

**FOREST-BASED BIOMASS SUPPLY CHAIN PLANNING CONSIDERING
UNCERTAINTIES AND GOVERNMENTAL POLICIES**

by

KIMIYA RAHMANI MOKARRARI

B.Sc., The University of Tehran, 2019

M.Sc., The University of Tehran, 2021

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

in

THE FACULTY OF GRADUATE AND POSTDOCTORAL STUDIES
(Forestry)

THE UNIVERSITY OF BRITISH COLUMBIA
(Vancouver)

June 2026

© Kimiya Rahmani Mokarrari, 2026

The following individuals certify that they have read, and recommend to the Faculty of Graduate and Postdoctoral Studies for acceptance, the dissertation entitled:

FOREST-BASED BIOMASS SUPPLY CHAIN PLANNING CONSIDERING
UNCERTAINTIES AND GOVERNMENTAL POLICIES

submitted by Kimiya Rahmani Mokarrari in partial fulfilment of the requirements for

the degree of Doctor of Philosophy

in Forestry

Examining Committee:

Dr. Taraneh Sowlati, Professor, Forestry, UBC

Supervisor

Dr. Hamish van der Ven, Assistance Professor, Forestry, UBC

Supervisory Committee Member

Dr. Qingshi Tu, Assistance Professor, Forestry, UBC

Supervisory Committee Member

Dr. Christopher Gaston, Associate Professor Emeritus, Forestry, UBC

University Examiner

Dr. Tony (Xiaotao) Bi, Professor, Chemical and Biological Engineering, UBC

University Examiner

Abstract

Environmental concerns have increased interest in advancing the bioeconomy, promoting the utilization of renewable resources, such as biomass, to produce value-added bioproducts. Forest-rich countries such as Canada have a significant advantage due to the abundance of biomass residues generated from logging activities and primary forest product industries. However, utilizing forest-based biomass for bioproduction faces challenges, with high supply chain costs and economic feasibility among the main barriers. Therefore, planning and design of forest-based biomass supply chains to optimize economic benefits presents a viable approach to address these challenges. Additionally, governments have introduced programs and policies to support the bioeconomy, and studies show that the success of bioproduction projects often depend on such support. Evaluating the role and impact of these policies is therefore essential, as overlooking them does not reflect real-world conditions. Moreover, policy-related and supply chain parameters are often subject to uncertainty, which should be incorporated into long-term planning, as overlooking them can significantly alter the outcomes.

In this research, unlike previous studies, governmental policies and their associated uncertainties are incorporated into the design and planning of a forest-based biomass supply chain for production of value-added bioproducts. Single-objective and bi-objective optimization models are developed to maximize the Net Present Value (NPV) and minimize greenhouse gas emissions. The models are implemented with and without policies, including feedstock subsidies, capital investment incentives, enhanced first-year depreciation allowances, and carbon pricing, and applied to the Williams Lake Timber Supply Area in British Columbia, Canada. Results show that considering all policies simultaneously increases the number of facility establishments and biomass utilization, yielding approximately \$44 million NPV over 20 years for 16 facilities, compared to \$29 million for 10 facilities without policies. Despite this increase, financial returns remain limited. Bi-objective results indicate that significant emission reduction can be obtained with modest decreases in NPV. For instance, a 47% reduction in emissions leads to only a 4.1% decrease in NPV. Incorporating uncertainty through possibilistic chance-constrained programming results in more conservative designs with fewer facilities, lower profits, and lower emissions compared to those from deterministic model (eight versus 16 facilities and a 43% decrease in NPV).

Lay Summary

This research focuses on using forest-based biomass residues from logging to produce value-added bioproducts instead of burning them and optimizing the supply chain. While using residues can reduce greenhouse gas emissions and create economic value, it is often challenged by high supply chain costs. Optimization-based mathematical models are developed in this research to design forest-based biomass supply chains that maximize the net present value (NPV) of the supply chain, while minimizing emissions. The impact of policies such as feedstock subsidies, capital investment incentives, depreciation allowances, and carbon pricing are also evaluated. Results show that, while the collective impact of policies can increase profitability and biomass utilization, the financial returns for bioproduction facilities remain limited. The results also show that substantial emission reductions can be achieved with only modest decreases in NPV. Uncertainty in policy, cost, and demand parameters are further incorporated, which suggests fewer facilities, lower profits, and lower emissions compared to those from the deterministic models.

Preface

The research presented in this dissertation, including the literature review; development of mathematical models; sensitivity analyses; result analysis; data cleaning; parameter estimation; creation of charts, figures, and graphs; writing of results; and revisions at every stage, was carried out by the author, Kimiya Rahmani Mokarrari, with the guidance and support of the research supervisor, Dr. Taraneh Sowlati.

The research supervisor, Dr. Taraneh Sowlati, and the author jointly identified the research problem and defined the steps and methods to address it. Dr. Sowlati also contributed to the analysis and writing of the results by providing feedback and comments throughout the program. OpenAI ChatGPT was used solely for language editing and clarity enhancement, including improving grammar and readability. It was not used for research design, model development, data analysis, interpretation of results, or generation of original research content. All aspects of the research, including model development, data analysis, and interpretation of results, were carried out by the author.

Dr. Sahar Ahmadvand (postdoctoral researcher), Salma Jahani, Aijun Wang, Jingyu Wang, and Shayan Razmi, graduate students in the Industrial Engineering Research Group, along with Dr. Sowlati, contributed to gathering real data and information from various sources, including equipment vendors, mills, FPIInnovations, and the literature. They also assisted in running some of the models developed in Chapter 3, recording the outputs, and participating in bi-weekly meetings with the Innovation, Bioeconomy and Indigenous Opportunities (IBIO) Branch at the BC Ministry of Forests.

A version of Chapter 2 is published. Rahmani Mokarrari, K., Kumar, G., & Sowlati, T. (2025). A Systematic Review of Forest-Based Biomass Supply Chain Optimization Incorporating Governmental Policies and Programs. *BioEnergy Research*, 18(1), 93. <https://doi.org/10.1007/s12155-025-10899-9>. I conducted a comprehensive literature review, categorized the reviewed studies, developed the manuscript, and created the visualizations.

A version of Chapter 2 and 3 is published. Rahmani Mokarrari, K., & Sowlati, T. (2026). Techno-Economic Assessment of Nanocellulose Production from Forest Harvesting Residues: Impacts of

Governmental Policies. *BioEnergy Research*, 19(1), 54. <https://doi.org/10.1007/s12155-026-10987-4>.

A version of chapters 4 and 5 are also under preparation for submission to a peer reviewed journal.

Rahmani Mokarrari, K., & Sowlati, T. (2026 – in progress). The Impact of Governmental Policies on the Optimal Design of a Forest-Based Biomass Supply Chain.

Rahmani Mokarrari, K., & Sowlati, T. (2026 – in progress). The Impact of Governmental Policies and Uncertainties on the Forest-Based Biomass Supply Chain Network Design: A Non-Deterministic Approach.

Table of Contents

Abstract.....	iii
Lay Summary	iv
Preface.....	v
Table of Contents	vii
List of Tables	xii
List of Figures.....	xx
Acknowledgements	xxiv
Dedication	xxv
Chapter 1: Introduction	1
1.1 Background	1
1.2 Research objective	4
1.3 Case study	5
1.3.1 Bioproducts	6
1.3.2 Production capacities and sizing of facilities.....	7
1.3.3 Case region and potential locations for bioproduction facilities	9
1.3.4 Supply chain pathways	10
1.4 Overview of the governmental policies and programs	12
1.4.1 Feedstock subsidies.....	13
1.4.2 Direct incentives for capital investment	14
1.4.3 Enhanced first-year allowance for depreciation	14
1.4.4 Output-based pricing system.....	14
1.5 Outline of the thesis	16
Chapter 2: Literature Review.....	17
2.1 Synopsis	17
2.2 Selection methodology.....	17
2.3 Overview of the governmental programs and policies	18
2.4 Deterministic models	21

2.4.1	Carbon-based policies and programs	21
2.4.2	Financial policies and programs	24
2.4.3	Market-based policies and programs	24
2.4.4	Tax-related policies and programs.....	26
2.4.5	Multiple programs and policies	27
2.5	Non-deterministic models.....	35
2.6	Summary and conclusions	38
Chapter 3: Techno-economic assessment		42
3.1	Synopsis	42
3.2	Economic analysis	42
3.2.1	Assumptions.....	42
3.2.2	Input data	43
3.2.3	Economic indicators and cash flow	47
3.3	Results and sensitivity analysis.....	48
3.3.1	Emission analysis for the output-based pricing system	48
3.3.2	Economic analysis without policies.....	50
3.3.3	Sensitivity analysis on financial parameters without policy considerations.....	51
3.3.4	Economic analysis with the policies	54
3.3.5	Sensitivity analysis on governmental policy parameters	58
3.4	Findings and conclusion	62
Chapter 4: Deterministic Supply Chain Network Design		66
4.1	Synopsis	66
4.2	Problem description	66
4.3	Deterministic single-objective model formulation without policies.....	68
4.4	Deterministic single objective model formulations with policies.....	71
4.4.1	Feedstock subsidies.....	71
4.4.2	Depreciation (enhanced first-year allowance)	72
4.4.3	Direct incentives for capital investments	72
4.4.4	Output-based pricing system (OBPS).....	72

4.4.5	All policies	76
4.5	Deterministic bi-objective model.....	76
4.6	Input parameters of the models	78
4.6.1	Supply	78
4.6.2	Transportation, preprocessing and handling costs	78
4.6.3	Bioproduction facilities costs.....	80
4.6.4	Bioproduct demands	83
4.6.5	Emissions	84
4.7	Results of the deterministic single objective models	86
4.7.1	Supply chain network designs	86
4.7.2	Computational characteristics and supply chain financials	89
4.7.3	Biomass and pathway utilization	92
4.7.4	Bioproduct production amounts.....	94
4.7.5	Output-based pricing system trading	99
4.7.6	Sensitivity analysis.....	103
4.8	Results of the deterministic bi-objective model.....	105
4.8.1	No-policy scenario	106
4.8.2	Feedstock subsidies.....	109
4.8.3	Depreciation (enhanced first-year allowance) policy scenario	111
4.8.4	Direct incentives for capital investment policy scenario	113
4.8.5	Output-based pricing system policy scenario	115
4.8.6	All-policy scenario.....	117
4.9	Conclusion	119
Chapter 5: Non-deterministic Supply Chain Network Design		123
5.1	Synopsis	123
5.2	Possibilistic chance constraint programming.....	123
5.3	Uncertain parameters	132
5.4	Non-deterministic single objective model	133
5.5	Non-deterministic bi-objective model	136

5.6	Results of the non-deterministic single objective model	136
5.7	Results of the non-deterministic bi-objective model	138
5.8	Comparison of pareto fronts across non-deterministic and deterministic models	143
5.9	Conclusion	144
Chapter 6: Conclusions, Strengths, Limitations, and Future Research Direction		146
6.1	Conclusions.....	146
6.2	Strengths	150
6.3	Limitations and future directions	152
Bibliography		155
Appendices.....		172
Appendix A (Input Data)		172
A.1	Input data for biomass transportation through different pathways	172
A.2	Input data for preprocessing and handling biomass at the biohubs	173
A.3	Input data for bioproduction technologies	179
A.4	Supply data.....	180
Appendix B (Emissions Calculations)		181
B.1	Roadside, preprocessing, and handling emissions	181
B.2	Transportation emissions	184
B.3	Bioproduction facilities emissions.....	185
Appendix C (Techno-economic Analysis without Policies).....		190
C.1	CNC and CNF.....	190
C.2	Biochar	195
C.3	AC	199
C.4	Bio-oil	200
C.5	Pellets.....	202
Appendix D (Techno-economic Analysis with Policies).....		207
D.1	Feedstock subsidies.....	207
D.2	Direct incentives for capital investments	211
D.3	Enhanced first-year allowance for depreciation	215

D.4	BC output-based pricing system	219
Appendix E (Market Analysis)		230
E.1	Biochar	230
E.2	Activated Carbon	231
E.3	Nanocellulose.....	232
E.4	Pellets	233
E.5	Estimating the Williams Lake market demand	233

List of Tables

Table 1-1. Technology, bioproducts, type of feedstock and yield of technologies.	7
Table 1-2. Bioproduct producers in Canada with their production capacities.....	8
Table 1-3. Production capacity and required annual input biomass for each capacity and bioproduct.	9
Table 1-4. List of equipment used at cut blocks and biohubs for ground slash pathway	10
Table 1-5. List of equipment pieces used at cut blocks and biohubs for bundled slash pathway.	11
Table 1-6. Equipment piece used at cut blocks and biohubs for small-diameter logs pathway. ..	11
Table 1-7. Credit usage limit (Government of BC, 2024b).	15
Table 2-1. Summary of deterministic forest-based biomass supply chain planning studies considering governmental policy and regulations.	32
Table 2-2. Summary of non-deterministic forest-based biomass supply chain planning studies considering governmental policy and regulations.	37
Table 2-3. Classification of studies based on how policies were incorporated in the optimization models.	39
Table 3-1. Original input data for cellulose nanocrystal (CNC) and cellulose nanofibrils (CNF) production using AVAP (American Value-Added Pulping) technology (Blair, 2020).	43
Table 3-2. Summary of emissions for Cellulose Nanocrystal (CNC) production using ground and bundled slash pathways.....	49
Table 3-3. Summary of emissions for Cellulose Nanofibrils (CNF) production using ground and bundled slash pathways.....	49
Table 3-4. Net present value (NPV) of cellulose nanocrystals (CNC) and cellulose nanofibrils (CNF) production scenarios without incorporating any governmental policies in the economic analysis.....	50
Table 3-5. Summary of the subsidy analysis for small-scale cellulose nanocrystals (CNC) production under different locations and pathways.	58
Table 4-1. Notations of the mathematical programming model without policy considerations...	68
Table 4-2. Additional notations required for the mathematical programming model under the output-based pricing policy.....	72
Table 4-3. Additional parameters required for the bio-objective model.	76
Table 4-4. Preprocessing and handling cost of biomass at the biohubs by supply chain pathway.	80

Table 4-5. Input data for small-scale bioproduction facilities.	81
Table 4-6. Input data for medium-scale bioproduction facilities.	82
Table 4-7. Input data for large-scale bioproduction facilities.	83
Table 4-8. Estimated demand for the bioproducts from 2024 to 2043.	84
Table 4-9. Emissions from roadside activities by the supply chain pathway.	84
Table 4-10. Emissions from activities performed at the bioproduction facilities (i.e, biohubs) including emissions from bioproduction, handling, and preprocessing.	85
Table 4-11. Number of constraints and variables, and solution time of the deterministic single objective mathematical models under the policy scenarios.	89
Table 4-12. Results of the deterministic single objective model under different policy scenarios.	90
Table 4-13. Bioproduction amount (yield of technologies $\times$ input biomass) at each facility under no-policy, feedstock subsidies, and enhanced first-year allowance scenarios (deterministic single objective model).	95
Table 4-14. Bioproduction amount (yield of technologies $\times$ input biomass) at each facility under output-based pricing policy (deterministic single objective model).	96
Table 4-15. Bioproduction amount (yield of technologies $\times$ input biomass) at each facility under direct incentives for capital investment policy (deterministic single objective model).	97
Table 4-16. Bioproduction amount (yield of technologies $\times$ input biomass) at each facility under all policies (deterministic single objective model).	98
Table 4-17. Parameters in the optimization model and their definitions.	103
Table 4-18. Prescribed bioproduction facility establishments under the no-policy scenario for three Pareto-optimal solutions (deterministic bi-objective model).	107
Table 4-19. Bioproduction facility establishments under the feedstock subsidy scenario for three Pareto-optimal solutions (deterministic bi-objective model).	110
Table 4-20. Bioproduction facility establishments under the enhanced first-year allowance scenario for three Pareto-optimal solutions (deterministic bi-objective model).	112
Table 4-21. Bioproduction facility establishments under the direct incentives for capital investments policy scenario for three Pareto-optimal solutions (deterministic bi-objective model).	114
Table 4-22. Bioproduction facility establishments under the direct incentives for the output-based pricing policy scenario for three Pareto-optimal solutions (deterministic bi-objective model).	116

