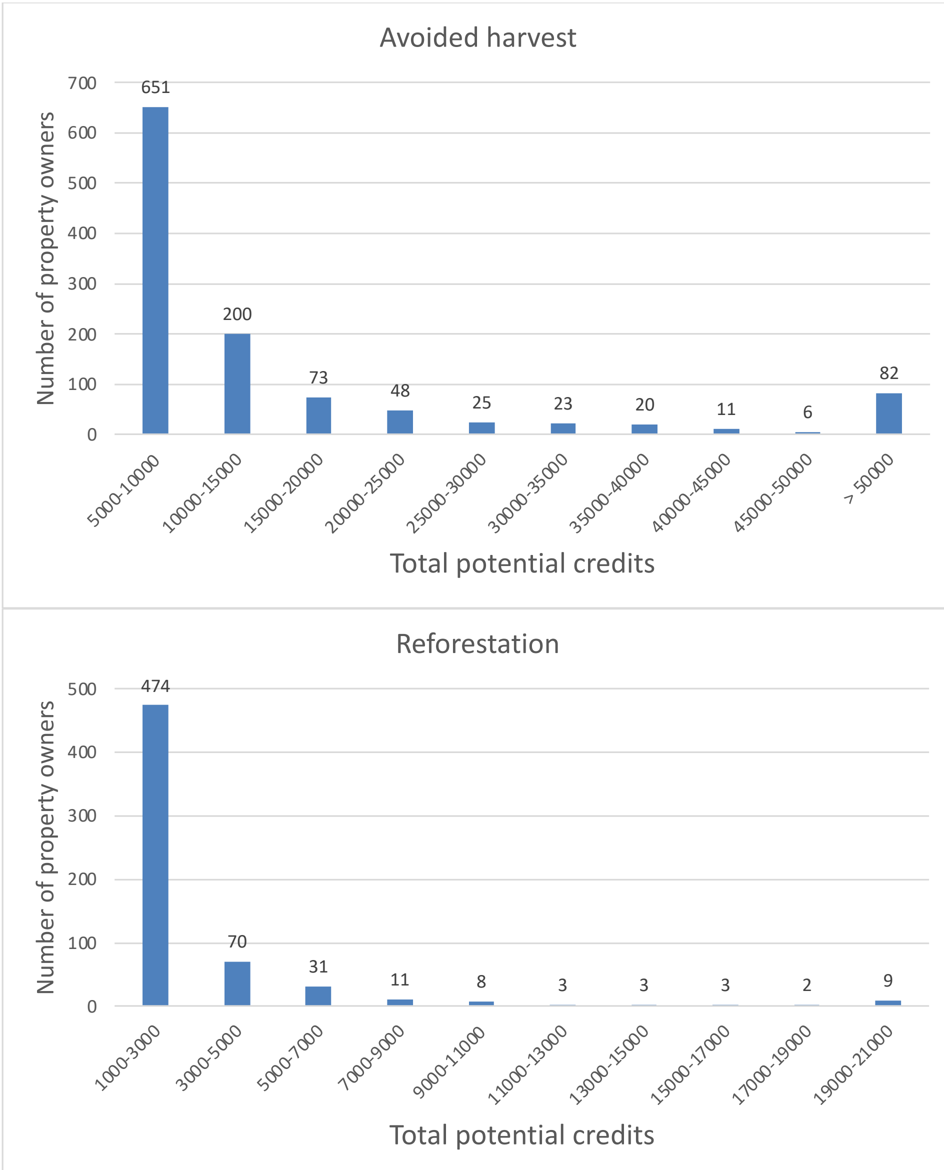


Figure 7. Frequency of properties in relation to their carbon credit potential for avoided harvest (top panel) and reforestation (bottom panel).

Strategies for building a grouped carbon project

Under a grouped project, additional instances of the project activity (in this case, avoided harvest and/or reforestation), which meet pre-established eligibility criteria (fee simple ownership), may be added after the project is successfully validated. In the case of the CDFCP, two decisions require careful consideration: 1. Initial property selection, and 2. The build-out process. A detailed assessment is beyond this scope of work, and so the following provides only basic guidelines.

Initial property selection

One, or more, of the larger avoided harvest properties should be used to anchor the grouped carbon project[10]. Property selection can be based on a variety of criteria, including:

- The absolute number of credits generated across the 30-year project length.
- The temporal pattern of credit generation (see Figure 6). Avoided harvest delivers immediate benefits but credits are much reduced over the long-term. Under reforestation, credits build progressive over time yield higher long-term benefits. This can pay off if carbon credit values increase significantly over time, which is expected.
- Geographical location – is it better to select a property located in an area that has already experienced, or will experience, development pressure, or areas that are more 'pristine' and whose overall integrity is better preserved?
- Does the property deliver benefits additional to carbon, such as habitat value or water quality? Certain habitat features or forest types within the CDF considered priorities for protection or rehabilitation could be prime candidates as an anchor property within the project. Examples include old growth or degraded forest types.

Developing the build-out strategy

The objective of a build-out strategy should be to maximize return on investment (financial, and otherwise) while ensuring that project risks are managed and held to acceptable levels. One approach is to develop a strategy that separates the decision-making process into is temporal and spatial components.

Time

If short-term return on investment is the predominant goal, then a strategy focused on avoided harvest makes the most sense. In this approach, property selection is exclusively on this project type, beginning with the largest available and building the portfolio progressively thereafter. Because of the pronounced decrease in credits (Figure 6), maintaining a healthy project cash flow depends on regular recruitment (see Figure 8 for a conceptual model of this concept). Fortunately, the population of potential properties is relatively large (Figure 7). Owner attrition (defaulting of responsibilities) is always a risk in grouped projects, but finances are less impacted by any given attrition event, at least once its initial credit flow has declined.

Basing a build-out strategy largely on reforestation will be challenging and high risk. Property availability is much less than for avoided harvest, as are expected credit amounts (Figure 7). For a given property, attrition that occurs early has a much smaller impact on project finances than if it occurs later (Figure 6). Credit losses from late-stage attrition also take much longer to recoup

[10] i.e., the initial instance of the carbon project is built around ('anchored') by a single large property and then additional, smaller properties are added periodically.

by recruiting new project instances; this effect is also compounded by the resulting discount in cash flows.

The most effective build-out strategy for hedging risk is a mixed portfolio of avoided harvest and reforestation. Avoided harvest generates short-term income and reforestation balances the potential long-term reduction in credit flows (see Figure 8).

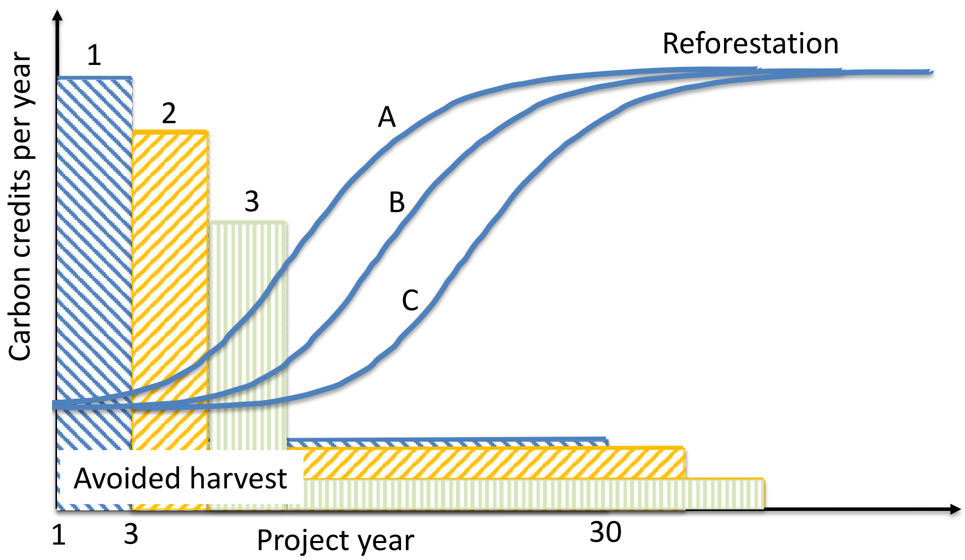
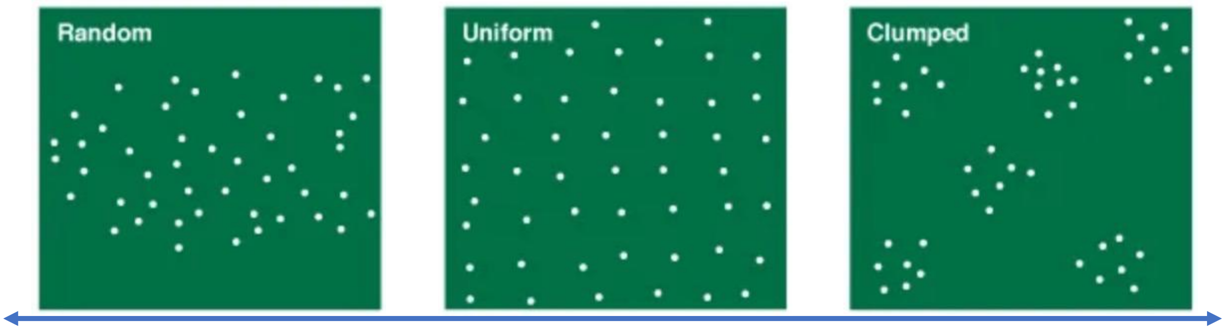