Table 4-23. Bioproduction facility establishments under the scenario where all policies are implemented for three Pareto-optimal solutions (deterministic bi-objective model).	118
Table 5-1. Notations of the non-deterministic mathematical programming model without policy considerations.	124
Table 5-2. Bioproduction facility establishments under the scenario where all policies are implemented deterministic and non-deterministic models	137
Table 5-3. Bioproduction facility establishments under the scenario where all policies are implemented for three Pareto-optimal solutions (non-deterministic bi-objective model).	140
Table 5-4. Bioproduction facility establishments under the scenario where all policies are implemented for three Pareto-optimal solutions (non-deterministic bi-objective model).	142
Table A-1. Input data for calculating the biomass delivered cost via the bundled slash pathway.....	172
Table A-2. Input data for calculating the biomass delivered cost via the small-diameter slash pathway.....	173
Table A-3. Input data for calculating unit cost (\$/odt) of handling biomass with front-end loader.....	173
Table A-4. Input data for calculating unit cost (\$/odt) of handling biomass with reclaim feeder.....	174
Table A-5. Input data for calculating unit cost (\$/odt) of handling biomass with scalping disk screener.....	174
Table A-6. Input data for calculating unit cost (\$/odt) of preprocessing biomass with drop feed hogger.....	175
Table A-7. Input data for calculating unit cost (\$/odt) of handling biomass with butt-n-top loader.....	176
Table A-8. Input data for calculating unit cost (\$/odt) of handling biomass with butt-n-top loader.....	176
Table A-9. Input data for calculating unit cost (\$/odt) of preprocessing biomass with debarker and chipper.....	177
Table A-10. Input data for calculating unit cost (\$/odt) of preprocessing biomass with debarker and chipper.....	178
Table A-11. Input data for calculating unit cost (\$/odt) of preprocessing biomass with rotary cascade dryer.	179
Table A-12. Original input data for bioproduction technologies.....	179
Table A-13. Original input data for bioproduction technologies.....	180
Table B-1. Greenhouse gas (GHG) emissions (tonne of CO ₂ -eq/odt) for preprocessing slash at road side.....	181

Table B-2. Greenhouse gas (GHG) emissions (tonne of CO ₂ -eq/odt) for handling and preprocessing of ground slash at bioproduction facilities (i.e., biohubs)	182
Table B-3. Greenhouse gas (GHG) emissions (tonne of CO ₂ -eq/odt) for activities at road side for bundled slash pathway.....	182
Table B-4. Greenhouse gas (GHG) emissions (tonne of CO ₂ -eq/odt) for handling and preprocessing of bundled slash at bioproduction facilities (i.e., biohubs)	183
Table B-5. Greenhouse gas (GHG) emissions (tonne of CO ₂ -eq/odt) for loading small diameter logs to trucks at road side.....	183
Table B-6. Greenhouse gas (GHG) emissions (tonne of CO ₂ -eq/odt) for handling and preprocessing of small-diameter logs at bioproduction facilities (i.e., biohubs)	184
Table B-7. Transportation data.....	184
Table B-8. Required information and assumptions to calculate natural gas demand for CNC (cellulose nanocrystal) production using AVAP (American value-added pulping)	185
Table B-9. GHG emissions (tonne of CO ₂ -eq/odt) from CNC (cellulose nanocrystal) production using AVAP (American value-added pulping)	186
Table B-10. Greenhouse gas (GHG) emissions (tonne of CO ₂ -eq/odt) for biochar conversion facility using dry and wet torrefaction.....	187
Table B-11. Greenhouse gas (GHG) emissions (tonne of CO ₂ -eq/odt) for activated carbon (AC) conversion facility.....	188
Table B-12. Greenhouse gas (GHG) emissions (tonne of CO ₂ -eq/odt) for pellet conversion facility.....	189
Table C-1. Economic data for Cellulose Nanocrystal (CNC) production for ground slash pathway.....	189
Table C-2. Economic data for Cellulose Nanocrystal (CNC) production for bundled slash pathway.....	191
Table C-3. Economic data for Cellulose Nanofibrils (CNF) production for ground slash pathway.....	192
Table C-4. Economic data for Cellulose Nanofibrils (CNF) production for bundled slash pathway.....	193
Table C-5. Economic data for biochar production using wet torrefaction for ground slash pathway.....	194
Table C-6. Economic data for biochar production using wet torrefaction for bundled slash pathway.....	195
Table C-7. Economic data for biochar production using dry torrefaction for ground slash pathway.....	196
Table C-8. Economic data for biochar production using dry torrefaction for bundled slash pathway.....	197

Table C-9. Economic data for production of Activated Carbon (AC) for small-diameter logs pathway.....	198
Table C-10. Economic data for production of bio-oil for ground slash pathway.....	200
Table C-11. Economic data for bio-oil production for bundled slash pathway.....	201
Table C-12. Economic data for pellets production for ground slash pathway.....	202
Table C-13. Economic data for pellets production for bundled slash pathway	203
Table C-14. Economic data for Pellets production for small-diameter logs pathway.....	204
Table C-15. NPV (net present value) of bioproduction scenarios without policy considerations.....	205
Table D-1. Required feedstock, feedstock delivered cost, subsidies, NPV (net present value) after subsidies, and the percentage of change in the NPV for CNC (cellulose nanocrystals) production scenarios considering carbon price of \$12/t CO ₂ -eq to calculate the subsidies.....	207
Table D-2. Required feedstock, feedstock delivered cost, subsidies, NPV (net present value) after subsidies, and the percentage of change in the NPV for CNF (cellulose nanofibrils) production scenarios considering carbon price of \$12/t CO ₂ -eq to calculate the subsidies.....	208
Table D-3. Required feedstock, feedstock delivered cost, subsidies, NPV (net present value) after subsidies, and the percentage of change in the NPV for biochar in dry torrefaction production scenarios considering carbon price of \$12/t CO ₂ -eq to calculate the subsidies.....	208
Table D-4. Required feedstock, feedstock delivered cost, subsidies, NPV (net present value) value after subsidies, and the percentage of change in the NPV for biochar in wet torrefaction production scenarios considering carbon price of \$12/t CO ₂ -eq to calculate the subsidies.....	209
Table D-5. Required feedstock, feedstock delivered cost, subsidies, NPV (net present value) after subsidies, and the percentage of change in the NPV for AC (activated carbon) production scenarios considering carbon price of \$12/t CO ₂ -eq to calculate the subsidies.....	210
Table D-6. Required feedstock, feedstock delivered cost, subsidies, NPV (net present value) after subsidies, and the percentage of change in the NPV for Pellet production scenarios considering carbon price of \$12/t CO ₂ -eq to calculate the subsidies.....	210
Table D-7. Required feedstock, capital cost, covered portion of the capital cost, NPV (net present value) after incentives, and the percentage of change in the NPV values for CNC (cellulose nanocrystal) production scenarios.....	211
Table D-8. Required feedstock, capital cost, covered portion of the capital cost, NPV (net present value) after incentives, and the percentage of change in the NPV values for CNF (cellulose nanofibrils) production scenarios.....	212
Table D-9. Required feedstock, capital cost, covered portion of the capital cost, NPV (net present value) after incentives, and the percentage of change in the NPV values for Biochar production in dry torrefaction scenarios.....	213
Table D-10. Required feedstock, capital cost, covered portion of the capital cost, NPV (net present value) after incentives, and the percentage of change in the NPV values for Biochar production in wet torrefaction scenarios.....	213

Table D-11. Required feedstock, capital cost, covered portion of the capital cost, NPV (net present value) after incentives, and the percentage of change in the NPV values for AC (activated carbon) production scenarios.....	214
Table D-12. Required feedstock, capital cost, covered portion of the capital cost, NPV (net present value) after incentives, and the percentage of change in the NPV values for Pellet production scenarios.....	214
Table D-13. Required feedstock, NPV (net present value) after the first-year enhanced allowance measure, and the percentage of change in the NPV values for CNC (cellulose nanocrystal) production scenarios.....	215
Table D-14. Required feedstock, NPV (net present value) before and after the first-year enhanced allowance measure, and the percentage of change in the NPV values for CNF (cellulose nanofibril) production scenarios.....	216
Table D-15. Required feedstock, NPV (net present value) after the first-year enhanced allowance measure, and the percentage of change in the NPV values for biochar production in dry torrefaction technology scenarios.....	217
Table D-16. Required feedstock, NPV (net present value) after the first-year enhanced allowance measure, and the percentage of change in the NPV values for biochar production in wet torrefaction technology scenarios.....	218
Table D-17. Required feedstock, NPV (net present value) the first-year enhanced allowance measure, and the percentage of change in the NPV values for AC (activated carbon) production scenarios.....	218
Table D-18. Required feedstock, NPV (net present value) after the first-year enhanced allowance measure, and the percentage of change in the NPV values for Pellet production scenarios.....	220
Table D-19. Inputs and emissions of CNC (cellulose nanocrystal) production with acid recovery.....	220
Table D-20. Inputs and emissions of CNC (cellulose nanocrystal) production without acid recovery.....	221
Table D-21. Inputs and emissions of CNC (cellulose nanocrystal) production with sulfuric acid hydrolysis.....	220
Table D-22. Average inputs and emissions of CNC (cellulose nanocrystal) production of two acid hydrolysis processes.....	221
Table D-23. Inputs and emissions of CNC (cellulose nanocrystal) production with chemical acid hydrolysis.....	221
Table D-24. NPV (net present value) comparison of CNC (cellulose nanocrystal) production scenarios with and without carbon pricing.....	221
Table D-25. Inputs and emissions of CNF (cellulose nanofibrils) production with enzymatic pre-treatment.....	222
Table D-26. Inputs and emissions of CNF (cellulose nanofibrils) production with carboxymethylation pre-treatment.....	222

Table D-27. Inputs and emissions of CNF (cellulose nanofibrils) production with mechanical pre-treatment.....	222
Table D-28. Inputs and emissions of CNF (cellulose nanofibrils) production with enzymatic pre-treatment.....	223
Table D-29. NPV (net present value) comparison of CNF (cellulose nanofibrils) production scenarios without BC output-based carbon pricing.....	223
Table D-30. Inputs and emissions of biochar production using slow pyrolysis.....	224
Table D-31. Inputs and emissions of biochar production using Biochar Solutin Incorporated (BSI).....	224
Table D-32. Inputs and emissions of biochar production using Air Curtain Burner (ACB).....	224
Table D-33. Inputs and emissions of biochar production.....	225
Table D-34. NPV (net present value) comparison of biochar production (wet torrefaction) scenarios with BC output-based carbon pricing.....	225
Table D-35. NPV (net present value) comparison of biochar production (dry torrefaction) scenarios with BC output-based carbon pricing.....	226
Table D-36. Inputs and emissions of AC (activated carbon) production.....	226
Table D-37. Outputs of AC (activated carbon) production using pyrolysis and chemical activation with ZnCl ₂	227
Table D-38. Outputs of AC (activated carbon) production using pyrolysis and chemical activation with H ₃ PO ₄)	227
Table D-39. NPV (net present value) comparison of AC (activated carbon) production scenarios with output-based carbon pricing.....	227
Table D-40. NPV (net present value) comparison of pellet production scenarios without BC output-based carbon pricing.....	228
Table E-1. Global market size for biochar in 2024 and 2033 (Research and Markets, 2025b), with equivalent values in CAD.....	230
Table E-2. Estimated global biochar demand derived from market size and average price.....	230
Table E-3. Estimated global and Canadian biochar market size (tonnes) from 2024 to 2043, assuming a constant 12.4% annual global growth rate and a stable 3.65% Canadian market share.....	231
Table E-4. Estimated global and Canadian activated carbon (AC) market size (tonnes) from 2024 to 2043, assuming an 8% annual growth rate and a stable 2.1% Canadian market share.....	231
Table E-5. Global market size for nanocellulose in 2024 and 2032 (Markets and Markets, 2024), with equivalent values in CAD.....	232

Table E-6. Estimated global nanocellulose demand derived from market size and average price.....	232
Table E-7. Estimated global and Canadian nanocellulose market size (tonnes) from 2024 to 2043, assuming an 23.7% annual growth rate and a stable 7.7% Canadian market share.....	233

List of Figures

Figure 1-1. Schematic of supply chain pathways with the activities at each supply chain stage.	12
Figure 2-1. Process of selecting papers for the review.	18
Figure 2-2. Categories of governmental programs and policies and their examples. The main categories obtained from (Daneshmandi et al., 2022; Mottaghi et al., 2022) are showed with a red-dashed border.	21
Figure 2-3. Classification of governmental policies and programs considered were reflected in the mathematical models for each policy group.	40
Figure 3-1. Capital investment and initial costs (in Millions CAD) for Cellulose Nanocrystal (CNC) production at different production scales.	45
Figure 3-2. Annual operating costs (in thousands CAD) for Cellulose Nanocrystal (CNC) production at different production scales.	45
Figure 3-3. Capital investment and initial costs (in millions of CAD) for Cellulose Nanofibrils (CNF) production at different scales.	46
Figure 3-4. Annual operating costs (in millions CAD) for Cellulose Nanofibrils (CNF) production at different production scales.	46
Figure 3-5. (a) Annual revenue from Cellulose Nanocrystal (CNC) sales and its co-products; (b) Annual revenue from Cellulose Nanofibrils (CNF) sales and its co-products.	47
Figure 3-6. Scenarios with highest NPV in each capital investment bracket.	51
Figure 3-7 (a-b). Sensitivity analysis of net present value (NPV) for CNC production under changes in five key input parameters across three production sizes (small, medium, large). Each subplot represents the percentage change in NPV in response to a variation in a specific parameter. Solid lines indicate the mean response across five biohub locations, and shaded areas represent the minimum and maximum NPV changes observed among the locations.	52
Figure 3-8 (a-b). Sensitivity analysis of net present value (NPV) for CNF production under changes in five key input parameters across three production sizes (Small, Medium, Large). Each subplot represents the percentage change in NPV in response to a variation in a specific parameter. Solid lines indicate the mean response across five biohub locations, and shaded areas represent the minimum and maximum NPV changes observed among the locations.	53
Figure 3-9 (a-c). Comparison of NPV for cellulose nanocrystals (CNC) production under no policy and various policy scenarios.	56
Figure 3-10 (a-c). Comparison of NPV for cellulose nanofibrils (CNF) production under no policy and various policy scenarios.	57

Figure 3-11 (a-f). Sensitivity analysis of average net present value (NPV) changes across all biohub locations in response to variations in output-based pricing system parameters for CNC production at different scales and pathways. (a-c) Results for ground slash supply at small (12.5 odt/year), medium (625 odt/year), and large (1,250 odt/year) production scales, respectively. (d-f) Results for bundled slash supply at small (12.5 odt/year), medium (625 odt/year), and large (1,250 odt/year) production scales, respectively.	60
Figure 3-12 (a-f). Sensitivity analysis of average net present value (NPV) changes across all biohub locations in response to variations in output-based pricing system parameters for CNF production at different scales and pathways. (a-c) Results for ground slash supply at small (136 odt/year), medium (8,974 odt/year), and large (18,846 odt/year) production scales, respectively. (d-f) Results for bundled slash supply at small (136 odt/year), medium (8,974 odt/year), and large (18,846 odt/year) production scales, respectively.	61
Figure 4-1. The schematic representation of the biomass supply chain, demonstrating activities at supply sources and bioproduction facility (i.e., biohub) locations for each pathway. HA: Hanceville, AL: Anahim Lake, HF: Horsefly, and WL: Williams Lake.	67
Figure 4-2. Suggested facilities to be established under the enhanced first-year allowance, feedstock subsidies, and no-policy scenarios.	87
Figure 4-3. Suggested facilities to be established under the direct incentives for capital investments policy.	87
Figure 4-4. Suggested facilities to be established under the output-based pricing policy.	88
Figure 4-5. Suggested facilities to be established under all-policy scenario.	89
Figure 4-6. Utilized biomass (odt) under each policy at each location compared with the total available biomass supply for each location over the 20-year planning horizon (deterministic single objective model).	93
Figure 4-7. Amount of biomass (odt) transported through different supply chain pathways under each policy scenario over the 20-year planning horizon.	94
Figure 4-8. Generated credits and decisions regarding banking them or selling them in pellets production facilities under the output-based pricing policy.	99
Figure 4-9. Excess emissions for CNF (cellulose nanofibrils) production facilities under the output-based pricing policy.	100
Figure 4-10. Generated credits and decisions regarding banking them or selling them in pellets and biochar production facilities under all-policy scenario.	101
Figure 4-11. Excess emissions for CNF (cellulose nanofibrils), AC (activated carbon), and biochar (wet torrefaction) production facilities under the all-policy scenario.	102

Figure 4-12. Changes in NPV (net present value) obtained by solving a single-objective NPV profit-maximization model under the all-policy scenario, for each input parameter variation. .	104
Figure 4-13. Pareto-optimal solutions showing the trade-off between NPV (net present value) and total greenhouse gas (GHG) emissions for the supply chain network under the considered policy scenarios (deterministic bi-objective model).	106
Figure 4-14. Pareto-optimal solutions illustrating changes in NPV (net present value) as the emission constraint varies under the no-policy scenario (deterministic bi-objective model).....	107
Figure 4-15. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the no-policy scenario for three Pareto-optimal solutions (deterministic bi-objective model).	108
Figure 4-16. Pareto-optimal solutions illustrating changes in NPV (net present value) as emission constraint varies under the feedstock subsidy scenario (deterministic bi-objective model).....	109
Figure 4-17. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the feedstock subsidy scenario for three Pareto-optimal solutions (deterministic bi-objective model).	111
Figure 4-18. Pareto-optimal solutions illustrating changes in NPV (net present value) as emissions vary under the enhanced first-year allowance scenario (deterministic bi-objective model).	111
Figure 4-19. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the enhanced first-year allowance scenario for three Pareto-optimal solutions (deterministic bi-objective model).....	113
Figure 4-20. Pareto-optimal solutions illustrating changes in NPV (net present value) as emissions vary under the direct incentives for capital investments policy scenario (deterministic bi-objective model).	113
Figure 4-21. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the capital investments policy scenario for three Pareto-optimal solutions (deterministic bi-objective model).....	115
Figure 4-22. Pareto-optimal solutions illustrating changes in NPV (net present value) as emissions vary under the output-based pricing policy scenario (deterministic bi-objective model).	116
Figure 4-23. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the direct incentives the output-based pricing policy scenario for three Pareto-optimal solutions (deterministic bi-objective model).....	117
Figure 4-24. Pareto-optimal solutions illustrating changes in NPV (net present value) as emissions vary under the scenario where all policies are implemented deterministic bi-objective model (deterministic bi-objective model).....	118

Figure 4-25. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the scenario where all policies are implemented for three Pareto-optimal solutions (deterministic bi-objective model).....	119
Figure 5-1. Trapezoidal possibility distributions of uncertain parameter f	128
Figure 5-2. Possibility and necessity degrees of $f x \leq r$ following (Inuiguchi & Ramík, 2000).	129
Figure 5-3. Possibility and necessity degrees of $f x \leq r$ following (Inuiguchi & Ramík, 2000).	130
Figure 5-4. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions for the deterministic solution and two non-deterministic solutions (confidence level = 0.5 and 1) under the all-policy scenario.	138
Figure 5-5. Pareto-optimal solutions of the non-deterministic bi-objective model (confidence level = 0.5) illustrating changes in NPV (net present value) as emissions vary under the scenario where all polices are implemented.	139
Figure 5-6. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the all-policy scenario for three Pareto-optimal solutions obtained from the bi-objective non-deterministic model (confidence level = 0.5).	141
Figure 5-7. Pareto-optimal solutions of the non-deterministic bi-objective model (confidence level = 1) illustrating changes in NPV (net present value) as emissions vary under the scenario where all polices are implemented.	141
Figure 5-8. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the all-policy scenario for three Pareto-optimal solutions obtained from the bi-objective non-deterministic model (confidence level = 1).	143
Figure 5-9. Comparison of Pareto fronts obtained from the deterministic model and the non-deterministic model under two confidence levels ($\alpha = \beta = 1$ and $\alpha = \beta = 0.5$).....	144

Acknowledgements

I would like to express my sincere gratitude to my supervisor, Dr. Taraneh Sowlati, for her continuous guidance, support, and encouragement throughout my PhD. Her insights, expertise, and thoughtful feedback have been invaluable at every stage of this research.

I would also like to thank my supervisory committee members, Dr. Hamish van der Ven and Dr. Qingshi Tu, for their valuable feedback, guidance, and support throughout my program. Their perspectives and suggestions have helped strengthen this research significantly. I am also very grateful to Dr. Christopher Gaston for his support and encouragement throughout my time as a teaching assistant and beyond.

I am also grateful to Dr. Sahar Ahmadvand for her support, collaboration, and valuable discussions that contributed to this work. My appreciation extends to all my colleagues in the Industrial Engineering Research Group (IERG), as well as past members Rohit Arora and Salar Ghotb, for their support, collaboration, and for creating a positive and inspiring research environment.

I would like to thank the Innovation, Bioeconomy and Indigenous Opportunities (IBIO) Branch at the BC Ministry of Forests for their collaboration, insights, and for providing valuable practical perspectives that strengthened this research.

I gratefully acknowledge the financial support provided by IBIO and the Natural Sciences and Engineering Research Council of Canada (NSERC RGPIN2019-04563), which made this research possible.

I would also like to express my deepest gratitude to my friends, Sina Tavasoli, Hanieh Edjlalipour, and Salma Jahani for bringing color into my life miles away from home, and for their constant support, kindness, and encouragement throughout this process.

Last but not least, I would like to thank my family for their unconditional support, encouragement, and patience throughout this journey. Their belief in me has been a constant source of strength.

Dedication

To my parents, Kati and Faramarz, who filled my life with love, strength, and endless encouragement, even from afar. With all my love and gratitude, always.

Chapter 1: Introduction

1.1 Background

Environmental issues have raised concerns about the current economic model and prompted a call for a transition to bioeconomy, which proposes an economic model based on utilization of renewable resources, such as biomass, to produce value-added bioproducts (Ferreira et al., 2022).

Forests could play a crucial role in enhancing the bioeconomy (Wolfslehner et al., 2016), serving as a vital source of biomass for various value-added bioproducts, including bioproducts, biofuels, and bioenergy. Forest-based biomass encompasses various sources, including residues left behind in forests from harvesting activities, wood processing residues generated at wood processing facilities such as pulp mills and sawmills, fast-growing plantations, construction and demolition wastes, and dead trees due to disturbances (Sowlati, 2016). Globally, forestry and harvesting activities produce up to approximately 4.6 billion oven-dry tons of biomass (Popp et al., 2021). The harvesting residues, along with wood processing residues, holds significant potential for the development of bioproducts (Sowlati, 2016). The utilization of biomass for bioproduct production has the potential to reduce reliance on fossil fuels (Acuna et al., 2019) and address issues related to climate change, resource scarcity, and energy insecurity (Lim et al., 2022).

However, the utilization of biomass for bioproduction and bioeconomy enhancement is significantly impacted by governmental programs and policies. A survey conducted by the German Bioeconomy Council from 282 global bioeconomy experts showed that the successful commercialization of bioproduction projects depends on the involvement of governmental bodies, including their support and investment to bring these products to market, and their efforts to improve the structures, rules, and systems that govern and support the functioning of the bioproduct market (Dietz et al., 2023). Similarly, Canada's Forest Bioeconomy Framework identified the design of effective regulations that reduce obstacles for biomass projects and encourage demand for bioproducts as a key role of governments in advancing bioeconomy development (Canadian Council of Forest Ministers, 2017). Moreover, in the context of the US bioeconomy, government investments, and research and development efforts were mentioned as key drivers in developing new bioproducts and enhancing their economic competitiveness with their fossil-based counterparts (Pascoli et al., 2022).

The positive impact of supportive government policies on the financial feasibility of bioproduction projects is such that there is almost no evidence of biomass-based power and heat plants operating without some form of subsidy, whether direct, indirect through electricity bills, or via loans from publicly funded or owned entities (Ahmadvand & Sowlati, 2023; Ernsting & van der Mark, 2019). For instance, in 2014, the European Union established the Bio-based Industries Joint Undertaking to attract investments, enhance research and development, and improve innovation in the bio-based industry (Dietz et al., 2023). Supported by €975M from the European Commission and €2.73B from the private sector, it helped reduce the risk of investments by funding 142 projects to develop environmentally friendly bio-based products (Dietz et al., 2023).

Another significant challenge for the commercial and large-scale utilization of biomass is supply chain hurdles, which necessitate effective planning and management of biomass supply chains (Mottaghi et al., 2022). To address this, researchers have developed mathematical models to optimize strategic, tactical, and operational decisions in biomass supply chains. Strategic decisions involve long-term planning, such as those related to facility locations, capacities, and technologies (Sowlati, 2016). Tactical decisions focus on medium-term plans, including production, inventory, and logistics (Sowlati, 2016). Operational decisions deal with short-term activities such as harvest scheduling and vehicle routing (Ba et al., 2016; Sowlati, 2016). Most previous studies have focused on strategic and tactical plans due to their strong influence on the economic, environmental, and social performance of the biomass supply chain and the bioeconomy's success (Acuna et al., 2019; Ba et al., 2016). By strategically planning and optimizing forest-based biomass supply chains, decision-makers can effectively tackle the inherent supply chain complexities, ultimately leading to the development of optimal designs and plans focused on cost reduction, profit maximization, or efficiency improvement. There are examples of biomass supply chain studies where different supply chain configurations have been compared to select the best one in terms of costs or environmental performances, similar to the studies done by Yazan et al. (2016) and Shadbahr et al. (2022). However, such studies cannot determine the optimal design and plan for supply chains. For such a purpose, optimizing the supply chains through developing mathematical programming models have proved useful in the literature (e.g., Ahmadvand et al., 2021; Akhtari & Sowlati, 2020; Cambero & Sowlati, 2016). Additionally, such models are capable

of incorporating risks and uncertainties in the decision-making process (Saghaei, Ghaderi, et al., 2020; Walther et al., 2012).

Given the significant role of governments in the commercial and large-scale utilization of biomass, it is essential to incorporate relevant regulations, programs, incentives and policies into the design, planning, and optimization of biomass and bioproduct supply chains. Overlooking these policies and programs can result in infeasible or ineffective plans for real-world scenarios (Daneshmandi et al., 2022). However, much of the literature consists of studies that have merely reviewed and analyzed policies and regulations without incorporating them into the planning models for the biomass supply chains (Daneshmandi et al., 2022).

It is worth noting that prior research studies have frequently referred to such governmental mechanisms as “policies and programs” when evaluating their role in the development of biomass energy projects (Brinley, 2021) and the production and consumption of bioenergy (Taylor et al., 2003). Therefore, throughout this dissertation, any governmental support, tool, regulation, program, policy, or incentive will collectively be referred to as “governmental policies and programs”.

While incorporating these programs and policies into supply chain planning models is important, it is equally important to account for uncertainties associated with them, as many of these policies are relatively new and their future trajectories may be uncertain. For instance, in British Columbia, the carbon tax increment before 2021 was \$5 per tonne of CO₂-eq per year (Government of BC, 2020a), but increased to \$15 per tonne of CO₂-eq per year till 2030, and the trajectory beyond that is currently unknown (Government of BC, 2024c).

To deal with uncertainties in supply chains, different non-deterministic decision-making approaches have been employed in the literature. The selection of these approaches depends on the type of uncertainty in the supply chain (Mottaghi et al., 2022). Robust optimization is suitable for cases where the ranges of uncertain parameters are known, whereas stochastic programming is suitable for cases where historical data and distributions of uncertain parameters are available and obtainable (Mottaghi et al., 2022). Furthermore, fuzzy mathematical programming can be used in cases of epistemic uncertainties in the biomass supply chain (Mottaghi et al., 2022). Another frequently employed approach is sensitivity analysis; however, it is considered a passive approach

that can only examine the impact of uncertain parameters on the outputs in certain scenarios (Mottaghi et al., 2022).

Studies in the literature have emphasized the importance of considering uncertainties in biomass supply chain planning models, as overlooking such uncertainties may result in infeasible supply chain configurations (Mottaghi et al., 2022). However, incorporating uncertainty in these models is still recognized as one of the gaps in the biomass-to-bioproducts literature (Helal et al., 2023).

1.2 Research objective

The primary objective of this research is to determine the optimal configuration and planning of a forest-based biomass supply chain, considering uncertainties and relevant governmental policies. The specific research questions that will be answered are as follows:

1. What is the optimal design of a forest-based biomass supply chain, considering strategic decisions from biomass collection to the production of bioproducts, including the determination of the locations and capacities of bioproduction facilities?
2. How do governmental policies and programs affect the planning and design of the forest-based biomass supply chain?
3. How can uncertainties in the forest-based biomass supply chain, as well as uncertainties associated with governmental programs and policies, impact the design and planning of the supply chain?

To answer the research questions, a mathematical programming model is developed to optimize a forest-based biomass-to-bioproduct supply chain and support strategic decisions regarding the configuration and planning of the supply chain over a 20-year planning horizon. These decisions include determining the location and capacity of bioproduction facilities, the flow of biomass, the supply chain pathways taken, and the amount of bioproducts produced. The main objective of the mathematical programming model is to maximize the supply chain profit; however, to account for emissions in the supply chain, bi-objective models considering both economic and environmental objectives are also developed.

Moreover, governmental policies and regulations are incorporated into the models to evaluate the effectiveness of current policy and regulatory tools. More importantly, uncertainties in the supply chain are also considered.

The research steps to achieve the primary goal of this study are as follows:

1. Developing deterministic single objective and bi-objective models to determine the optimum design of a forest-based biomass to bioproduct supply chain considering both economic and environmental aspects. The economic aspect will focus on profit maximization, and the environmental aspect will focus on the CO₂-eq emissions of the supply chain. The results of these two models will be compared with each other.
2. Incorporating the governmental programs and policies into the models and evaluating the impact of the policies on the configuration of the supply chain and the suggested plans. The focus of the governmental programs and policies will be on federal and provincial policies that are employed in the province of BC, Canada. Also, the scope of the considered programs and policies will specifically encompass climate change related governmental programs and policies that support the use of biomass for bioproduct production. Furthermore, the reviewed policies and programs are limited to those directly impacting parts of the forest-based biomass supply chain.
3. Adding the uncertainty aspect to the models and developing non-deterministic models to account for different sources of uncertainties. The deterministic and non-deterministic models will be compared in terms of the outcomes.
4. Applying the models to a case study in BC, Canada.

1.3 Case study

Previous Canadian forest bioeconomy studies (Forest Products Association of Canada, 2010, 2011) have highlighted the potential for the forest sector to diversify beyond conventional products by using wood fibre residues for bioenergy, biochemicals, and biomaterials. These studies examined emerging forest-based bioproduct pathways and emphasized the importance of fibre availability, market readiness, investment conditions, policy support, and integration with existing forest industry infrastructure.

In British Columbia (BC), Canada, this broader bioeconomy opportunity is directly linked to the use of forest harvest residues, which are commonly disposed of through slash-pile burning, resulting in an average annual emission of approximately 5 million tonnes of CO₂-eq from 2002 to 2021 (Nance, 2023). To address the environmental and resource use concerns associated with

slash-pile burning, increasing attention has been given to using slash to support bioeconomy development in BC. The CleanBC roadmap to 2030 document (CleanBC - Roadmap to 2030, 2021) highlights the importance of reducing slash-pile burning and increasing fiber utilization in BC. Accordingly, alternative uses for harvest residues, such as bioproduction, should be explored.

Given this growing attention to bioeconomy development in BC, Canada, a collaboration was initiated with the Bioeconomy and Indigenous Opportunity branch (IBIO) at the BC Ministry of Forests to investigate the establishment of a forest-based biomass supply chain and evaluate the use of harvest residues instead of burning them.

1.3.1 Bioproducts

In terms of bioproducts, IBIO expressed interest in a mix of both emerging and traditional bioproducts. The focus of this research is on newer, high-value products with diverse applications that have not been widely studied in the literature, rather than limiting the scope to bioenergy and biofuels, which have been extensively explored. The bioproducts considered in this research include cellulose nanocrystals (CNC) and cellulose nanofibrils (CNF), which have diverse applications in energy and electronics, advanced materials and composites, and biomedical and pharmaceutical fields (Agate et al., 2018; Dufresne, 2019; Gómez H. et al., 2016; Kim et al., 2019; Seabra et al., 2018); activated carbon (AC), which is used as an adsorbent for pollutants and for water and gas purification (Gayathiri et al., 2022; Gu et al., 2018); biochar, which can be used as soil improvement (Dziejarski et al., 2023) or even as a replacement for cement (Legan et al., 2022); and bio-oil and pellets, which are used as renewable fuels for heating and power (Brammer et al., 2006; Sikkema et al., 2010). The details regarding the required technology, feedstock, and yield for these bioproducts are shown in Table 1-1.