Figure 8. The carbon credit flows anticipated with the progressive addition of project instances (properties) under avoided harvest (1-3) and reforestation (A-C). Axes are not to scale

Space

If building out the project property portfolio is so important, which areas should be targeted for recruitment? Spatial configuration affects the risk that unplanned reversals will have a catastrophic impact on carbon stocks. For example, a series of contiguous ("clumped") properties (see Figure 9) could all be lost in a single catastrophic wildfire. Conversely, connectivity and interior forest habitat are maximized by close localized grouping of properties, key quality attributes. Widely distributed properties (either uniform or random; Figure 9) will have low connectivity, but the trade-off is that they are not likely to be affected simultaneously by a single disturbance event.

Potential property Distributions



- Unplanned reversals affecting significant carbon stocks (variable to low risk)
- Connectivity (variable to low)
- Edges (high)
- Interior habitat (Low)

- Unplanned reversals affecting significant carbon stocks (low risk)
- Connectivity (low)
- Edges (high)
- Interior habitat (low)

- Unplanned reversals affecting significant carbon stocks (high risk)
- Connectivity (high)
- Edges (low)
- Interior habitat (high)

Figure 9. Conceptual distributions of properties enrolled in a grouped carbon project. Each has benefits and costs.

In summary, the trade-offs that define potential options should be articulated within a broader planning process and used to underpin the build-out strategy. A hierarchical approach will likely be necessary as a means of ordering priorities and integrating both the temporal and spatial components of the project build-out.

Section 4 – Understanding Carbon Offset Credits

The Carbon Marketplace

There are two carbon markets: voluntary and regulatory.

In **Voluntary markets**, companies or individuals buy carbon credits to demonstrate a commitment to reducing their carbon footprint and for corporate social responsibility goals.

Voluntary markets are a viable option for a forest carbon project supported by the CDFCP:

- These markets have proven to be robust despite significant economic and political headwinds. Recent reviews indicate strong growth potential. Ecosystem Marketplace[11], a leading global source of information on environmental finance, markets, and payments for ecosystem services, reports traded carbon volumes in the Forestry and Land Use category in 2017, 2018, and 2019, of 16.6, 50.7, and 36.7 million tCO_2e, respectively.

[11] https://www.ecosystemmarketplace.com/carbon-markets/

Definitive data for 2020 were difficult to acquire as the global pandemic took hold. However, EM reports that Voluntary Carbon Market transactions hit a record $1 Billion in 2021, despite COVID-19.

- Offset prices trending positively, with quality projects currently selling credits at premium prices ($15 USD per t CO_2e, and more).
- Strong growth forecasted: demand from corporations with sustainability goals surging to 1 billion metric tons of carbon dioxide equivalent (Gt CO_2e) in 2030 and 5.2 Gt CO_2e in 2050 – the latter of which is equivalent to 10% of global emissions today[10].
- Well-established voluntary standards and associated methodologies. These are essential for ensuring project integrity and securing full market value.

Price discovery is an ongoing issue in the carbon offset marketplace because: 1. The lack of a futures market inhibits transparency, 2. Project quality varies widely with prices reflected accordingly, and 3. Transactions are considered proprietary and not typically reported on financial spreadsheets. The Canadian compliance market, once established, will incentivize project development which should in turn tighten supply for non-covered entities (companies that are not subject to the emission limits), thereby driving up voluntary credit prices. The latter are still likely to trade at a discount to compliance credits, however, since they are not mandated and serve to satisfy voluntary ESG[12] initiatives around net-zero and carbon-neutral commitments rather than 'hard' emission limits. The voluntary market is anticipated to grow exponentially over the next 30 years, with prices exceeding $50 per t CO_2e (some projections are much higher). Demand for voluntary carbon credits should be sustained as governments and corporations strive to meet the goals of the 2015 Paris Agreement. At least one-fifth of the world's largest 2,000 public companies have committed to meeting net-zero targets by mid-century or sooner through various initiatives, of which offsets will be one. The new Carbon Offset and Reduction Scheme for International Aviation (CORSIA), voluntary emissions offset system for airlines, should spur considerable demand for credits.

A range of factors influence price, including project type and location, and co-benefits (additional to carbon). In the case of the CDFCP, a carbon project located within its operating area would have considerable appeal.

- This zone has the highest number of species and ecosystems at risk in B.C., many of which are ranked globally as imperilled or critically imperilled. There are 271 known Red and Blue listed species within the CDF, and 110 species at risk.
- Its old growth forests are among the highest carbon-storing ecosystems in the world.
- Its forests play a critical role in building watershed and wildfire resilience against climate change.
- The CDF has been most altered by human activities than any other zone in the province. Less than 1% of the CDF remains in old growth forests and 49% of the land base has been permanently converted by human activities.

[12] Environmental, social, and governance

- Its ecosystems are highly fragmented with only 11% currently protected in conservation areas.

Compliance markets are the result of emission limits imposed by national and subnational governments on major industrial emitters. In 2016, the federal government established the Pan-Canadian Framework on Clean Growth and Climate Change (the 'Framework'), which is intended to provide a national plan to meet Canada's 2030 emission reduction target (a 55% reduction in overall GHG emissions using a 2005 baseline). *The 2018 Greenhouse Gas Pollution Pricing Act* (the Act), legalized the Framework and the carbon pollution pricing system. The Act has two parts: Part 1 applies a charge to 21 types of fuel and combustible waste (Fuel Charge). Part 2 is an output-based pricing system (OBPS) for large industrial emitters (all facilities that emit 50,000 tonnes or more per year of GHG, in CO_2 equivalent units; 'covered' entities[13]). The OBPS applies in jurisdictions that do not meet the federal pricing and emissions reduction standards. With its carbon tax pegged to the federal carbon price, BC is not subject to the OBPS.

Under the proposed *Greenhouse Gas Offset Credit System Regulations*[14], a GHG offset system will be established as part of the government's carbon pollution pricing system. Offsets are one option for compliance with the government's emissions limit (or cap); a covered entity whose emissions exceed the cap can, as one option, purchase offsets equivalent to the differential. The 2019-2021 compliance periods have no limits on the number of offsets that can be used, whereas the 2022 compliance period has a 75% limit[15]. Entities will be able to use offsets derived under the Federal GHG Offset System and Recognized Offset Units from approved provincial offset systems. There are, however, currently no approved methodologies for generating forestry offsets compliant with the federal program. Several are under active development, both provincially (e.g., the British Columbia Forest Carbon Offset Protocol v2; BC FCOP) and federally (an Improved Forest Management methodology) and could see release dates later this year[16].

Given that no forestry-based offsets have been created for trade within the Canadian compliance market, prices are unknown. It seems likely, however, that the Federal Government's intended carbon pricing trends as part of the Canadian Output Based Pricing System, will serve to benchmark offset prices. In that regard, year 2022 pricing is $50 CAD per t CO2e, rising by $15 annually until it reaches $170 CAD per ton in 2030. Once established, the Canadian compliance market will incentivize project development which should in turn tighten supply for non-covered entities (companies that are not subject to the emission limits), thereby driving up voluntary credit prices also. The latter may trade at a discount to compliance credits, however, since they

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[13] Facilities that emit over 10,000 tCO2e in regulated sectors can opt-in to the OBPS at any time. OBPS sectors are: Oil and gas production, Mineral processing, Chemicals, Pharmaceuticals, Iron and steel, Mining and ore processing, Lime and nitrogen fertilizers, Food processing, Pulp and paper, Automotive, Electricity generation, and Cement.

[14] https://canadagazette.gc.ca/rp-pr/p1/2021/2021-03-06/html/reg1-eng.html

[15]https://www.ieta.org/resources/Resources/CarbonMarketBusinessBrief/2021/CarbonMarketBusinessBrief_CanadaOBPS2021.pdf

[16] Federal protocols will be applicable in all provinces and territories *except jurisdictions in which the same project activity is covered by a current protocol in a provincial or territorial offset program* (once released, the BC FCOP therefore will be the required methodology for Improved Forest Management carbon projects in the province).

are not mandated and satisfy ESG initiatives around net-zero and carbon-neutral commitments rather than 'hard' emission limits.

Forest Carbon Project Types

Three different project types are eligible to produce forest carbon offsets; afforestation or reforestation, avoided conversion, and improved forest management (IFM) (Table 1). Project developers must be able to show that their forests are sequestering more carbon than a 'business-as-usual' scenario across the three forest project types. Each forest project has different costs and benefits, and approaches to carbon accounting.

Table 1. Types of forest carbon offset projects.

Project Type	Description
Afforestation/Reforestation (AR)	• Projects involve restoring tree cover to previously non-forested land. • Requires significant site preparation and maintenance
Avoided Conversion (AC)	• Prevent land-use change - the conversion of forested land to non-forested land. • AC project developers must demonstrate that the forested land is under significant threat of conversion for an AC project to be viable.
Improved Forest Management (IFM)	• Land management activities that increase or at a minimum maintain the current level of carbon stocking. Avoided harvest is one example.

Carbon Credit Registries

The serialization of carbon credits occurs on a registry. Registries require projects undertake a formal validation and verification process to ensure integrity of the resulting credits. Five registries potentially suitable for CDFCP consideration are Verra, The American Carbon Registry, The Climate Action Reserve, and the British Columbia Carbon Registry (not yet accepting new projects).

Verra (formerly the Verified Carbon Standard)

Once credits have been certified, they are issued on the registry as Verified Carbon Units (VCUs). VCUs can be sold on the registry or the spot market and retired by individuals and companies to offset emissions. Verra is the world's most widely used voluntary GHG program.

Permanence requirement: A minimum crediting period of 20 years (and a minimum project length of 30 years) with the option of renewing up to four times for a total of 100 years. Based on a project's risk assessment, a percent of credits must be set aside as a buffer to compensate for unplanned reversals.

Aggregated (Grouped) Projects are permitted. The requirements are:

- **Predetermined eligibility**. The project proponent sets the geographic boundaries for the grouped project, including where new project activity instances (i.e., individual landowners) may be added, and establishes criteria for determining the eligibility of future instances.
- **Complete initial validation**. The project proponent contracts an independent validation/verification body (VVB) to assess the grouped project and whether the eligibility criteria are appropriate for determining the validity of future instances.
- **Undergo verification**. The project proponent contracts a VVB to ensure the emission reduction or removals are real.
- **Add new instances**. The project proponent may include new project activity instances during a verification event.

Verra has several methodologies suitable for projects within the CDF zone. Three examples are VM0010, VM0012, and VM0034.

American Carbon Registry (ACR)

The American Carbon Registry is a registry for both the voluntary market and the California Air Resources Board compliance market. It was the first voluntary greenhouse gas registry in the world. Most ACR projects are situated within the conterminous US.

Permanence requirement: A minimum commitment of 40 years for Improved Forest Management projects. Any potential loss of sequestered carbon must be addressed by means of either a buffer pool or insurance. The risk assessment is made following the ACR Tool for Risk Analysis and Buffer Determination.

Aggregated Projects: While aggregation is allowed, projects are advised against aggregating multiple forest types, or utilizing a geographic region that is overly large.

One ACR methodology is applicable to private lands within Canada.

Climate Action Reserve (CAR)

CAR is a carbon registry that operates for the voluntary carbon market and serves as an Offset Project Registry for California’s compliance cap-and-trade program.

Permanence requirement: Crediting period lengths depend on the project methodology. For most non- sequestration projects, there is a 10-year crediting period that may be renewed one time for a maximum of two 10-year periods, or 20 years total. For sequestration projects, the crediting period may be up to 100 years.

Aggregated Projects: Aggregation of projects is allowed. Only parcels of less than 5,000 acres may enroll in an aggregate. Each participant in the aggregate registers independently and holds a separate account on the Reserve software system. There are no aggregation projects listed as of 2018.

CAR has two methodologies applicable within Canada.

British Columbia Offset Registry

The British Columbia Forest Carbon Offset Protocol (BC FCOPv2) is the only methodology applicable to carbon-based forest projects on the Registry. BC FCOPv1 was withdrawn from use in 2015 and is being replaced by version 2. Having undergone a public review process, the latter may be released in 2022. Until its release, no forest carbon projects can acquire eligibility for registering offsets.

Aggregated Projects: Indications are that BC FCOP v2.0 will permit aggregated forest carbon projects.

Section 5 – Additional Considerations

Conservation Easements

A conservation easement is generally defined as a voluntary agreement between a landowner and an easement holder (a governmental agency or a qualified non-profit organization) whereby the former relinquishes certain rights to develop, encumber, or otherwise modify the land in favour of the latter. Conservation easements can enhance project appeal, reduce uncertainty (enhance permanence), and improve project credit flows.

Key considerations for carbon offsets and conservation easements are[17]:

- **Carbon Credit Ownership (Proof of Right).** All projects must demonstrate an entity's right to all and any GHG emission reductions or removals generated by the project or program during the crediting period or verification period, as the case may be. In a grouped project, each participant will require Proof of Right (PoR) for that portion of the project area over which they exert control. The complexity introduced by multiple PoR claims will impact how land trusts draft conservation easements and develop and manage carbon offset projects. Ideally, to mitigate the risk of legal disputes with landowners, land trusts should secure unambiguous ownership of carbon rights through the conservation easement or another legally binding agreement with the landowner to avoid ambiguity over offset ownership.
- **Double Payments.** To maintain the integrity of carbon offsets, it is imperative to avoid erroneous emission reduction claims from an offset project by paying landowners twice for the same action. Landowners can receive compensation for granting a conservation easement, typically through tax incentives[18], but they might also qualify for carbon credits

[17] https://wecprotects.org/wp-content/uploads/2020/11/Carbon-Offsets-in-Conservation-Easements.pdf

[18] The federal ecological gift program, for example: https://www.canada.ca/en/environment-climate-change/services/environmental-funding/ecological-gifts-program/overview.html. Also, the Islands Trust Fund provides property tax exemptions of up to 65% for portions of land that are subject to a conservation covenant registered under the Natural Areas Protection Tax Exemption Program (NAPTEP). This program covers many of the Gulf Islands. For more information see http://www.islandstrustfund.bc.ca/initiatives/privateconservation/naptep.aspx . A broader discussion of land sale and gifting options is provided at: https://ltabc.ca/wp-content/uploads/2017/UP/Natural%20Legacies-

after undertaking certain activities—or, in many cases, restricting certain activities—on their land to increase the carbon stocks or to avoid the release of carbon and other GHG emissions. These issues are addressed as follows:

1. Include in the carbon offset project baseline the details of any conservation easement recorded more than one year prior to the establishment of the carbon offset project. This ensures the project will not credit the landowner for activities that are already required by an existing conservation easement. Conservation easements recorded after the project start date are treated as supporting the project and do not affect the baseline emission calculations.
2. By ensuring Proof of Right is clearly established at the project outset such that only a single entity can legally claim any resulting credits.

- **Valuation.** Conservation easements associated with carbon offset projects may complicate the interpretation of easement appraisals. Price discovery in terms of credit value is a challenge. Typically, carbon offsets are not ranked as highest and best use and so appraisal value is derived from assessing the underlying timber resource.
- **Funding Considerations.** Entities funding conservation easements may seek compensation in a variety of ways: through direct payment and/or as a share of the resulting credit tranche. Each approach has implications for the easement holder in terms of payment scheduling and timing.

Case study 1 – Cold Hollow Carbon and the Vermont Land Trust[19]

The Vermont Land Trust is a statewide, member-supported, non-profit land conservation organization. Since 1977, the Trust has protected 2,000 parcels of land covering nearly 600,000 acres

In partnership with the Cold Hollow to Canada group, the University of Vermont, and The Nature Conservancy of Vermont, the Vermont Land Trust piloted the first forest carbon aggregation project in the US. The project spanned 8,625 acres across 12 parcels and has 10 landowners collectively enrolled in the voluntary carbon market through the American Carbon Registry (ACR).

Key learnings from the Vermont Land Trust project:

- *A strong, sustainable forest management, conservation, and climate change mitigation ethic in Vermont was the foundation for carbon project development.*
- *Partnerships and patience were critical to success and in building capacity.*

%20Conservation%20Covenants%20in%20BC%20-%20Financial%20Benefits%20from%20Nature%20Conservations.pdf.

[19] https://www.coldhollowtocanada.org/fileadmin/files/Case_Profile_Cold_Hollow_Carbon_VT_03_24_21_.pdf

- *Mitigating risk for forestland owners participating in an aggregated carbon project is critical.*
  Forestland owners preferred a direct contractual relationship with Vermont Forest Carbon Company, a subsidiary of VLT created through the course of the project, as a way to mitigate risk rather than a pooled ownership structure.
- *Land trusts and their subsidiaries can serve as an appropriate home for carbon co-op projects.*
- *Social capital, personal relationships, and trust were key to success.*

This approach has value as a template for the CDFCP.