It should be noted that although the most common method of biochar production is slow pyrolysis (Antonangelo et al., 2021), torrefaction was considered in this study because it has gained attention in recent years due to the favorable properties of torrefied and densified biomass, the technology's progress toward commercialization (Akbari et al., 2020) and also the input data was available to based our study on. The solid products obtained from wet and dry torrefaction are commonly referred to as hydrochar and biochar, respectively. Although these products differ in their physicochemical properties and carbon contents (Akbari et al., 2020), they are collectively referred

to as biochar in this study for simplicity. Based on the input data used in this study, the product from wet torrefaction was assumed to have a higher carbon content (Akbari et al., 2020) and, therefore, a higher selling price than the product from dry torrefaction.

ypTable 1-1. Technology, bioproducts, type of feedstock and yield of technologies.

Bioproduct	Technology	Required type of feedstock	Yield	Reference
Cellulose Nanocrystal	American value-added pulping (AVAP)	feedstock-agnostic	28%	(Blair, 2020)
Cellulose Nanofibrils	American value-added pulping (AVAP)	feedstock-agnostic	39%	(Blair, 2020)
Pellets (high quality)	Pelletization	Clean woodchips	72%	(Yun et al., 2020b)
Pellets (low quality)	Pelletization	feedstock-agnostic	72%	(Yun et al., 2020b)
Biochar	Dry torrefaction (DT)	feedstock-agnostic	80%	(Akbari et al., 2020)
Biochar	Wet torrefaction (WT)	feedstock-agnostic	50%	(Akbari et al., 2020)
Activated Carbon	Elevated Tucker RNG	Clean woodchips	45%	(Shaheen et al., 2022)
Bio-oil	Pyrolysis	feedstock-agnostic	23%	(van Schalkwyk et al., 2020)

1.3.2 Production capacities and sizing of facilities

For each bioproduct, based on the capacities of current bioproduction facilities in Canada (Table 1-2) and assuming 350 operating days per year, three potential capacities (i.e., small, medium, large) are defined. For instance, InnoTech operates at the smallest CNC production scale, producing one kg per day (3.5 tonnes annually), while CelluForce has the largest capacity at one tonne per day production (350 tonnes annually). A medium scale is represented by Anomera, with a production of 175 tonnes of CNC per year. Considering AC, AdvEn is planning to start the commercialization of their technology in Alberta by producing 400 tonnes of activated carbon annually and scaling up the production to 1,200 tonnes per year later on (AdvEn, 2021). Therefore, for AC, annual production capacities of 400, 800, and 1,200 tonnes are considered as small-, medium-, and large- capacities.

Table 1-2. Bioproduct producers in Canada with their production capacities.

Company	Product	Location	Capacity	Reference
InnoTech	CNC (Cellulose Nanocrystal) CNF (Cellulose Nanofibrils)	Alberta	1 kg/day 5 kg/day	(Innovation, Bioeconomy and Indigenous Opportunities Branch of the BC Ministry of Forests, personal communication, 28 March 2024)
Performance BioFilaments	CNF (Cellulose Nanofibrils)	Quebec	21 tonnes/day	
Blue Goose Biorefineries	CNC (Cellulose Nanocrystal)	Saskatchewan	10 kg/day	
FPInnovations	CNC (Cellulose Nanocrystal)	Ontario	1.5 kg/day	
CelluloseLab	CNC (Cellulose Nanocrystal) CNF (Cellulose Nanofibrils)	New Brunswick	10 kg/day 50 kg/day	
Anomera	CNC (Cellulose Nanocrystal)	Ontario	175 tonnes/year	
CelluForce	CNC (Cellulose Nanocrystal)	Quebec	1 tonne/day	(Wood Pellet Association of Canada, 2021, 2024)
Drax	Pellets	British Columbia	365,000 tonnes/year 72,000 tonnes/year	
Spruce Products Limited (SPL)	Pellets	Manitoba	2,000 tonnes/year	
Vanderhoof Specialty Wood Products	Pellets	British Columbia	30,000 tonnes/year	
Prairie Pellet	Pellets	Manitoba	10,000 tonne/year	(Airex, 2025)
Airex Energy	Biochar	British Columbia Quebec	10,000 tonne/year 15,000 tonne/year	
Emergent Waste Solutions	Biochar	British Columbia	40 tonne/year	(Financial Post, 2023)
Adven	AC (Activated Carbon)	Alberta	400 tonne/year	(AdvEn, 2021)
Ensyn	Bio-oil	Ontario	3,000,000 gal/year	(Ensyn, 2026b)
Vytterra Renewables	Bio-oil	Nova Scotia	10,000,000 gal/year	(Ensyn, 2026a)

Therefore, the annual production capacity and biomass processing capacity of each capacity sizes can be calculated as shown in

Table 1-3. The amount of required biomass for AC and high-quality pellet is calculated considering their production yield and 29% bark in small-diameter logs.

Table 1-3. Production capacity and required annual input biomass for each capacity and bioproduct.

Product	Annual production capacity (tonne)			Annual input biomass (odt)		
	Small	Medium	Large	Small	Medium	Large
CNC (Cellulose Nanocrystal)	3.5	175	350	12.5	625	1,250
CNF (Cellulose Nanofibrils)	53	3,500	7,350	135	8,974	18,846
Biochar (dry torrefaction)	40	10,000	15,000	50	12,500	18,750
Biochar using (wet torrefaction)	40	10,000	15,000	80	20,000	30,000
AC (Activated Carbon)	400	800	1,200	1,252	2,504	3,756
Pellet (low quality)	2,000	72,000	365,000	2,778	100,000	506,944
Pellet (high quality)	2,000	72,000	365,000	3,912	140,845	714,006

1.3.3 Case region and potential locations for bioproduction facilities

To conduct this study, the Williams Lake Timber Supply Area (TSA) located in Cariboo-Chilcotin Natural Resource District of BC, Canada, is selected as the case study. This TSA is one of the most significant in the region due to its large size, relatively high allowable annual cut and harvest residue generation, and a regional economy strongly tied to the forestry sector (Peak Solutions Consulting Inc., 2018). Moreover, widespread infestations and recent wildfires have increased the availability of harvest residues (i.e., slash) and dry biomass (Cambero & Sowlati, 2016; Lamb-Yorski, 2024). However, the area has faced economic and social challenges resulting from mill closures and layoffs (Canadian Forest Industries, 2024). Therefore, establishing new biomass conversion facilities could potentially help create jobs, mitigate economic losses, strengthen the local bioeconomy, and reduce the environmental impacts of slash burning, which remains the common disposal method in the region (Nance, 2023), while providing additional economic and social benefits.

According to estimates by FPInnovations using the FPInterface tool (Friesen, 2012), approximately 30.4 million odt of harvest residues would be available from 1,592 aggregated cut blocks between 2012 and 2032. The biomass supply data are divided into two types: small-diameter logs and other residues generated after harvesting.

Four locations including Hanceville, Anahim Lake, Horsefly, and Williams Lake are identified as potential locations to preprocess residues and establish bioproduction facilities, referred to as biohubs (IEA, 2022), potentially providing cost advantages from reducing material transportation and handling activities (Valipour et al., 2024). The four locations considered in this study were

selected based on their identification as biomass delivery points in existing provincial and FPInnovations biomass supply assessments for the Williams Lake TSA, as well as their population, spatial distribution, and potential for future development in this forestry-dependent region (Friesen, 2018).

1.3.4 Supply chain pathways

To supply slash to potential biohubs, three supply chain pathways are considered, differing by the location and method of preprocessing. In the first pathway, the slash is comminuted at roadside using mobile chippers and directly loaded into chip vans for transportation to biohubs. Grinding and transportation costs are reported jointly in FPInterface report (Friesen, 2012). At the biohub, a front-end loader unloads the ground slash, and a reclaim feeder and screener screen and transfer the ground slash to the bioproduction technology (Khadivi, 2022).

The equipment pieces used at the cut blocks and biohubs for this pathway are listed in Table 1-4.

Table 1-4. List of equipment used at cut blocks and biohubs for ground slash pathway

Equipment at cut blocks	Reference	Equipment at biohubs	Reference
Mobile grinder	FPInterface	Front-end loader	(Khadivi, 2022)
		Reclaim feeder	
		Scalping disk screener	

The second pathway, which is more common in Nordic countries (Lindroos et al., 2011), is the bundled slash pathway. Here, slash is bundled at cut blocks using a bundler and transported to biohubs using a grapple loader to load bundles onto seven-axle short-log trucks (Lindroos et al., 2011). At the biohub, bundles are unloaded using a butt-n-top loader, then ground with a stationary grinder (Khadivi, 2022). The ground slash is then handled with a front-end loader, screened and transferred using a scalping disk screener and reclaim feeder (Khadivi, 2022).

The equipment pieces used at the cut blocks and biohub for this pathway are shown in Table 1-5.

Table 1-5. List of equipment pieces used at cut blocks and biohubs for bundled slash pathway

Equipment at cut blocks	Reference	Equipment at biohub	Reference
Bundler	(Lindroos et al., 2011)	Butt-n-top loader	(Araki, 2002)
Grapple loader	(Lindroos et al., 2011)	Reclaim feeder	(Khadivi, 2022)
		Scalping disk screener	
		Drop feed hogger (stationary grinder)	

In the third pathway, only small-diameter logs are transported to biohubs, where they are debarked and chipped to generate clean woodchips for bioproduction technologies that would only require clean woodchips. A grapple loader at the cut blocks is used to load the logs into seven-axle short-log trucks for transportation to the biohubs. At the biohub, a butt-n-top loader (Araki, 2002) unloads the logs, feeding them into a debarker and chipper system (Araki, 2002). The resulting chips are reclaimed, screened, and fed into the bioproduction technology using a reclaim feeder and a scalping disk screener (Khadivi, 2022). The equipment pieces used at the cut blocks and biohubs for this pathway are shown in Table 1-6.

Table 1-6. Equipment piece used at cut blocks and biohubs for small-diameter logs pathway.

Equipment at cut blocks	Reference	Equipment at biohub	Reference
Grapple loader	(Lindroos et al., 2011)	Butt-n-top loader	(Araki, 2002)
		Debarker and chipper system	
		Reclaim feeder	(Khadivi, 2022)
		Scalping disk screener	

Figure 1-1 shows these supply chain pathways.

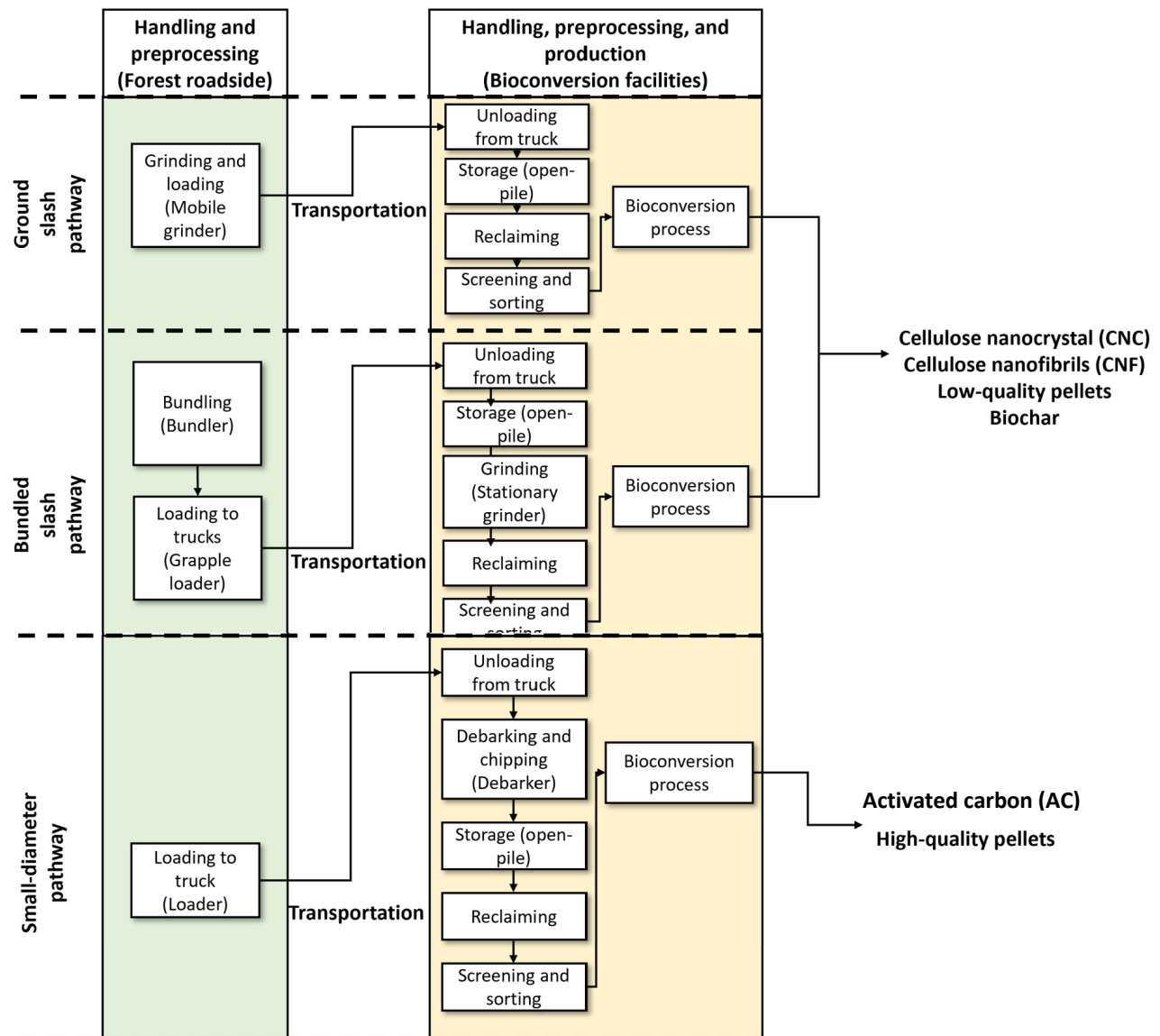


Figure 1-1. Schematic of supply chain pathways with the activities at each supply chain stage.

1.4 Overview of the governmental policies and programs

After reviewing the existing federal and provincial policies in Canada and BC that affect bioproduction and discussions with forest policy experts in BC (Innovation, Bioeconomy and Indigenous Opportunities Branch of the BC Ministry of Forests, personal communication, 28 March 2025), four relevant governmental policies that could impact bioproduction within the selected case study are examined. It is worth noting that, in BC, fibre utilization policies and related

initiatives aim to increase the recovery and productive use of lower-quality fibre, including material left at roadsides, landings, and within cutblocks, while reducing waste and greenhouse gas emissions from slash-pile burning (Government of BC, 2020b). In addition, BC's residue and waste framework requires licensees to assess merchantable timber and waste remaining after primary harvesting, with waste volume data used for billing and cut-control purposes (Timber Pricing Branch, BC Ministry of Forests, 2026). Therefore, utilization policies can influence forest biomass supply chains by affecting residual fibre availability, recovery incentives, and the economic attractiveness of using harvest residues for bioenergy and bioproducts. The economic aspect of residual fibre recovery was partially captured through feedstock subsidies; however, the broader supply-side implications of utilization policies were considered outside the scope of this research, as they were assumed to be reflected in the recoverable biomass supply data used in the model.

1.4.1 Feedstock subsidies

The first policy is feedstock subsidies. High feedstock costs are among the main barriers to biomass utilization (Lin et al., 2024). To address this challenge and simultaneously reduce slash-pile burning in BC by procuring biomass for bioproduction, subsidies on delivered feedstock cost could be implemented. Feedstock subsidy programs already exist in countries like the United States and China (Lin et al., 2024). While there are currently no specific subsidy programs to cover feedstock delivery costs in BC, discussions with forest policy experts and authorities in the province (Innovation, Bioeconomy and Indigenous Opportunities Branch of the BC Ministry of Forests, personal communication, 28 March 2025) suggested evaluating the potential impact of such a policy to help inform future policy design. To calculate the subsidies, it is assumed that the same amount of residues used in bioproduction would otherwise be burned in slash-pile burning. Using an emission factor of 2.25 t CO₂-eq per oven-dry tonne (odt) (Forest Carbon Initiative, 2020) of slash burned in piles, we estimate the total CO₂-eq released. The subsidy is then calculated based on a carbon price of \$12 per tonne of CO₂-eq. This price was used based on the guidance of IBIO, which suggested \$12/ CO₂-eq as a representative estimate for forest-based carbon offsets, informed by the Province of British Columbia's offset portfolio pricing (Government of BC, 2024a).