Case study 2 - Aggregation of Carbon Credits from No-Till and Reduced Till Agricultural Practice

Carbon offsets generated from the direct and indirect reductions of greenhouse gas (GHG) emissions through no-till and reduced till cultivation systems on agricultural lands in Alberta. The reduction in frequency and intensity of tillage under a reduced till or no-till system results in reduced fossil fuel use by farm equipment, reduced fossil fuel use for the production of fertilizer and other amendments, and a decrease in the amount of soil carbon and nitrogen released to the atmosphere.

The project aggregates individual farm operators to provide larger quantities of carbon offsets for purchase. The carbon offsets are generated in accordance with the Quantification Protocol for Tillage System Management, under the Alberta Emissions Offset Registry (AEOR).

Key point learned from Alberta Offset System Tillage Systems Protocol:

- The aggregation project consists of pooling the carbon offsets generated on individual fields within individual farm operations. As such, the project site can vary from year to year and may be composed of several farm fields.
- The Quantification Protocol for Tillage System Management uses an adjusted baseline. The adjusted baseline accounts for carbon gains from current adoption levels of reduced-till and no-till practices within the given region, adjusted with farm census data from Statistics Canada. Therefore, project proponents do not have to prove a particular baseline at the project start date.

The conditions and circumstances of this program appear to have little value as a template for the CDFCP.

Appendix 1.

Coastal Douglas-Fir Carbon Project: Supervised Landcover Classification and Forest Attribute Modelling

1. Introduction:

The rationale for this analysis is that forest cover and attribute data is required for carbon modelling in the CDF zone. However, the primary source of forest attributed data in BC used for carbon modelling, the Vegetation Resource Inventory (VRI), does not provide data for private lands. In the ~5000 km^2 study site, VRI data only covers ~3000km^2, leaving approximately ~2000km^2 (40%) of the area without forest attribute data. As such, the goal of this analysis is to provide forest attribute data to support carbon modelling in the Coastal Douglas-Fir (CDF) zone on the cost of British Columbia. This goal was achieved by completing the following objectives: 1) classify landcover types in the study area; 2) estimate stand age by forest type (conifer vs. deciduous); 3) estimate aboveground biomass (AGB).

2. Satellite Imagery:

The baseline data used in this analysis was Sentinel-2 satellite imagery. A Sentinel-2 cloud free composite was developed in Google Earth Engine (GEE) using a cloud masking algorithm recommended for Sentinel imagery (Google, 2022a). Cloudy areas in the composite were filled using images captured between June 1st to September 29th, 2021, prioritizing more recent imagery. A total of 217 images were used to build the composite, with median reflectance values used. The composite included bands 2 – 8a, in addition to bands 11 and 12, all of which were resampled to a 20m spatial resolution (European Space Agency, 2022).

3. Supervised Landcover Classification

3.1 Background

Supervised landcover classification was performed to differentiate between six landcover classes in the study site: coniferous forest, deciduous forest, non-forest vegetation (agriculture, grassland, greenspace, etc.), water, urban areas, and recent cutblocks (including barren soil). These landcover classes were selected because they represent major components of the landscape and are feasible to differentiated in terms of spectral properties.

Supervised landcover classification has historically been performed for many environmental management and forestry purposes. Supervised classification involves 4 general steps: 1) collecting training samples representative of the different landcover classes; 2) training a classifier algorithm to develop relationships between spectral signatures and landcover classes; 3) implementing the classification algorithm on the target imagery; 4) performing an accuracy assessment of the classification (Stehman & Foody, 2019). Excluding sample polygon collection, the classification process was performed using GEE. A link to the complete GEE script is provided in the Appendix.

3.2 Collecting Landcover Samples

Landcover sample polygons were collected in ArcGIS Pro by identifying representative area in the Sentinel-2 image for each landcover type. Table 1 provides a summary of the 144 landcover samples collected for this study. Sample polygons were sampled to represent natural variation in each landcover class and were intentionally spread evenly throughout the study area. Figure 1 provides a map of landcover sample polygons. Non-forested sample polygons were collected by simply identifying representative landcover examples in the Sentinel-2 image and verifying their class using reference high resolution imagery provided in the ArcGIS Pro basemap. For forest classes (conifer and deciduous), the 2020 VRI dataset provided by the Government of British

Columbia was used as reference for collecting sample polygons (Government of British Columbia, 2021). Since the VRI is not comprehensively updated every year, only polygons updated as recent as 2017 were used as reference to distinguish between coniferous and deciduous forested areas.

Table 1: Summary of sample polygons collected in the biogeoclimatic zone for the purpose of supervised landcover classification. The total sampled pixels refers to the sum of pixels extracted from the Sentinel-2 composite within each of the sample polygons.

Landcover Code	Landcover Class	Number of Polygons	Total Sampled Area
1	Water	11	6.16
2	Cutblock	13	1.19
3	Non-Forest Veg	21	3.82
4	Urban	34	5.04
5	Coniferous	21	6.31
6	Deciduous	44	6.26

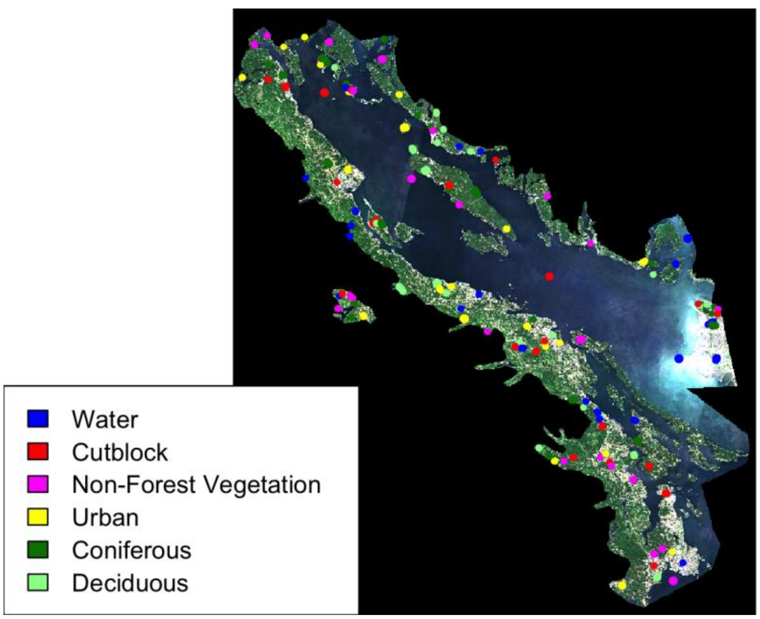


Figure 1: Landcover samples (n = 144) retrieved from the Coastal-Douglas-Fir biogeoclimatic zone for the purpose of supervised landcover classification. Note that the size of each sample polygon is exaggerated in this map to make their location more apparent.

3.3 Training Classifier Algorithm

In supervised landcover classification, the classifier is typically a machine learning algorithm that learns through training data how to differentiate between various landcover classes. This analysis tested three common classifier algorithms in GEE: Random Forest (RF), Classification and Regression Trees Classification (CART), and Support Vector Machines (SVM). An essential factor in landcover classification is differences between the spectral signatures of each landcover class (Rujoiu-Mare et al., 2017). Figure 2 provides the spectral signatures of each landcover class. To train the classifier algorithm, a random subset of 70% of the sample polygons was selected, with even representation of each landcover type. Within each training polygons, the Sentinel-2 image pixels were extracted and then further randomly subsampled in GEE to train the classifier.

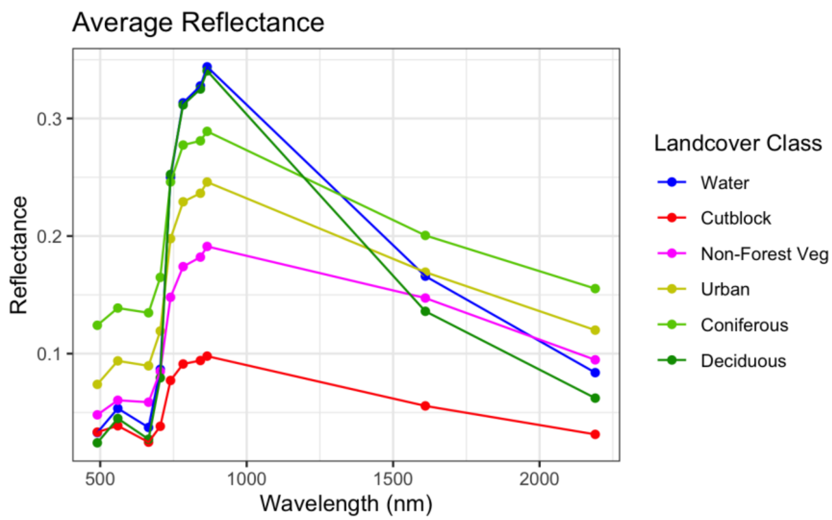


Figure 2: Mean reflectance of each landcover class for each of the 10 Sentinel-2 bands used in the classification ranging from 490 – 2190 nm. This figure provides an approximation of the spectral signatures of each landcover class. Note that atmospheric effects distort the spectral signatures of each landcover's mean reflectance at a given wavelength.

3.4 Implementing Classifier

Each classifier was implemented using their respective function in GEE (Google, 2022b). The RF, CART, and SVM classifiers were selected for use in this study since they are commonly used in satellite imagery supervised landcover classification and have been demonstrated to be effective by previous research (Abdi, 2020; Shao & Lunetta, 2012). Generally, machine learning algorithms perform better when their hyperparameters are subjected to tuning and experimentation. However, this was beyond the scope of this analysis, so the generic parameters for each algorithm was used. The only parameter which was altered was the number of decision trees generated for RF, which was found to be optimal at 50 trees.

3.5 Accuracy Assessment

The 30% validation subset from the original sample data was applied to evaluate the accuracy of the three classification algorithms. In landcover classification, accuracy assessment involves the creation of a confusion matrix, which summarizes whether each pixel in the validation data was classified correctly or incorrectly by the classifier algorithm. The confusion matrices for each classifier can be viewed by running the GEE script (see Appendix). The confusion matrices for each classifier are provided in Table 2. From the confusion matrices, three accuracy metrics can be calculated: User's Accuracy (UA), Producer's Accuracy (PA), and Overall Accuracy (OA). The UA corresponds to errors of commission (i.e., pixels predicted as the wrong landcover class), whereas the PA corresponds to errors of omission (i.e., pixels omitted from the correct landcover class). The OA represents the proportion of correctly classified pixels across all landcover classes.

The three classifiers had similar OA, but had differing UA and PA across the landcover classes. Since the primary objective of this classification was to differentiate between forested and non-forested areas, the accuracy metrics of primary concern are the UA and PA for coniferous and deciduous forest classes. Overall, the RF algorithm was selected as the most accurate classifier because it had an OA of 79%, in addition to the highest UA and PA for the coniferous and deciduous forest classes. Specifically, of the 13,040 pixels classified for conifer and deciduous forests, the RF algorithm only mis-classified 62 pixels (0.5%) as non-forest landcover types (non-forest vegetation and urban). Most of the error associated with the RF classified can be attributed to misclassification between the two forest classes. The RF algorithm classified 17% of deciduous pixels as coniferous, and 28% of coniferous pixels as deciduous. Finally, the RF algorithm had an associated Kappa coefficient of 0.74, meaning that there is a 26% probability of this level of agreement between the predicted and observed values occurring by random chance (McHugh, 2012).

In sum, the RF algorithm was able to effectively distinguish between forest and non-forest classes but was not particularly effective at distinguishing between coniferous and deciduous stands. This may be because the sample polygons used to train the RF algorithm mostly contained mixed stands that were not purely coniferous or deciduous. For the purpose of this analysis, the accuracy of the RF landcover classification was deemed sufficient. Figure 3 provides the final RF landcover classified image.

Table 2: Confusion matrices for the three classifier algorithms implemented for a supervised landcover classification of the Coastal-Douglas-Fir biogeoclimatic zone. For each classifier, the top row of landcover classes represent the observed data and the left column of classes represents the predicted data. The bolded diagonal cells are the number of correctly classified pixels for a given landcover class. The shaded rows and columns provide the users and producers accuracies for each landcover class.

RF Confusion Matrix								
		Observed Values						
		Water	**Cutblock**	**Non-Forest Vegetation**	**Urban**	**Coniferous**	**Deciduous**	**User's Accuracy**
Predic	**Water**	**3058**	0	0	0	0	0	100%
	Cutblock	0	**476**	573	48	0	0	80%
	Non-Forest	0	93	**3537**	1110	0	872	80%

t e	**Vegetation**							
d V	**Urban**	0	25	243	**6521**	4	355	85%
a l	**Coniferous**	0	0	0	0	**5812**	1164	78%
u e s	**Deciduous**	0	0	56	6	1683	**4319**	64%
	Producer's Accuracy	100%	43%	63%	91%	83%	71%	

SVM Confusion Matrix

		Observed Values						
		Water	Cutblock	Non-Forest Vegetation	Urban	Coniferous	Deciduous	**User's Accuracy**
Predicted Values	Water	**3058**	0	0	0	0	0	100%
	Cutblock	0	**626**	469	2	0	0	85%
	Non-Forest Vegetation	0	79	**4079**	935	0	519	75%
	Urban	0	29	806	**6247**	6	60	87%
	Coniferous	0	0	0	0	**5795**	1181	74%
	Deciduous	0	0	92	1	2021	**3950**	69%
	Producer's Accuracy	100%	57%	73%	87%	83%	65%	

CART Confusion Matrix

		Observed Values						
		Water	**Cutblock**	**Non-Forest Vegetation**	**Urban**	**Coniferous**	**Deciduous**	**User's Accuracy**
Predicted Values	Water	**3058**	0	0	0	0	0	100%
	Cutblock	0	**541**	427	129	0	0	71%
	Non-Forest Vegetation	0	105	**3238**	1201	49	1019	77%
	Urban	0	115	465	**6194**	25	349	82%
	Coniferous	0	0	3	0	**5886**	1087	76%
	Deciduous	0	3	78	8	1840	**4135**	62%
	Producer's Accuracy	100%	49%	58%	87%	84%	68%	

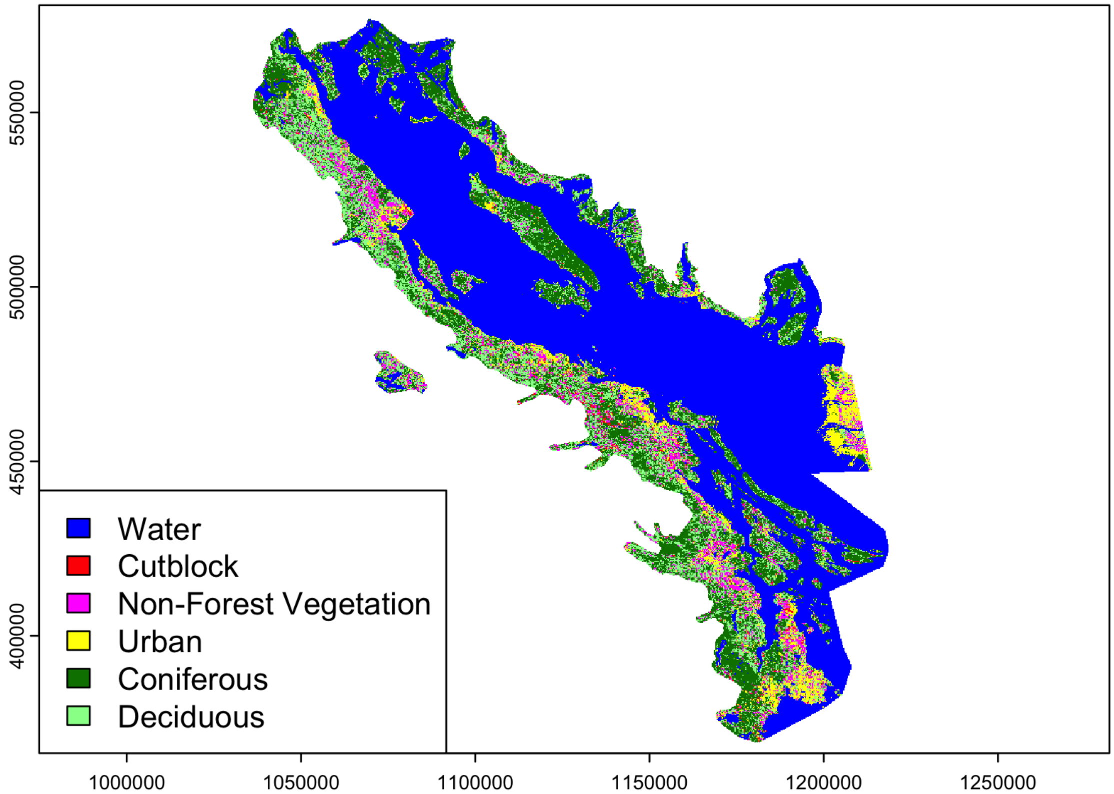


Figure 3: Random Forest (RF) classified Sentinel-2 image showing the distribution of the six predicted landcover classes. This classification had an overall accuracy of 0.79, with a Kappa coefficient of 0.74.