1.4.2 Direct incentives for capital investment

The second policy is the financial incentives that the government provides to cover a portion of the initial capital investment costs. For instance, the Investments in Forest Industry Transformation program (Investments in Forest Industry Transformation (IFIT), 2024) covers 50% of eligible capital costs, with a maximum contribution of \$10 million per project. This program supports projects related to commercialization of novel technologies, diversification of product streams, and enhancement of the environmental performance of the Canadian forest sector.

1.4.3 Enhanced first-year allowance for depreciation

The third policy is related to depreciation calculation for corporate tax purposes, which allows 75% of the capital cost of equipment to be written off as depreciation, if the equipment was acquired and put into use in 2024 (Technical Guide to Class 43.1 and 43.2, 2020). While this measure is specified to encourage investments in clean energy generation and energy conservation equipment, it could be informative to test it for other bioproduction technologies, as considered in the present study. According to the guidelines (Technical Guide to Class 43.1 and 43.2, 2020), the eligible properties include feedstock preprocessing equipment such as shredders or hoggers and the conversion technology itself. However, it does not include equipment used for collection, storage, or transportation of biomass.

1.4.4 Output-based pricing system

The last policy is the carbon pricing policy. The BC Output-Based Pricing System (OBPS) (British Columbia's Carbon Tax, 2024) is a new system introduced to calculate the carbon tax of industries and incentivize the emitters to reduce their GHG emissions. Although CNC, CNF, biochar, and AC are not included in the list of products mentioned in the guidelines, the impact of this carbon pricing system for these products will be evaluated as the list of bio-products in the policy is not finalized and may be updated in the future.

Under this system, facility emissions (i.e., attributable emissions) are evaluated against an emissions limit. A facility's attributable emissions include emissions from general stationary combustion, industrial processes, on-site transportation, and waste and wastewater treatment, where applicable (Government of BC, 2024c). Although emissions associated with purchased electricity are not treated as direct compliance emissions under the BC Output-Based Pricing

System, they were included in this study to provide a more complete estimate of the operational GHG emissions associated with each bioproduct pathway.

If the attributable emissions are below the limit, the facility can bank or sell the generated credits (difference between the emissions and the limit, where one tonne of CO₂-eq is equal to one credit), and if the attributable emissions are above the limit, the facility needs to pay for the excess emissions through either direct payment, previously banked credits, purchased credits from another operation, or a combination of these methods. Using or purchasing credits is allowed up to a defined credit usage limit (Table 1-7).

Table 1-7. Credit usage limit (Government of BC, 2024c).

Year	Credit usage limit (%)
2024	50%
2025	40%
2026	30%
2027	30%
2028	30%
2029	30%
2030	30%

The carbon price for credit purchase or sale is assumed to be based on the average of voluntary market price, assumed to be \$20/t CO₂-eq (personal communications with IBIO-BC Ministry of Forests), and the carbon tax for the given year, \$80/t CO₂-eq in 2024, increasing by \$15 annually (Government of BC, 2024c). As a result, the average carbon price for selling and purchasing carbon credits is \$50/t CO₂-eq in 2024, increasing by \$7.5 per year. It is also important to note that this study assumes there is always sufficient demand for generated credits to be sold.

The BC OBPS and carbon price are planned until 2030; however, the planning horizon of the project considered in this study is from 2023 till 2043. For the years after 2030, it is assumed that the existing trend continues, meaning that the credit usage limit remains at 30% and the carbon price increases annually by \$15/t CO₂-eq.

The emission limit can be calculated as shown in Eq. 1-1 (Government of BC, 2024c).

$$\text{Emission limit for year } i = \text{Production amount in year } i \times$$

Eq. 1-1

$$\left(PWAEI \times \left(RF - \left(1 - \frac{IPE_i}{CE_i} \right) \times TR(i - 2024) \right) \right)$$

where PWAEI is the production-weighted average emission intensity of product p in t CO₂-eq/unit of product p, RF is reduction factor, which is 65% for majority of the products; IPE_i represents emissions from industrial processes, which means the emissions resulting from chemical reactions in production; CE_i refers to the total attributable emissions in a given year, and TR is the tightening rate which is 1% (Government of BC, 2024b).

The PWAEI is not given in the guidelines for CNC, CNF, biochar, and AC. Therefore, in this study, it is estimated based on the data obtained from the literature as shown in Section D.4.

1.5 Outline of the thesis

This dissertation is organized as follows:

Chapter 2 provides a review of the relevant literature and identifies key research gaps.

Chapter 3 presents the techno-economic assessment of bioproduction pathways under scenarios with and without policy interventions. In this chapter, cellulose nanocrystals (CNC) and cellulose nanofibrils (CNF) are provided as representative examples, while the results for other bioproducts are included in 0 and 0

Chapter 4 introduces the deterministic supply chain network models considering policies, including both single-objective and bi-objective formulations.

Chapter 5 focuses on non-deterministic models and evaluates the impact of uncertainty on supply chain network design under different policy scenarios.

Chapter 6 presents the concluding remarks, discusses the limitations of the study, and outlines directions for future research.

Chapter 2: Literature Review

2.1 Synopsis

This chapter presents a review of the literature on the optimization of biomass supply chain design and planning that has considered governmental programs and policies, with a specific focus on forest-based biomass supply chains. The main goal is to provide an extensive overview of studies that have employed mathematical programming models for the design and planning of forest-based biomass supply chains and have considered governmental policies in them, in order to identify key findings and highlight gaps in the existing literature.

To that end, first an overview of the governmental policies is given. Then, the reviewed papers are divided into two main categories based on uncertainty considerations in their mathematical models: 1) deterministic, and 2) non-deterministic. This structured review enables a comprehensive understanding of how government policy instruments influence decision-making and modeling strategies across the supply chain, ranging from biomass harvesting and transportation to conversion processes and market delivery.

2.2 Selection methodology

The world's leading citation database, Web of Science (Web of Science, 2024), was selected to search for relevant articles for . The search phrase was as follows:

("biomass" or "biofuel" or "bioenergy" OR "bioproduct") AND ("forest" OR "wood" OR "mill") AND ("supply chain") AND ("optimization" OR "optimisation" OR "mathematical programming" OR "nonlinear programming" OR "linear programming" OR "network design") AND ("regulations" OR "government" OR "policy" OR "policies" OR "carbon pricing" OR "carbon price" OR "carbon tax" OR "carbon offset" OR "cap-and-trade" OR "incentive" OR "mandate" OR "tax" OR "direct support" OR "indirect support").

These keywords were searched in all the search fields, including the topic, title, and abstract. Majority of the articles were published in Elsevier, Springer Nature, Wiley, and Taylor & Francis. By July 30, 2025, 81 articles were identified through this search. After reviewing the titles and abstracts, 35 papers were selected for further review. By analyzing the full text of these papers, 19 papers within the scope were considered for the review. The exclusion criteria were as follows:

- Papers that did not mention any governmental policies and programs.
- Papers that did not consider forest-based residues, including harvesting and wood processing residues, as part of the biomass feedstock.
- Papers that did not utilize or propose a mathematical programming model for biomass supply chain design and planning.

After reviewing these 19 papers, an additional 11 papers were identified by searching the reference lists and citations of those 20 papers and relevant review papers including (Daneshmandi et al., 2022) and (Mottaghi et al., 2022). Ultimately, 30 papers in the area of forest-based biomass supply chain design and planning with governmental policy considerations were recognized for the review. The process of selecting papers for the review is shown in Figure 2-1.

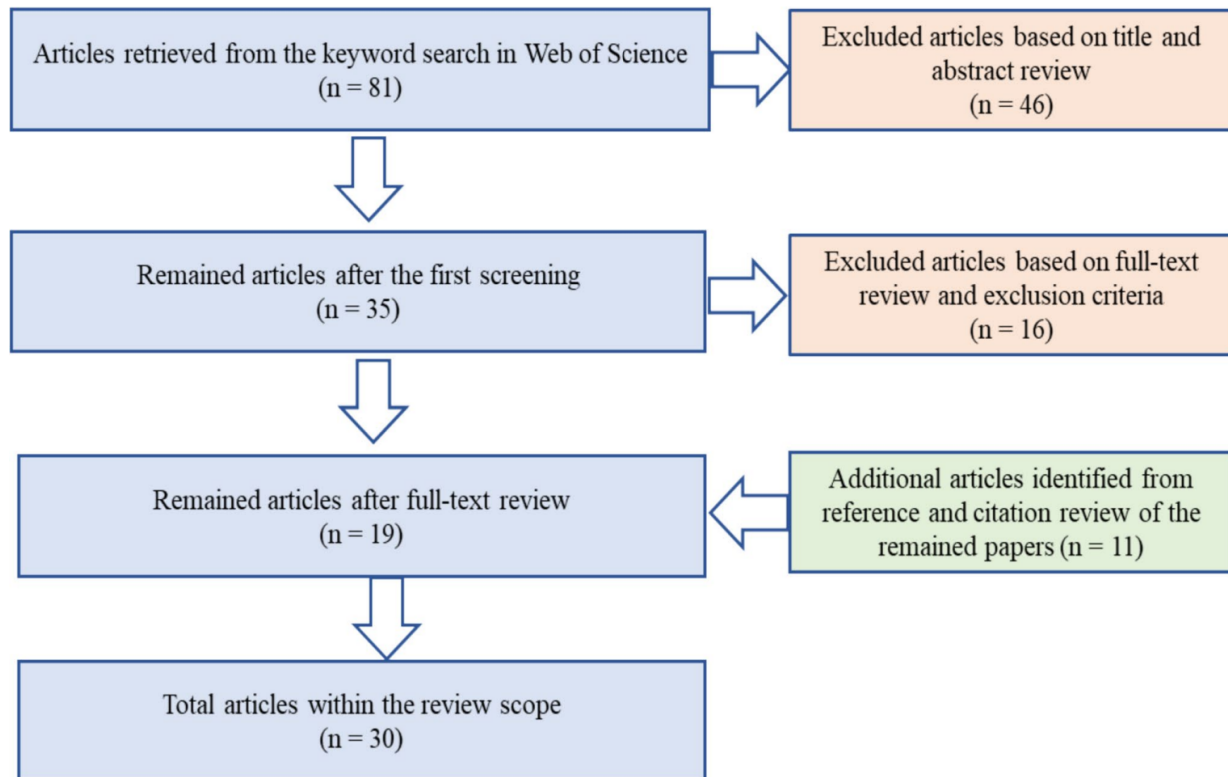


Figure 2-1. Process of selecting papers for the review.

2.3 Overview of the governmental programs and policies

The governmental policies and programs can be classified into different policy groups. The classification that (Daneshmandi et al., 2022) has proposed for policies and regulations in

bioenergy context is: 1) indirect support, 2) direct support, 3) market-based policies, and 4) tax-related policies.

Indirect support as suggested in (Daneshmandi et al., 2022) included environmental tax, emission limits or carbon pricing policies. Regarding this policy group, the majority of papers in the forest-based biomass supply chain planning area focused on carbon pricing policies (e.g., Ahmadvand & Sowlati, 2023; Akgul et al., 2014; Liu et al., 2017; Malladi & Sowlati, 2020b; Palak et al., 2014). The three main carbon pricing policies include: 1) carbon tax, 2) carbon cap-and-trade, and 3) carbon offset (Malladi & Sowlati, 2020b). The carbon tax policy sets a price on greenhouse gas emissions or the carbon content of fossil fuels with the hope of encouraging the production of cleaner fuels and energy (Conway et al., 2017; Malladi & Sowlati, 2020b). The carbon tax policy is used in different regions, including parts of Canada such as the province of British Columbia, parts of Europe (e.g., Sweden, Poland, and the UK), Mexico, and India (Conway et al., 2017). The carbon cap-and-trade policy employs an emission trading system where a cap is placed on emissions and emitters can trade emission allowances on the carbon market, if their total emissions are below or above the initial allowance (Malladi & Sowlati, 2020b). The carbon cap-and-trade policy has been used in different regions, such as California in the USA, Quebec in Canada, and Switzerland (Raymond, 2019). In carbon offset policy, a limit for emissions is set and the emitters with emissions beyond this limit are taxed. This policy has been implemented in Australia (Malladi & Sowlati, 2020a).

Direct support refers to any monetary support given by governments in various forms, including subsidies, grants, non-reimbursable funds, or zero-percent loans, to encourage investments in the bioeconomy (Daneshmandi et al., 2022). For instance, in Germany, low-interest loans and subsidies are offered to support the establishment of biogas production (Daneshmandi et al., 2022). In Canada, there are various programs providing funding for bioeconomy projects, such as the Energy Innovation Program – Clean Fuels and Industrial Fuel Switching, which offers up to 50% non-repayable contributions for demonstration projects that produce clean fuels or develop technologies to reduce energy intensity and greenhouse gas emissions in industrial processes using feedstock or low-carbon fuels (Energy Innovation Program – Clean Fuels and Industrial Fuel Switching, 2022). In the literature of forest-based biomass supply chain planning, few papers have considered this policy group (e.g., (Boukherroub et al., 2017)).

Another category of governmental policies includes market-based policies, which drive the demand for bioproducts and bring about economies of scale (Daneshmandi et al., 2022). For instance, in the province of British Columbia in Canada, the Renewable and Low Carbon Fuel Requirement have set mandates of 5% annual average renewable content in gasoline and 4% renewable content in diesel (LCFS Requirements, 2023). Some papers have considered governmental market-based policies, such as blending mandates (e.g., (Gutierrez-Franco et al., 2021; Hombach et al., 2016; Memişoğlu & Üster, 2016)) and renewable energy production targets (e.g., Akgul et al., 2014), in their supply chain decision-making models as support mechanisms for the production and consumption of biofuel and bioenergy. Majority of these papers; however, only used the blending mandates and renewable energy targets to estimate the demand for biofuel or bioenergy as an input to their models, without any further analysis of the impact of this governmental policy.

Tax-related policies include tax exemptions, reductions, rebates (Daneshmandi et al., 2022), specific depreciation calculation methods that can reduce taxable income for bioproduction facilities (Ben Daya & Nourelfath, 2019), or simply the taxes on profits or sales (Theozzo & Teles dos Santos, 2021).

Another classification was proposed in (Mottaghi et al., 2022) in the context of renewable energy production: 1) blending mandates, 2) carbon-related policies such as carbon pricing or carbon cap, and 3) incentives and supporting policies such as subsidies.

Considering the two classifications in (Mottaghi et al., 2022) and (Daneshmandi et al., 2022), this study classifies the reviewed studies under groups as shown in Figure 2-2.

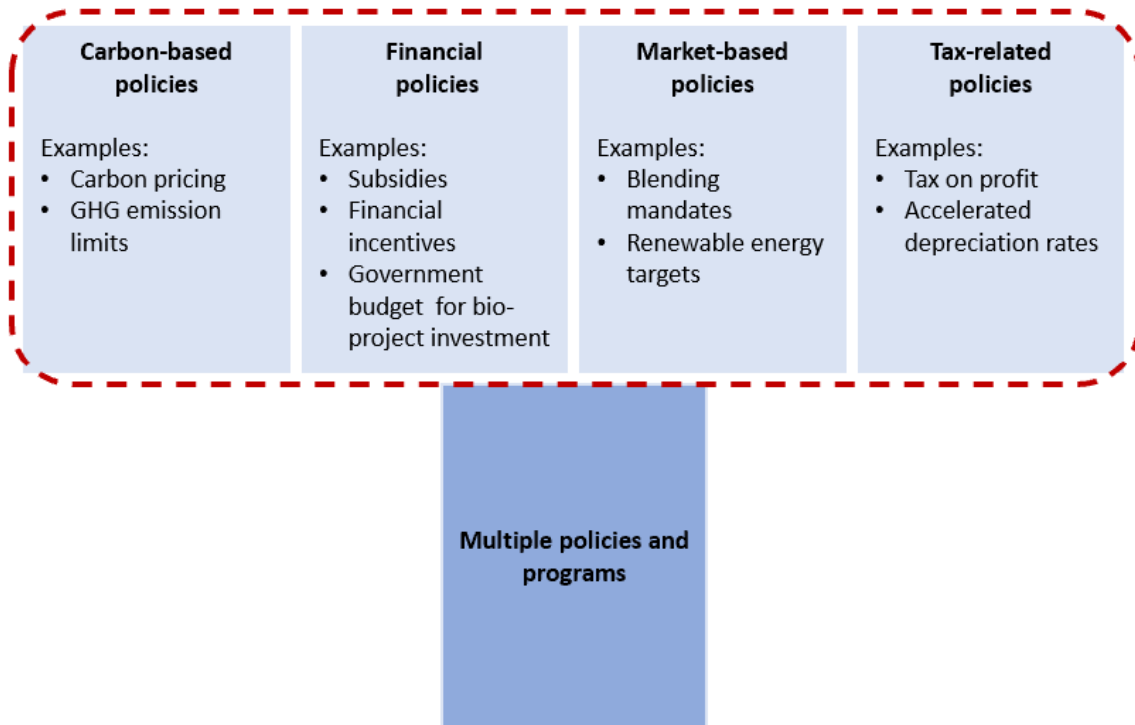


Figure 2-2. Categories of governmental programs and policies and their examples. The main categories obtained from (Daneshmandi et al., 2022; Mottaghi et al., 2022) are showed with a red-dashed border.