4. Forest Age Classification

4.1 Background

Carbon storage in a stand is related to forest age class. As such, in areas without VRI data, it is also necessary to estimate stand age. Previous research has demonstrated that Sentinel-2 imagery can be applied to estimate age class for temperate coniferous and deciduous stands (Grabska & Socha, 2021). While it is possible to estimate stand age using of satellite imagery in a regression model, this was beyond the scope of this analysis. Instead, stand age was estimated for conifer and deciduous stands using age classes based on the VRI data.

4.2 Age Classes

Age class models were developed using the available VRI polygons updated since 2017 including 737 polygons for conifers (total of 78.4 km^2) and 45 polygons for deciduous stands (total of 5.2 km^2). The pixels in the Senitel-2 image intersecting with the sample polygons are shown in Figure 4. Spectral signatures for each age class and for each tree type were estimated and are provided in Figure 5. Based on the spectral signatures for the conifer age classes, there are two spectrally distinct age groups: the "young" group, which includes the 1 and 2 age classes, representing 0 – 40 years and the “older” group, which includes the 3 – 9 age classes, representing 41 – 251 (or greater) years. Thus, the younger and older aggregated age classes were selected since there was too much spectral overlap for more specific age class prediction. While there were greater differences between the deciduous VRI age classes, the same aggregated age classes were applied to deciduous stands for consistency. Figure 5 shows that for both coniferous and deciduous stands, the spectral difference between younger and older stands is sufficient for differentiation using the Sentinel-2 imagery.

Coniferous VRI Samples | **Deciduous VRI Samples**

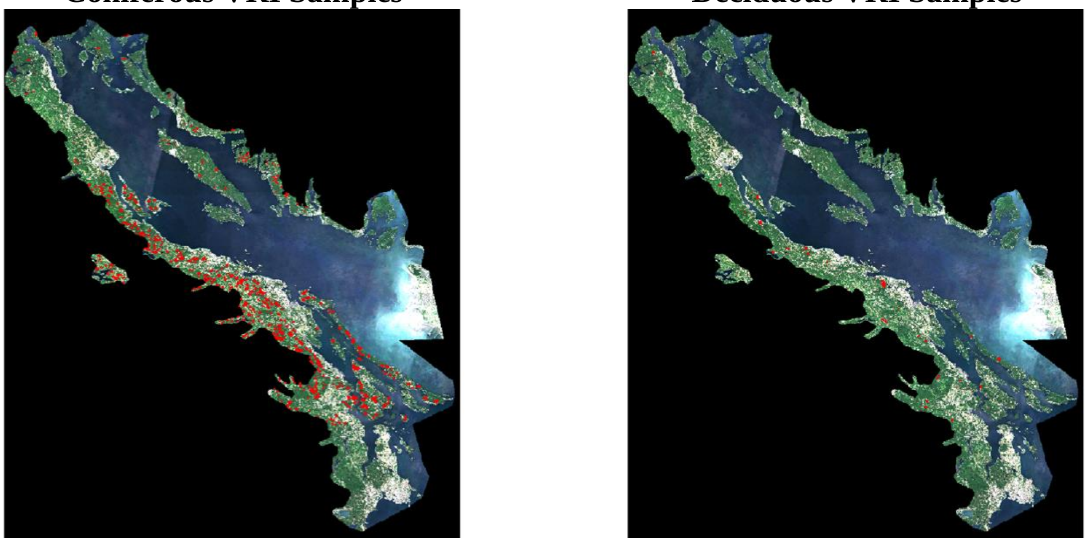
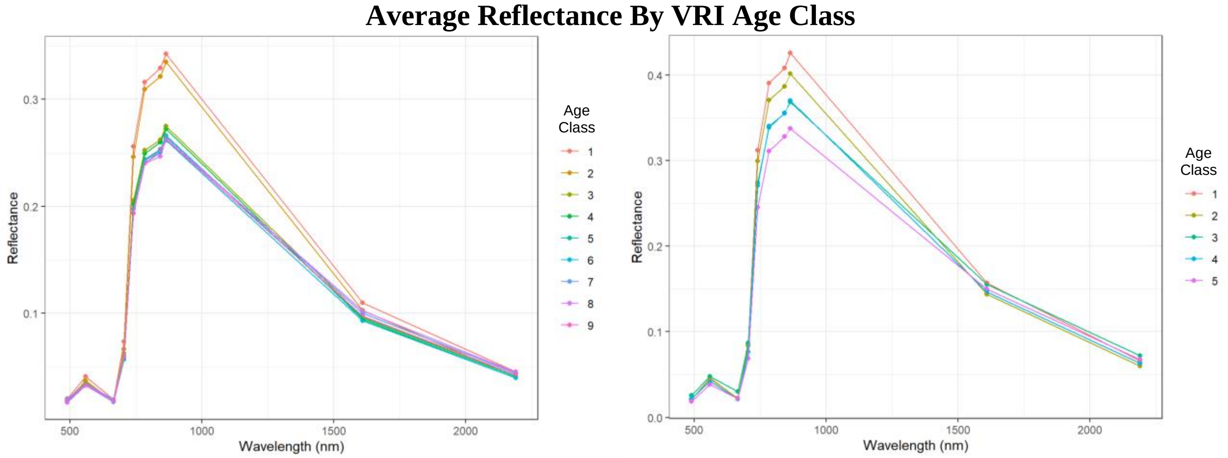


Figure 4: Sample pixels (shown in red) used for developing coniferous and deciduous forest age class prediction model for the Coastal Douglas-Fir biogeoclimatic zone.

Coniferous	**Deciduous**

Average Reflectance By VRI Age Class



Average Reflectance By Aggregated Age Class

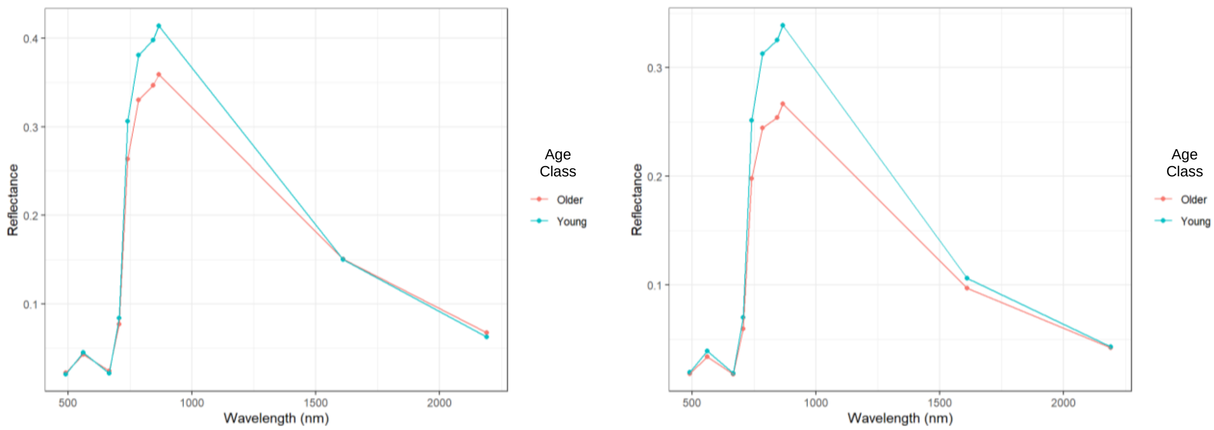


Figure 5: Spectral signatures of Vegetation Resource Inventory (VRI) age classes and aggregated age classes for coniferous and deciduous stands. The "Young" aggregated age class includes the 1 and 2 age classes, which represents the 0 – 40 years age range. The "Older" aggregated age class includes the 3 – 9 age classes, which represents the 41 – 251 (or greater) years age range.

4.3 Preparing Data for Age Class Modelling

Instead of GEE, aggregated age class prediction was performed using R software (v. 4.1.3). All age class modelling was performed separately for coniferous and deciduous trees. For age prediction, all the Sentinel-2 image pixels within the VRI sample polygons were extracted and divided into training (70%) and validation (30%) subsets. Since for both coniferous and deciduous stands there were far more older samples than there was younger, the training and validation samples of older pixels were randomly sampled such that the sample size for young and older age classes were even.

4.4 Development of Age Class Model

While there are many options for machine learning modelling for satellite imagery based prediction such as RF, CART, and SVM, an extreme gradient boosting (XGB) algorithm was selected for age class prediction (Tianqi Chen, 2022). The XGB approach was chosen because it is well suited for large datasets and has been shown to be effective for Sentinel-2 imagery forest classification (Abdi, 2020). In addition, the XGB is especially useful for binary machine learning classification (Bhagwat & Shankar, 2019) of satellite imagery.

The XGB model was developed within the caret package in R (Kuhn, 2022). Model training was performed using cross validation with three folds and a random search function. The linear version of the algorithm was implemented (xgbLinear) with default hyperparameters. All Sentinel-2 bands were used as predictor variables in the algorithm except for bands 11 and 12 since these had minimal spectral differences for the young and older age classes.

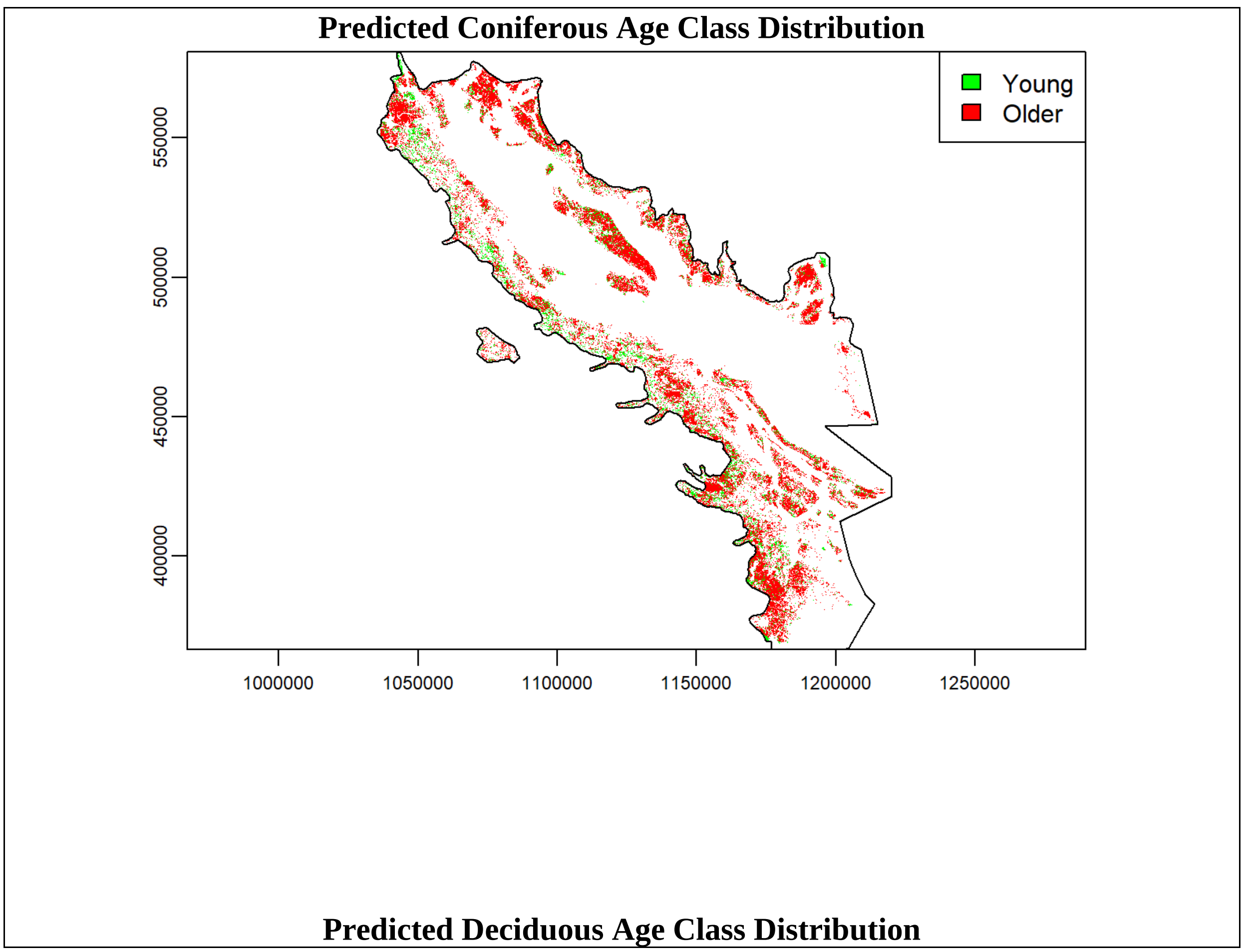
4.5 Accuracy Assessment of Age Class Model

An accuracy assessment was performed to evaluate the XGB performance on the validation data. The XGB model was implemented on the validation data, and classified the coniferous and deciduous age classes with accuracies of 85% and 81%, respectively ($p < 2^{-16}$; Kappa = 0.70 and 0.62, respectively). Errors of omission and commission were spread evenly between young and older age classes for both coniferous and deciduous forests, with UA and PA of 78% for both age classes and both tree types.

4.6 Implementation of Age Class Model

The XGB age class model was then implemented for coniferous and deciduous species separately using the Sentinel-2 image. Specifically, the each XGB model for coniferous and deciduous forests were only applied to Sentinel-2 pixels that were previously classified as their respective landcover class in the GEE RF model. The resulting wall-to-wall prediction of age class by tree type is provided in Figure 6. The predicted forest composition by tree type and age combining the GEE landcover classification and XGB age prediction is as follows: 12% Young Conifer; 46% Older Conifer; 14% Young Deciduous; 28% Older Deciduous.

Annotated versions of the complete age class prediction R scripts for both deciduous and coniferous stands are included as supplementary HTML, PDF, and RMD files.



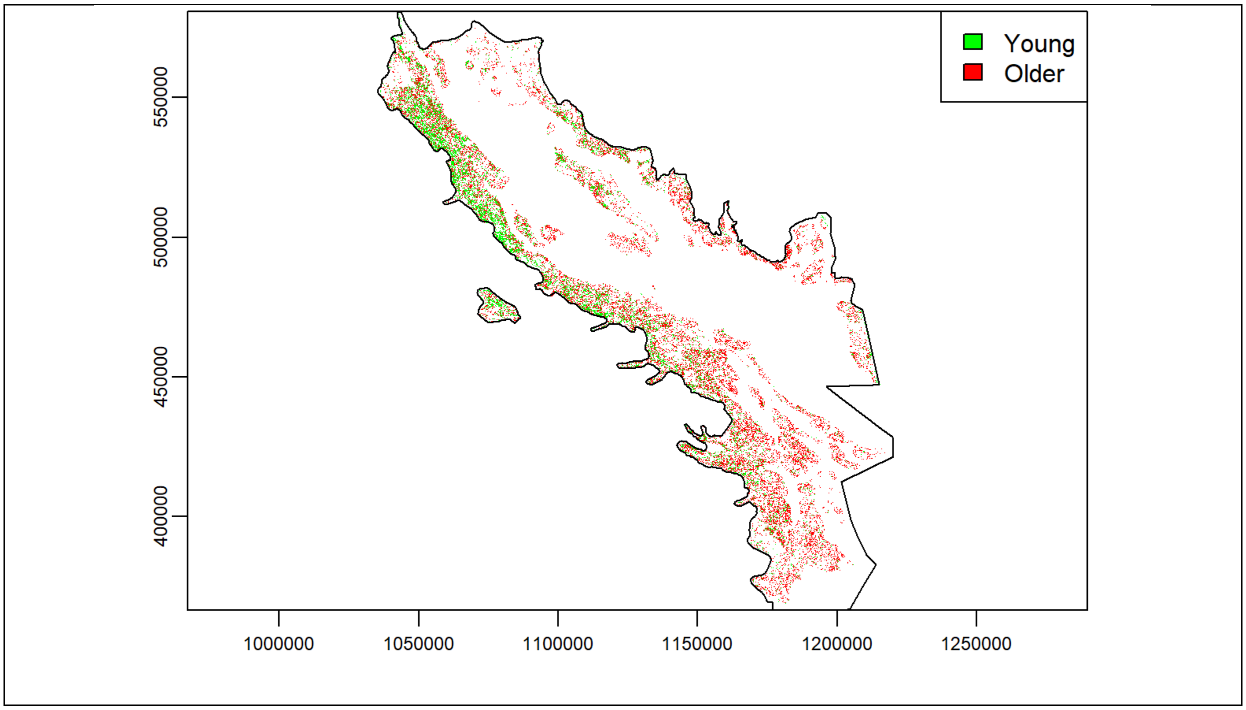


Figure 6: Predicted coniferous and deciduous age class distribution in the Coastal-Douglas-Fir biogeoclimatic zone.

5. Above Ground Biomass Modelling

5.1 Background

Above ground biomass (AGB) is another important predictor of carbon presence in a forest. To support CDF carbon modelling, this analysis also used Sentinel-2 data to predict AGB per hectare across the study site. Substantial prior research has demonstrated the capacity of satellite imagery for forest AGB prediction in Canadian forests (Ahmed et al., 2014; Matasci et al., 2018). Specifically, research has applied Sentinel-2 data for effective AGB mapping(Pandit et al., 2018).