2.4 Deterministic models

2.4.1 Carbon-based policies and programs

The carbon pricing policies have been considered in both bioenergy and biofuel supply chains. Palak et al. (2014) focused on tactical decisions in forest-based bioethanol supply chain with the objective of minimizing the supply chain costs under carbon pricing policies, including carbon tax, carbon cap-and-trade, and carbon offset. Each policy altered the cost-minimizing objective function differently: carbon tax added a fee per CO₂ unit emitted; cap-and-trade included costs/revenues from trading credits and enforced a strict emissions cap; carbon offsets added costs for emissions above the cap, which could be expanded with purchased offsets. The results showed that tighter carbon caps, higher carbon taxes, or rising carbon trading prices encouraged local biomass sourcing to reduce emission costs. Cap changes impacted supply chain flows more than tax changes. Also, cap-and-trade and offset mechanisms had similar effects when caps were tight, but diverged when caps were loose, as only cap-and-trade provided financial incentives for emitting less than the cap.

The co-production of electricity and bioethanol using logging and mill residues as feedstock at the tactical level with a profit maximization objective was examined by Liu et al. (2017). Carbon emission costs were considered to account for the environmental costs in the profit objective function. The results indicated that the co-production model yielded more profit than independent operations. However, increasing the carbon emission costs reduced the advantage of co-production model and could turn the supply chain's profit negative.

While most studies treated carbon pricing as an input parameter, Ahmadvand and Sowlati (2023) considered it as a decision variable. In this study, the carbon price increment was considered in an objective function, where it was maximized while ensuring that cash flows remain positive for syngas production using harvesting and mill residues in a gasification plant in BC, Canada. The outputs of this model were then used in a bi-objective model to maximize both cost savings and GHG savings for the supply chain. The results suggested that the maximum carbon tax increment that would keep the annual cash flows of the pulp mill positive, was \$7.71 per tonne of CO₂ eq, which was significantly lower than the scheduled increment in BC (\$15 per tonne of CO₂ eq).

The substitution of natural gas for producing heat in residential boilers with pellets derived from both forest-based and agricultural-based biomass was investigated in (Cifuentes García et al., 2024). In this study, a multi-objective approach was taken considering economic, social, and environmental objectives, combining them into a single objective function using a weighted sum approach with equal weights. From the policy perspective, the paper included a carbon tax of 80 €/t in the environmental objective function, in line with Spanish policies for CO₂ emissions mitigation. The strategic-tactical decisions included biomass flow allocation, production quantities, and pellet production facility locations. The results showed a 98% substitution of natural gas by deploying thirteen pellet plants, including eleven utilizing pinewood and two using corn stover, resulting in about 95% reduction in emissions from residential boilers. Notably, the carbon tax rate remained unchanged during the analysis.

In the context of using forest-based biomass in the chemical industry, a mixed-integer linear programming model was proposed in (Jeong et al., 2025) for establishing a large-scale green-loop hydrogen-ammonia production system from unused lignocellulosic biomass in South Korea, while ensuring a stable feedstock supply. The cost objective included transportation and installation

costs, offset by carbon credits based on the amount of CO₂ captured through carbon capture and storage technology during hydrogen-ammonia production. Additional techno-economic and environmental analyses were also conducted. However, additional analysis on carbon tax and its effect on the supply chain was not performed.

Operational decisions regarding the biomass feedstock (i.e., wood chips, pellets, and briquettes) delivery to satisfy the demand of a heating plant in BC, Canada were addressed in (Malladi & Sowlati, 2020b, 2020a).

Malladi and Sowlati (2020b) determined the optimal feedstock mix of the heating plant and the required number of truckloads to procure the biomass by minimizing the total costs of the supply chain. The carbon pricing policies (carbon tax, carbon cap-and-trade, and carbon offset) were incorporated to evaluate their impact on the supply chain. The model indicated that with an increase in the carbon price, denser biomass types, such as pellets and briquettes, favored over wood residues. The comparison between carbon pricing policies showed that for equal carbon prices, models related to carbon tax and carbon cap-and-trade mechanisms resulted in equal optimal solutions and emissions under the same carbon price and if emissions were higher than the allowance. Moreover, the study concluded that the cost of the carbon tax model was higher than that of the carbon offset model, regardless of the carbon price. However, a carbon tax could result in less emission because the carbon offset policy would not encourage emitters to decrease the emissions beyond the compliance target.

Malladi and Sowlati (2020a) developed a bi-objective model to minimize the costs and carbon emissions separately. Similar to the previous study, the carbon pricing policies were considered in the cost objective function. The results showed that variations in carbon price affected the number of Pareto solutions and total costs, while the initial emission allowance only impacted total costs. The comparison between the carbon pricing policies showed that, to mitigate emissions by a specific quantity, the total supply chain cost under the carbon offset model increased more than under the carbon tax and carbon cap-and-trade models. Similar to the previous study, it was demonstrated that the optimal supply chain cost under the carbon tax policy was higher than the costs under the other two carbon pricing policies.

2.4.2 Financial policies and programs

This governmental support mechanism was considered in a tactical and operational model focusing on profit maximization in a supply chain where harvest and sawmill residues were used for pellet production (Boukherroub et al., 2017). They evaluated two types of government support: reduced cutting right fees and full reimbursement of road construction and maintenance costs. Their findings indicated that large-scale pellet production in Eastern Canada could be profitable with government support and cost-sharing between pellet and forest companies. However, profitability could still be achieved without support if the feedstock mix included both forest and sawmill residues.

Zetterholm, Ahlström, et al. (2020) also focused on financial support; however, they did not propose a new mathematical programming model and used pre-designed models specific to Sweden. Using the framework presented in (Zetterholm, Bryngemark, et al., 2020), which included both a supply chain model and a market model, Zetterholm, Ahlström, et al. (2020) investigated the policy support levels required to help with high investment costs of large-scale biofuel production plants and maintain a long-term high production level despite changes in biomass market in Sweden. The analyses showed that 32-38 €/MWh policy support level was required to have a profitable investment in liquified biomethane in sawmills.

2.4.3 Market-based policies and programs

Blending mandates, which fall under the market-based policy category, were considered in (Memişoğlu & Üster, 2016), (Gutierrez-Franco et al., 2021), and (Akter et al., 2025). The blending mandates were considered as an input to estimate the demands for bioproducts in the mathematical models. However, no further comparison or analysis was done regarding this governmental policy. Both of the mentioned studies investigated strategic and tactical decisions in a biofuel production context.

Memişoğlu and Üster (2016) and Gutierrez-Franco et al. (2021) considered bioethanol production from different sources. Memişoğlu and Üster (2016) analyzed different biomass feedstock, including forest residues, mill residues, agricultural residues, and urban woody biomass for ethanol production, while Gutierrez-Franco et al. (2021) specifically examined forest residues such as pine and eucalyptus. To estimate the ethanol demand, Gutierrez-Franco et al. (2021) considered the

ethanol percentage that should be blended in gasoline in Colombia, and Memişoğlu and Üster (2016) considered the ratio in Texas. Both of these studies examined the establishment of bioproduction plants and collection centers.

Memişoğlu and Üster (2016) developed a supply chain network design model with a cost minimization objective function. Their findings suggested that large biorefineries should be established close to demand points and primary sources of woody biomass supply. Collection facilities, however, were suggested to be established between regions with rich woody biomass supply and crop-related biomass. Moreover, even when the supply and demand were not fluctuating, it was still suggested that collection facilities be established to act as a consolidation center.

In addition to the economic aspect of supply chains, Gutierrez-Franco et al. (2021) covered the environmental and social aspects of designing a forest-based biofuel supply chain. Their results indicated that biorefinery locations in the proximity of the largest consumption centers resulted in better employment opportunities and reduced GHG emissions. They found that lower GHG emissions did not necessarily result in less profit, but economic performance was sensitive to social objectives such as job creation.

Akter et al. (2025) optimized the supply chain for producing sustainable aviation fuel (SAF) from logging residues in Georgia, USA. The model determined the optimal processing and biorefinery facility locations, as well as the material flows, with SAF demand based on a 50% blending limit set by the U.S. Department of Energy for second-generation biofuels. The supply chain achieved an average of 70% carbon savings compared to conventional aviation fuel. Although SAF remains more costly, its lower emissions make it a strong candidate for policy incentives like subsidies or tax credits. However, the study did not explore the economic effects of such incentives. However, the study did not provide further analysis on the economic implications of these incentives.

Zetterholm, Bryngemark, et al. (2020) developed an assessment framework that integrated dynamic biomass market models, techno-economic analysis and supply chain design to evaluate the development of large-scale biorefineries. As a market-based policy, they limited the biomass feedstock for liquefied biomethane production to forest-based biomass, in accordance with the EU renewable energy directive, which restricts the use of primary biomass for biofuel production.

Although they employed the pre-existing BeWhere model rather than introducing a new one, this feedstock limitation appears to have been implemented as an additional constraint within the model.

Focusing solely on the environmental aspects, Vadenbo et al. (2018) used a consequential life cycle assessment and a previously developed linear programming model to determine the environmentally optimal use of biomass for energy in Switzerland under three future energy scenarios, each representing a different supply and demand configuration. These scenarios included BAU-C (business-as-usual), NEP-C (a policy-driven scenario aligned with the Swiss Energy Strategy 2050), and E[R] (a Greenpeace scenario envisioning deep decarbonization without nuclear energy). The findings indicated that more ambitious policy frameworks, such as NEP-C and E[R], would support greater use of domestic energy wood and manure compared with business-as-usual.

2.4.4 Tax-related policies and programs

Taxes on the profit of bioproduction facilities and taxes paid by timberland owners were considered in (Theozzo & Teles dos Santos, 2021) and (Masum et al., 2022), respectively. Theozzo and Teles dos Santos (2021) addressed a strategic and tactical problem to design a biorefinery network to maximize net present value (NPV). They focused on producing different bioproducts, including pulp wood, chips, lignin, electricity, and steam from forest residues in Brazil. The results showed that taxes on profit and sales were negative contributors to the NPV of the biorefinery network. Moreover, despite higher transportation costs, meeting market demand from biorefineries in regions with lower tax rates was more economical. This highlights the significant influence of tax policies on the profitability of biorefineries.

In another study (Masum et al., 2022), a strategic model was proposed to determine the optimal location for timber harvesting, torrefaction plant locations, and biomass flow in Georgia, USA, aiming to replace coal with torrefied biomass in power plants and maximize social welfare over a 50-year planning horizon. The social welfare maximization objective accounted for landowners' timber sale, taxes paid by landowners, and the costs of harvesting and plant operations. Three scenarios were evaluated: no coal replacement, 100% replacement with pulpwood, and 100% replacement with pulpwood and logging residues. The latter two scenarios achieved 240 million

tons of carbon savings, but resulted in negative social welfare under the study's definition. However, this did not imply cost-ineffectiveness, but rather reflected the lowest-cost paths for meeting timber and biomass demand. While taxes paid to landowners were included in the model, their impacts were not further analyzed.

2.4.5 Multiple programs and policies

Several studies have examined the simultaneous impact of multiple governmental policies. The cost-effectiveness of policy instruments supporting bioenergy production in Austria was investigated in (Schmidt et al., 2011). A mixed-integer programming model that captured the bioenergy supply chain from biomass production (forestry and agriculture) to the distribution of heat, electricity, and transport fuels was developed. The objective function of the model was to minimize the total costs under varying policy scenarios. Five policy instruments were assessed: 1) a carbon tax, applied to all fossil fuel emissions and modeled as a cost parameter in the objective function; 2) an emissions trading scheme, which applied CO₂ pricing only to the power and district heating sectors; 3) feed-in tariffs, which guaranteed fixed prices for biomass electricity and were modeled as increased revenue; 4) a biofuel mandate, introduced as a constraint requiring a minimum biofuel share in transport; and 5) subsidies for pellet and fuelwood boilers, modeled as reduced capital investment costs. Results indicated that the carbon tax was the most cost-effective policy in the absence of carbon capture and storage, achieving both high GHG emission reductions and fossil fuel substitution. When carbon capture and storage was available, carbon tax and trading scheme remained the most effective instrument for emissions reduction; however, fossil fuel substitution declined due to the deployment of bioenergy. In contrast, feed-in tariffs achieved higher fossil fuel substitution but limited GHG savings. The biofuel mandate and pellet subsidies were found to be the least cost-effective policy instruments for emission reduction and fossil fuel substitution.

Market-based policies and direct financial support was considered in (Ouhimmou et al., 2021). In this study, the integration of bioproducts into existing forest value chain networks was investigated using a strategic decision-making model with the aim of maximizing the NPV of the network over a ten-year planning horizon. A case study in Quebec's Mauricie region was considered, and different bioproducts and production technologies were taken into account. The products included

cellulosic pulp, hemicellulosic sugars, lignin, crude bio-oil, acetic acid, furfural, levulinic acid, and formic acid, produced through technologies such as fast pyrolysis, pressurized hot water extraction, organosolv fractionation, and kraft lignin recovery. The blending mandate of 2% renewable mix in diesel was used to estimate the demand for renewable diesel. In one of the scenarios, this percentage was increased to 5% from year three to ten of the planning horizon. The establishment of more biorefineries was the result of such change. Moreover, a crude bio-oil price increment of 5% yearly and governmental subsidies covering 35% of capital investment costs were considered. Despite these considerations, the initial cash investment was not reimbursed. However, with a 25% increase in the bio-oil price, in addition to the 35% capital investment subsidies, a positive NPV could be achieved. The overall conclusion of the paper was that benefits of adding biorefinery activities to the existing forest value chain networks was highly affected by the governmental subsidies.

Wetterlund et al. (2013) used an existing mixed-integer linear programming model to analyze the combined effects of carbon pricing (i.e., carbon-based policies and programs) and biofuel support policies (i.e., financial policies and programs) on a European bioenergy and biofuel supply chain over a 20-year horizon. The model optimized plant locations and material flows to minimize supply chain and emission costs, assuming a 3% target for second-generation biofuels in transportation. At a carbon price of 50 EUR/t CO₂, all forest residues were utilized, primarily in CHP plants due to their greater emission reductions. However, with direct policy support for biofuels (around 10 EUR/GJ), a larger share of biomass was directed to biofuel production. Despite meeting the biofuel target, overall CO₂ reductions were lower under the biofuel support policy, revealing a trade-off between policy goals.

Cifuentes García et al. (2025) expanded their previous study (Cifuentes García et al., 2024), and in addition to carbon tax considered national (1158.0 M€) and regional energy (1589.6 M€) budgets set by Spanish Ministry of Industry for energy-related purposes as a form of financial policy and analyzed the strategic establishment of thermal power stations and pellet plants using residues of pinewood, eucalyptus wood and corn stover to replace natural gas in boilers in Spain. The model without the budget constraints prescribed 18 thermal power stations and three pellet plants with an investment of about 2173.5 M€. Under the national budget constraint, the installation of 8 facilities (six pellet plants and two thermal power stations) were recommended.

When regional budgets were used instead, establishing eight more thermal power stations and one more pinewood pellet plant were established, with a total of 17 facilities. However, no more analysis was carried out on the carbon tax.

A carbon tax–subsidy scheme was examined in a study (Song et al., 2015), where taxes collected from fossil-fuel sectors were redistributed to bioenergy industries. GHG emission constraints were also incorporated into a dynamic optimization simulation model, based on an input–output analysis, developed to maximize gross regional product (i.e., summation of values from all industries) over a 16-year planning horizon. The study highlighted trade-offs between economic growth and emission reduction, showing that stricter GHG limits yielded greater emission cuts but lower gross regional products. Compared to a baseline with no carbon-tax subsidy or GHG limits, the subsidy scenario resulted in lower cumulative emissions, but a modest reduction in the production of gross regional product.