5.2 Data Preparation for Modelling

Similar to the forest age class prediction, AGB prediction was accomplished using the same set of deciduous and coniferous VRI polygons updated since 2017. One challenge for this approach is that the area of each sample polygon varies substantially, from less than 0.1 km^2 to 1.5 km^2. Summarizing the biomass per ha over larger polygons leads to increased noise and makes it more challenging to develop a relationship between spectral properties and biomass. Another important challenge is the small amount of deciduous sample data containing biomass estimates. Of the VRI polygons used for age prediction, coniferous forest had 315 samples (54.0 km^2), and deciduous forest had only 33 samples (3.5 km^2). Given the small number of samples, and the fact that many stands in the study site are mixed, deciduous and coniferous samples were aggregated for biomass modelling. For each sample polygon, the mean reflectance value was extracted for each Sentinel-2 band within each plot. The 348 samples were then divided into training (70%) and validation (30%) sets.

5.3 Spectral Indices

While the Sentinel-2 band measured reflectance values can be sufficient as predictor variables for AGB forest biomass, most studies include spectral indices as additional predictor variables (Ahmed et al., 2014; Askar et al., 2018). Spectral indices are mathematical band combinations that exaggerate certain spectral properties. For example, the Normalized Difference Vegetation Index (NDVI) is a common spectral index that combines red and near infrared wavelengths and is used as a proxy for vegetation presence and health. While a wide variety of spectral indices have been applied to predict AGB biomass, most studies tend to include indices that represent wetness and vegetation characteristics (Matasci et al., 2018). As such, this analysis included four spectral indices that capture wetness and vegetation characteristics: NDVI, Enhanced Vegetation Index (EVI), Normalized Difference Moisture Index (NDMI), and Simple Ratio of Red to Near Infrared (SR). While the inclusion of additional spectral indices may be able to improve model accuracy, the relatively small sample size of only 348 samples limits the number of predictor variables.

5.4 Biomass Model Development and Implementation

Similar to forest age, AGB biomass can be modelled using a variety of machine learning methods. For this application, RF was selected because it is commonly used for AGB prediction (Matasci et al., 2018; Pandit et al., 2018). RF was implemented using the caret package in R using cross validation with five folds and a grid search function. Three hyperparameters were tuned to optimize model performance: 1) number of variables to use at each split in each decision tree (MTRY); 2) maximum number of terminal nodes trees in the forest can have (MAXNODES); 3) number of decision trees generated (NTREE). The optimal hyperparameter tunings were as follows: MTRY = 9; MAXNODES = 15; NTREE = 2000. All other RF parameters were left as default.

5.5 Biomass Model Accuracy Assessment

The optimized RF model had an R^2 of 0.49 and a AGB biomass Root Mean Squared Error (RMSE) equal to 119.5 tons/ha. To evaluate the accuracy of the AGB model, the developed RF model was tested on the training data set. The RF model RMSE was computed for the validation data and was compared to that calculated during the cross validation of the training data. The AGB biomass RMSE computed for the validation data was 107.1 tons/ha. Since the difference in RMSE between training and validation data was negligible, the model was deemed to effectively generalize to new data and was thus acceptable for the purpose of this analysis. Figure 7 shows a fitted line plot comparing observed versus predicted biomass. The RF biomass model was then applied to all of the pixels classified as coniferous or deciduous forest in the GEE landcover classification. The wall-to-wall biomass prediction is provided in Figure 8.

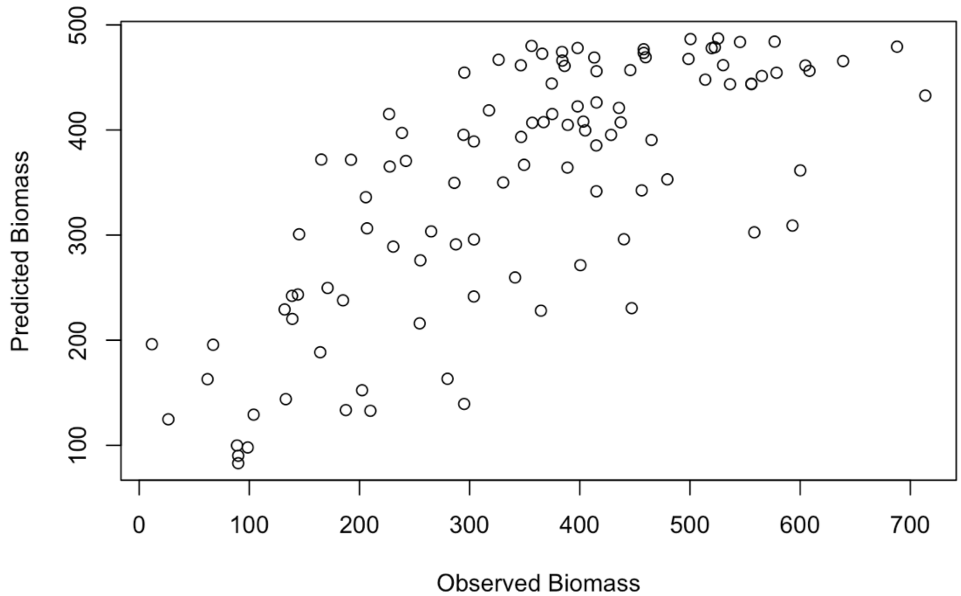


Figure 7: Fitted line plot showing the Vegetataion Resource Inventory observed biomass values versus Random Forest (RF) predicted biomass values for 105 validation samples. The RF model had an R^2 = 0.49 and an RMSE of 107.1 tons/ha.

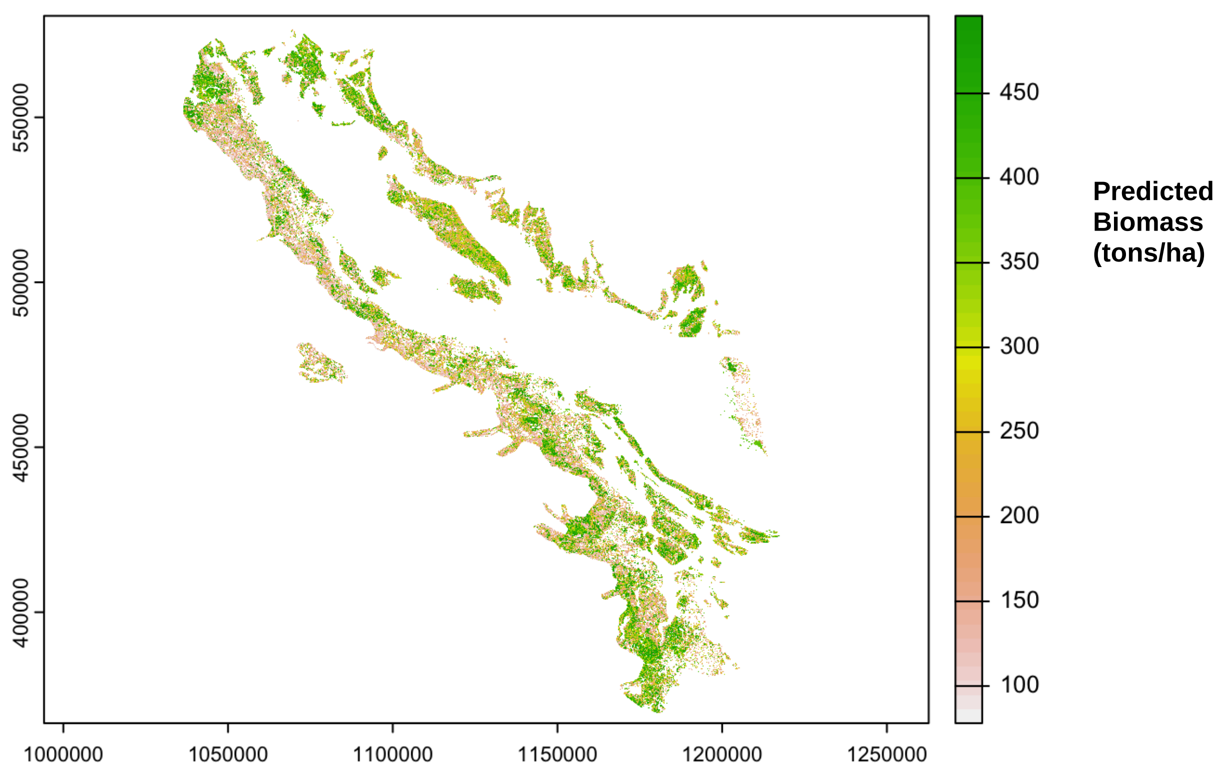


Figure 9: Biomass values (tons/ha) predicted in areas within the Coastal Douglas-Fir zone classified as forested. The values were predicted using a Random Forest algorithm with a R^2 = 0.49 and a Root Mean Squared Error of 107.1 tons/ha.

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Appendix 2

Google Earth Engine (GEE) Supervised Landcover Classification Script Link:
https://code.earthengine.google.com/f941a75ef5f61642dab4cf08ade6677b