The impact of carbon-based and market-based policies and programs in bioenergy and biofuel supply chains were explored in (Akgul et al., 2014) and (Hombach et al., 2016). Akgul et al. (2014) developed a bi-objective model to minimize costs and carbon intensity for forest-based biomass in co-firing systems in the UK, incorporating renewable energy targets (governmental market-based policies) and CO₂ capture and storage (indirect support). The carbon intensity was calculated within the constraints, and the carbon cost was then calculated accordingly and included in the total supply chain cost objective function. The results indicated that carbon prices between £30 and £50 per tonne could reduce carbon intensity in bioenergy production. However, the carbon price should rise to £120-175/tonne to achieve carbon-negative electricity generation.

In a related study, a biofuel production network from agricultural and forest-based biomass was designed to maximize the supply chain NPV (Hombach et al., 2016), with different regulations related to biofuel production incorporated in the constraints, including restrictions on the land areas that could be used for biomass supply, maximum and minimum market share of first- and second-generation biofuels, biofuel blending mandates, and minimum GHG emission-saving requirements. The findings revealed a trade-off, which showed regulatory changes that improved supply chain profitability often reduced GHG emission savings, and vice versa. Specifically, changes in GHG emission-saving requirements, the minimum market share of second-generation,

and the maximum market share of first-generation biodiesel had the highest impact on the NPV of the supply chain.

Tax-related and financial policies (i.e., subsidies) in bioenergy and biofuel supply chains were considered in (Tan et al., 2017) and (Ben Daya & Nourelfath, 2019). Tan et al. (2017) proposed a bi-objective model for a biomass-to-electricity supply chain from both agricultural and forest-based biomass sources to address tactical decisions. Their model aimed to maximize both the power plant's profit and social welfare, including consumer surplus and government revenue, and environmental benefit. The government's revenue in the social welfare objective function encompasses the taxes received from biomass power plants and subsidies given per kWh of generated electricity. The sensitivity analysis on government subsidies showed that if the subsidies decreased, the biomass power plant could not generate profit. On the other hand, if it increased to 0.7 Yuan/kWh, the social welfare objective would be negative and generating electricity from biomass would not be beneficial for the society.

Furthermore, Ben Daya and Nourelfath (2019) investigated implementation of forest biorefinery activities in Canadian pulp and paper mills. They proposed a bi-objective model considering GHG emission minimization obtained from the LCA approach and profit maximization. The considered financial policies included direct incentives. There are federal and provincial programs in Canada that support ethanol industry through subsidies for production, investment, and distribution. In this study, it was assumed that the subsidies allocated for bioethanol production would result in an increase in the ethanol price. Additionally, an accelerated depreciation rate of 50% was considered for tax purposes. This depreciation reduces taxable income and, consequently, the taxes owed. The results showed that the considered incentives could increase investments in clean production and reduce emissions. The accelerated depreciation rate could also reduce emissions and increase economic performance (increasing the IRR from 16.47% to 18.38%).

Ahlström et al. (2020) used an existing supply chain model (i.e., BeWhere) to investigate whether liquefied biomethane (LBG) could replace fossil fuels in Sweden's iron and steel industry (ISI). The objective function of the model was to minimize the total costs, while satisfying liquified biomethane demand over a single year for the iron and steel industry and other sectors such as transportation. The model included a carbon tax (i.e., carbon-based policies) in the objective

function and biofuel policy support (i.e., financial policies) for the transportation sector. The authors found that at the current carbon tax levels ($\sim 5 \text{ €/t CO}_2$), switching to liquefied biomethane was not cost-effective for the iron and steel industry, and a tax above 200 €/t CO_2 would be needed.

Table 2-1 shows the summary of all the reviewed papers that proposed new deterministic models rather than using existing models for analysis.

Table 2-1. Summary of deterministic forest-based biomass supply chain planning studies considering governmental policy and regulations.

Policy group	Planning level	Main decisions	Planning horizon	Single/multi objective function	Biomass category	Product category	Governmental policies/regulations	Case study	References
Carbon-based	Strategic	• Location • Flow • Production	1 year	Multi-obj: • Max. Profit • Max. Social benefits • Min. Emission costs	• Forest-based • Agricultural	Biofuel	• Carbon tax	Spain	(Cifuentes García et al., 2024)
	Tactical	• Flow • Transportation mode • Storage	1 year - monthly time steps	Single obj: Min. Costs	• Forest-based	Biofuel	• Carbon tax • Carbon cap-and-trade • Carbon offset	Canada	(Palak et al., 2014)
	Tactical	• Flow • Production	1 year - monthly time steps	Single obj: • Max. Profit	• Forest-based	Biofuel Bioenergy	• Carbon cost		(Liu et al., 2017)
	Tactical	• Minimum syngas offtake price • Carbon tax increments	1 year - monthly time steps	Single obj: • Max. carbon tax increment or Min. syngas price	• Forest-based	Biofuel	• Carbon tax	Kraft pulp mill in BC, Canada	(Ahmadvand & Sowlati, 2023)
	Operational	• Transportation & routing • Flow • Production • Storage	Daily	Single obj: • Min. Costs	• Wood chips • Pellets & briquettes	Bioenergy	• Carbon tax • Carbon cap-and-trade • Carbon offset	Heating plant at UBC, Canada	(Malladi & Sowlati, 2020b)
	Operational	• Transportation & routing • Flow • Production • Storage	Daily	Multi-obj: • Min. Costs • Min. Emissions	• Wood chips • Pellets & briquettes	Bioenergy	• Carbon tax • Carbon cap-and-trade • Carbon offset	Heating plant at UBC, Canada	(Malladi & Sowlati, 2020a)

Policy group	Planning level	Main decisions	Planning horizon	Single/multi objective function	Biomass category	Product category	Governmental policies/regulations	Case study	References
Financial	Tactical & operational	• Flow • Production	1 year - weekly time steps	Single obj: • Max. Profit	• Forest-based	Biofuel	• Financial supports	Eastern Canada	(Boukherroub et al., 2017)
Market-based	Strategic & tactical	• Location • Flow • Storage	10 years - yearly time steps	Single obj: • Min. Costs	• Forest-based • Agricultural • Urban wood residues	Biofuel	• Blending mandates	Texas, USA	(Memişoğlu & Üster, 2016)
	Strategic & tactical	• Location • Flow	10 years - yearly time steps	Single obj: • Min. Costs	• Forest-based	Biofuel	• Blending mandates	Georgia, USA	(Akter et al., 2025)
	Strategic & tactical	• Location • Flow • Production and subcontracted production • Storage	4 years - yearly time steps	Multi-obj: • Min. Employment costs • Max. Profit • Min. CO₂ emissions	• Forest-based	Biofuel	• Blending mandates	Colombia	(Gutierrez-Franco et al., 2021)
Tax-related	Strategic	• Location • Flow	50 years - 5-yearly time steps	Single obj: Max. Welfare NPV	• Forest-based	Bioenergy	• Tax paid by landowners	Power plants in Georgia, USA	(Masum et al., 2022)
	Strategic & tactical	• Flow • Storage	20 years - yearly time steps	Single obj: Max. NPV	• Forest-based	Biofuel Bioenergy Biochemical	• Tax on profit	Eucalyptus-based biorefinery in Brazil	(Theozzo & Teles dos Santos, 2021)
Carbon-based and market-based	Strategic & tactical	• Location, size & technology • Flow	20 years - yearly time steps	Single obj: • Max. NPV	• Forest-based • Agricultural	Biofuel	• Limiting land area used for biomass supply • Max and min market share for biofuel • Blending mandates	Western Germany	(Hombach et al., 2016)

Policy group	Planning level	Main decisions	Planning horizon	Single/multi objective function	Biomass category	Product category	Governmental policies/regulations	Case study	References
							• Max allowed GHG emissions		
	Strategic & tactical	• Location & size • Flow • Production • Carbon intensity of bio-plants	1 year - no subperiod	Multi-obj: • Min. Costs • Min. Carbon intensity	• Forest-based	Bioenergy	• Renewable energy supply targets • Carbon costs	UK	(Akgul et al., 2014)
Financial, carbon-based, and market-based	Strategic	• Location & technology • Flow • Production • Transportation mode selection	10 years – yearly time steps	Single obj: • Max. NPV	• Forest-based	Biofuel Bioproducts	• Blending mandates • Subsidies • GHG emission fees	Mauricie, Quebec, Canada	(Ouhimmou et al., 2021)
Financial and tax-related	Strategic	• Technology • Production • Flow	20 years - 5-year time steps	Multi-obj: • Max. profit • Min. GHG emissions	• Forest-based • Agricultural • Industrial/ municipal	Biofuel Bioenergy Pulp & paper product	• Subsidies • Accelerated depreciation rate	Canadian pulp and paper mills	(Ben Daya & Nourelfath, 2019)
	Tactical	• Flow • Production • Inventory	1 year - monthly time steps	Multi-obj: • Max. Profit • Max. Social welfare	• Agricultural • Forest-based	Bioenergy	• Subsidies • Tax on profit	Heilongjiang Province in Northeast China	(Tan et al., 2017)
Carbon-based, market-based, and financial	Strategic & tactical	• Location • Technology • Flow • Production • Emissions	1 year - winter and summer	Single obj: • Min. Costs	• Agricultural • Forest-based	Bioenergy Biofuel	• Carbon tax • Emission trading • Feed-in tariff • Boiler subsidy • Blending mandates	Austria	(Schmidt et al., 2011)

2.5 Non-deterministic models

Walther et al. (2012) investigated a bio-diesel supply chain, considering biomass availability, investment costs, and demand for biodiesel as uncertain parameters and considered different risk attitudes when calculating the NPV objective function. The results suggested lower investments at the early stages of the project and higher flexibility in future capacity adjustments for risk-averse decision makers, whereas more investments in the first periods were suggested for risk-seeking decision makers. However, the risk-seeking decision makers could only be advantageous if demand grew high enough to provide economies of scale. Regarding the governmental programs and policies, Walther et al. (2012) only considered biofuel mandates (a market-based policy) from EU directives to determine the demand for bio-diesel in Germany, which served as an input for their proposed model.

A fuzzy-based approach is another approach that can be used to deal with epistemic uncertainties in biomass supply chains (Abusaq et al., 2022). A robust possibilistic programming approach was taken in this study to account for uncertainties in costs, emissions, supply amount, and biomass-to-pellet conversion rate in the design of a wood pellet production supply chain. Moreover, emission penalties and CO₂ taxes were considered in the cost minimization objective function as a carbon-based policy. However, no further analyses were carried out on the carbon pricing.

Saghaei, Dehghanimadvar, et al. (2020) introduced a two-stage stochastic programming model to minimize biomass-to-bioelectricity supply chain costs considering pre- and post-disaster stages. The strategic and tactical decisions were made in the first and second stages, respectively. The uncertainties regarding material availability, material quality, and demand were considered in the second stage. The study compared the effects of carbon-based policies (i.e., carbon tax, carbon offset, and carbon capture and storage (CCS)) on supply chain costs. Each policy was modeled with specific constraints, except for the carbon tax, which required none. Results showed that CCS incurred the highest costs, followed by carbon tax and then carbon offset. The carbon tax policy also posed the greatest downside risk due to uncertainty.

Fu et al. (2023) also took a two-stage stochastic approach to address a hybrid-fuel management problem in a biofuel-integrated district heating system, under multiple uncertainties, including heat demand, fuel availability, and economic factors like CO₂ prices and penalties. Focusing on a

system blending pellet biofuel (from crop and forest residues) with coal, the study incorporated carbon cap-and-trade (i.e., carbon-based policy) and biofuel subsidies based on CO₂ reduction (i.e., financial policy). The model aimed to minimize costs while determining the optimal biofuel-coal mix and carbon reduction strategy. Results showed that a 5% biofuel blending ratio was the most cost-effective and environmentally beneficial option for Dalian City over a three-year planning horizon.

Table 2-2 shows the summary of all the reviewed papers with non-deterministic models.

Table 2-2. Summary of non-deterministic forest-based biomass supply chain planning studies considering governmental policy and regulations.

Policy group	Planning level	Main decisions	Planning horizon	Single/multi objective function	Biomass category	Product category	Risk/uncertainty sources	Approach of dealing with risk/uncertainty	Governmental policies/regulations	Case study	References
Carbon-based	Strategic & tactical	- Location & size - Flow - Production - Storage	Pre-disaster stage: 1 year - monthly time steps Post-disaster stage: 3 years	Single obj: Min. Costs	Forest-based	Bioenergy	- Demand - Biomass availability and quality	Two-stage stochastic programming Downside risk in constraints	- Carbon tax - Carbon offset - Carbon capture and storage	Mississippi, USA	(Saghaci, Dehghanimadvar, et al., 2020)
		- Location & size - Flow	Not mentioned	Single obj: Min. Costs	- Agricultural - Agricultural & forest-based	Biofuel	- Costs - Emissions - Supply amount - Conversion rate	Robust possibilistic programming	Carbon tax	Pakistan	(Abusaq et al., 2022)
Market-based		- Location, size & technology - Flow	20 years - yearly time steps	Single obj: Max. NPV	- Agricultural - Forest-based	Biofuel	- Demand - Biomass availability - Costs	Different risk attitudes in the objective function	- Blending mandates	Niedersachsen, Germany	(Walther et al., 2012)
Carbon-based, financial, and market-based	Tactical	- Flow - Carbon traded or removed - Whether biofuel co-combustion is executed	3 years - yearly time steps	Single obj: Min. Costs	- Agricultural - Forest-based	Bioenergy	- Heat demand - Fuel availability - Economic factors	Two-stage stochastic programming	- Carbon cap-and-trade and carbon reduction technologies - Biofuel subsidies - Blending ratio	Dalian City, China	(Fu et al., 2023)

2.6 Summary and conclusions

The literature review revealed several key findings regarding the role of governmental policies and programs in the context of forest-based biomass supply chain design and planning. It highlighted that this area has been overlooked, with only few studies exploring it.

Moreover, the literature review highlighted a strong emphasis on carbon-based policies, such as carbon tax, carbon cap-and-trades and carbon offset policies, which were incorporated in 18 studies. Financial and market-based policies were each covered in 10 and 11 studies, respectively, while only four studies addressed tax-related policies. Of these four studies, three (Tan et al., 2017; Theozzo & Teles dos Santos, 2021; Masum et al., 2022) focused solely on taxes payable to the government by businesses and were not designed to encourage bioproduction. In contrast, Ben Daya and Nourelfath (2019) considered accelerated depreciation rates, which increase depreciation and thereby reduce taxes to support bioenergy production from wood residues.

Additionally, only three studies (Ouhimmou et al., 2021; Schmidt et al., 2011; Wetterlund et al., 2013) considered three policy groups of carbon-based, market-based, and financial policies. Schmidt et al. (2011) included: 1) carbon-based policies such as carbon tax, emission trading; 2) financial policies like feed-in tariffs and subsidies; and 3) blending mandate as a market-based policy in their study. Ouhimmou et al. (2021) incorporated: 1) GHG emission fees as a carbon-based policy in the objective function, 2) blending mandates as a market-based policy to estimate demand for renewable diesel, and 3) government financial support covering a portion of the capital investment. While Wetterlund et al. (2013) did not develop a new mathematical programming model, carbon cost as a carbon-based policy, biofuel support as a financial policy, and biofuel share as a market-based policy were examined using an existing model.

Table 2-3 shows how policies influenced the mathematical programming models and were reflected within them. It indicates whether policies 1) influenced an input parameter, for example, blending mandates were used only to calculate bioproducts demand (e.g., Memişoğlu & Üster, 2016; Gutierrez-Franco et al., 2021; Akter et al., 2025), 2) were incorporated as constraints to limit the feasible region, such as a biofuel mandate requiring a minimum biofuel share in (Schmidt et al., 2011), or 3) included as elements in the objective function, such as carbon tax policies added

to the cost minimization objective (e.g., Abusaq et al., 2022). Moreover, Table 2-3 shows that in the majority of studies, policies were reflected in the objective function.

Table 2-3. Classification of studies based on how policies were incorporated in the optimization models.

Reference	Changes in:		
	Input parameters	Constraints	Objective function
(Ahmadvand & Sowlati, 2023); (Tan et al., 2017); (Liu et al., 2017); (Theozzo & Teles dos Santos, 2021); (Cifuentes García et al., 2024); (Jeong et al., 2025); (Masum et al., 2022); (Abusaq et al., 2022)			✓
(Zetterholm, Bryngemark, et al., 2020); (Hombach et al., 2016); (Song et al., 2015)		✓	
(Walther et al., 2012); (Boukherroub et al., 2017); (Memişoğlu & Üster, 2016); (Gutierrez-Franco et al., 2021); (Zetterholm, Ahlström, et al., 2020); (Akter et al., 2025); (Vadenbo et al., 2018)	✓		
(Palak et al., 2014); (Malladi & Sowlati, 2020b); (Malladi & Sowlati, 2020a); (Cifuentes García et al., 2025); (Saghaei, Dehghanimadvar, et al., 2020); (Fu et al., 2023)		✓	✓
(Akgul et al., 2014); (Ben Daya & Noureldath, 2019); (Ouhimmou et al., 2021); (Wetterlund et al., 2013); (Ahlström et al., 2020)	✓		✓
(Schmidt et al., 2011)	✓	✓	✓
Percentage of total studies	45%	32%	65%

To provide a deeper analysis, for each policy group, Figure 2-3 shows which component of the mathematical programming model was impacted (objective function, input parameters, or constraints). As shown, carbon-based policies are often incorporated as elements in the objective function. For example, carbon tax policies that include costs or taxes related to GHG emissions were added within the cost minimization objective (e.g., Abusaq et al., 2022). Additionally, some carbon-based policies were included as constraints that limit emissions, while also accounting for their costs, such as carbon offset policies (e.g., Malladi & Sowlati, 2020a; Malladi & Sowlati, 2020b). Another example is the study by Hombach et al. (2016), in which the maximum allowable GHG emissions was incorporated as a constraint representing a carbon-based policy.

Tax-related policies were only included in the objective function (e.g., Theozzo & Teles dos Santos, 2021; Masum et al., 2022). Market-based policies were often reflected in input parameters, such as blending mandates used to estimate the demand for bioproducts (e.g., Walther et al., 2012;

Memişoğlu & Üster, 2016), or in constraints, such as in (Hombach et al., 2016), which incorporated biofuel market shares and established minimum and maximum biofuel blend quotas. Financial policies were incorporated into all components: objective functions, constraints and input parameters. For example, Ben Daya and Noureldath (2019) treated subsidies for bioethanol production, which increased ethanol prices, as an input parameter. Tan et al. (2017) introduced a social welfare maximization objective that accounted for government subsidies for electricity generation. Fu et al. (2023) also included the biofuel subsidies based on CO₂ reduction in their cost minimization objective function. Cifuentes García et al. (2025) considered national and regional budgets as a constraint, limiting the number of bioenergy and biofuel facilities that could be established. Similarly, Song et al. (2015) added constraints to their model to calculate subsidies for bioenergy industries, funded by taxes collected from fossil-fuel sectors.

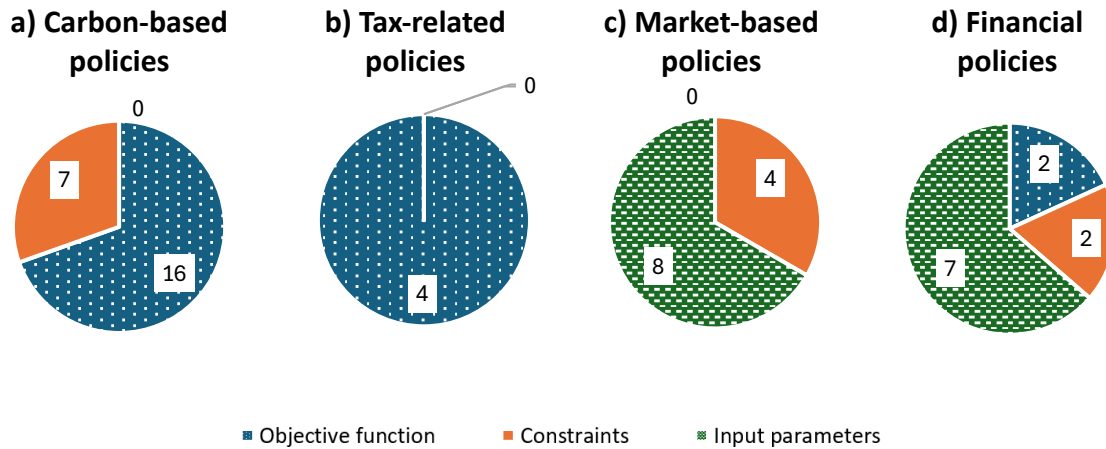


Figure 2-3. Classification of governmental policies and programs considered were reflected in the mathematical models for each policy group.

Moreover, most studies in forest-based biomass supply chain design and planning under governmental policies and programs have primarily focused on deterministic decision-making environments. This focus does not reflect reality, as various sources of uncertainty can affect supply chains in most real-world scenarios. In other words, there is a gap in the literature with respect to the simultaneous consideration of governmental policies and uncertainties in biomass supply chain planning. Only a few studies have explored this intersection (Abusaq et al., 2022; Fu et al., 2023; Saghaei, Dehghanmadvar, et al., 2020; Walther et al., 2012). In these studies,

uncertainties related to costs, emissions, bioproduct demands, biomass availability and quality were considered. It is worth noting that none of these studies investigated the uncertainties related to the parameters associated with governmental policies. This consideration is particularly important for long-term strategic planning due to the nature of governmental policies and programs that can be updated and are susceptible to change. For instance, in Canada, the carbon price is known only until 2030 (CleanBC - Roadmap to 2030, 2021). Therefore, the uncertainty in this parameter should be taken into account for longer planning horizons. Overlooking such uncertainties can result in infeasible supply chain plans and configurations (Mottaghi et al., 2022).

Regarding the level of decisions incorporated into the models, most studies have primarily focused on strategic and tactical decisions. The emphasis on these two decision levels can be attributed to the significant impact of long-term decisions on supply chain performance. Moreover, most bio-projects are new endeavors for which initial strategic and tactical plans are necessary before delving into lower-level decisions within the system. However, there is still an untapped potential in addressing strategic and tactical decisions within a long-term planning horizon, while considering both uncertainties and governmental policies. Only Walther et al. (2012) considered a 20-year planning horizon to make strategic and tactical decisions for a biofuel supply chain, while taking supply chain uncertainties and governmental policies into account. However, it is important to highlight that Walther et al. (2012) solely took blending mandates as the governmental policy into account, which only indicated biofuel demand without providing deeper analyses or insights into this governmental too.

Based on the findings, the gaps in the literature were identified to guide the present research. Firstly, the role of governments in forest-based biomass supply chain design and planning has been relatively unexplored, as there are limited studies in this area. Secondly, the majority of the studies considered carbon pricing policies, suggesting that other policy groups could be explored more in the future. Lastly, most of the papers presented deterministic models, indicating potential for considering uncertainties in forest-based supply chains when making design and planning decisions. More importantly, considering uncertainties in parameters related to governmental policies, such as the carbon tax, could further enrich the literature and provide insights. The aim of present research is to bridge these gaps and provide further insight into the role of governmental programs and policies in the forest-based biomass supply chains.

Chapter 3: Techno-economic assessment

3.1 Synopsis

In this chapter, the economic assessment of two bioproducts (i.e., cellulose nanocrystals and cellulose nanofibrils) from the list of considered bioproducts is presented in detail as an example. The techno-economic assessments of the other bioproducts (i.e., biochar, pellets, and activated carbon) are provided in the Appendix C and Appendix D. These evaluations are conducted to identify infeasible products so that they can be excluded from the optimization models. The techno-economic analysis is performed to calculate the net present value (NPV) and evaluate feasibility across three production scales (small, medium, large) at four locations in the Williams Lake Timber Supply Area, BC, Canada. The impacts of the mentioned governmental policies, including feedstock subsidies, direct capital investment incentives, enhanced first-year depreciation allowances, and BC's carbon pricing system are also evaluated to assess their effectiveness in improving the economic performance. The economic analysis was conducted to evaluate the viability of different bioproduct options and assess how each bioproduction pathway performs. This analysis served as a prerequisite for the optimization model, allowing infeasible bioproducts to be excluded from further consideration when they were not viable under any scenario, including location, capacity, pathway, and policy conditions.

3.2 Economic analysis

The economic analysis is performed for each bioproduction facility at each production scale and each location, i.e., Hanceville, Horsefly, Anahim Lake, and Williams Lake, considering the potential supply chain pathways.

3.2.1 Assumptions

The assumptions made for the economic analysis are as follows:

- Project's lifetime is 20 years, and starts from 2023.
- The discount rate after-tax is considered to be 10% (Blair, 2020).
- It is assumed that a loan can be received that pays for the initial capital investment to acquire the bioproduction technology, land, handling and preprocessing equipment

pieces. The loan payment period is 10 years, and the interest on loan is 10% (Blair, 2020).

- The interest on loan for working capital is considered 12.2% (*Best Business Lines of Credit in Canada for 2024*, 2024).
- Equipment depreciation rate is 30% and the Half-Year rule is employed to calculate the depreciation (*Classes of Depreciable Property*, 2023).
- The corporate tax rate is considered to be 27% (*Corporation Tax Rates*, 2024), which is used to calculate taxes based on the taxable income.
- The annual increase rate of land prices in Williams Lake area is considered to be 1.5%.
- Bundling, chipping, and loading activities done at cut blocks for bundled slash pathway are contracted out.
- Transportation of residues is done by third-party; therefore, purchase cost of trucks is not considered.
- Feedstock costs are calculated from the cut blocks to the gate of biohub. Therefore, the handling operations done at the cut blocks to chip or load the residues into the trucks and transporting them to the facilities are considered in the feedstock cost.
- All the produced bioproducts can be sold.

3.2.2 Input data

The land and storage data at each facility location were estimated based on the area required to accommodate all the available residue at that location and the average commercial land price found through an online search. It is considered that each thousand cubic meters of loose wood requires 200 square meters of area (Akhtari et al., 2014), and each cubic meter of residues corresponds to 0.39 odt on average (Ahmadvand, 2023).

For CNC and CNF, the initial financial data of the bioproduction process were sourced from (Blair, 2020), for an annual capacity of 150,000 odt (Table 3-1).

Table 3-1. Original input data for cellulose nanocrystal (CNC) and cellulose nanofibrils (CNF) production using AVAP (American Value-Added Pulping) technology (Blair, 2020).

Input data type	Value (million USD in 2019)	Comments and assumptions
AVAP equipment cost	191.9	-
Engineering and management	42.4	22% of installed equipment cost

Contingency	41	20% of installed equipment cost
Land and site preparation	8.5	4% of installed equipment cost
Variable operating costs	31.9	-
Fixed operating costs	11.5	6% of installed equipment cost
Working capital	21.8	20% of variable operating cost

Using Eq. 3-1, the capital investment costs were adjusted based on the considered capacity. In this equation, the capital cost (C_2) of equipment with capacity (P_2) can be calculated using the known capital cost (C_1) with capacity (P_1). For chemical facilities, a recommended value of $n = 0.7$ is utilized (Perry et al., 2019). Similarly, to calculate the capital costs of handling and preprocessing equipment pieces, the same formula is employed, but with a recommended value of $n = 0.77$ (Khadivi, 2022).

$$C_2 = C_1 \left(\frac{P_2}{P_1} \right)^n \quad \text{Eq. 3-1}$$

The annual operating and maintenance (O&M) costs of the bioproduction facility are also estimated using the capacity and related costs from the reference papers. Eq. 3-2 illustrates how the O&M cost (OMC_2) for a specific capacity (P_2) is estimated using the known O&M cost (OMC_1) for capacity P_1 .

$$OMC_2 = OMC_1 \left(\frac{P_2}{P_1} \right) \quad \text{Eq. 3-2}$$

According to Eq. (3-1) and Eq. (3-2), and considering exchange rate of 1.33 (CAD/USD) (Annual Exchange Rates, 2024) and cumulative inflation factor of 16% (Inflation Calculator, 2024), the adjusted input cost data for the economic analysis can be found in Figure 3-1 to Figure 3-4.

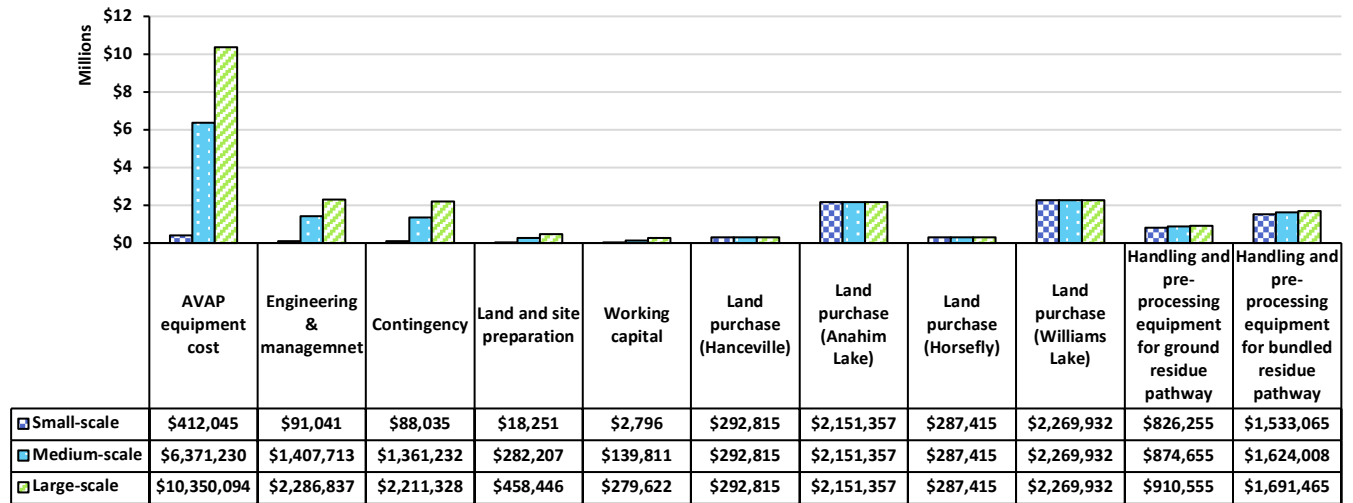


Figure 3-1. Capital investment and initial costs (in Millions CAD) for Cellulose Nanocrystal (CNC) production at different production scales.

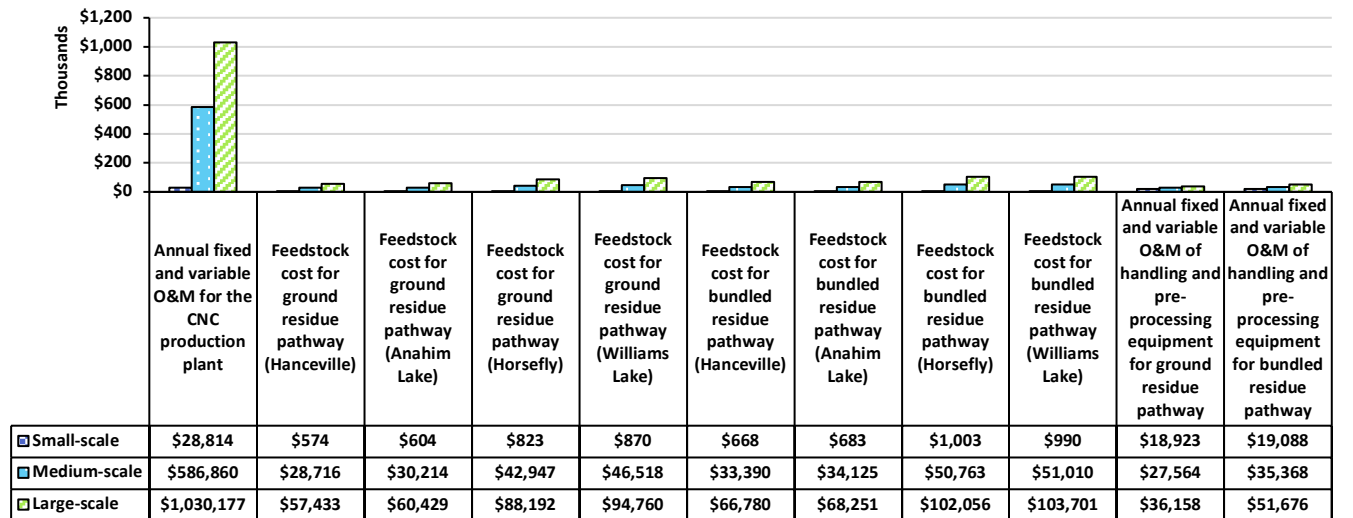


Figure 3-2. Annual operating costs (in thousands CAD) for Cellulose Nanocrystal (CNC) production at different production scales.

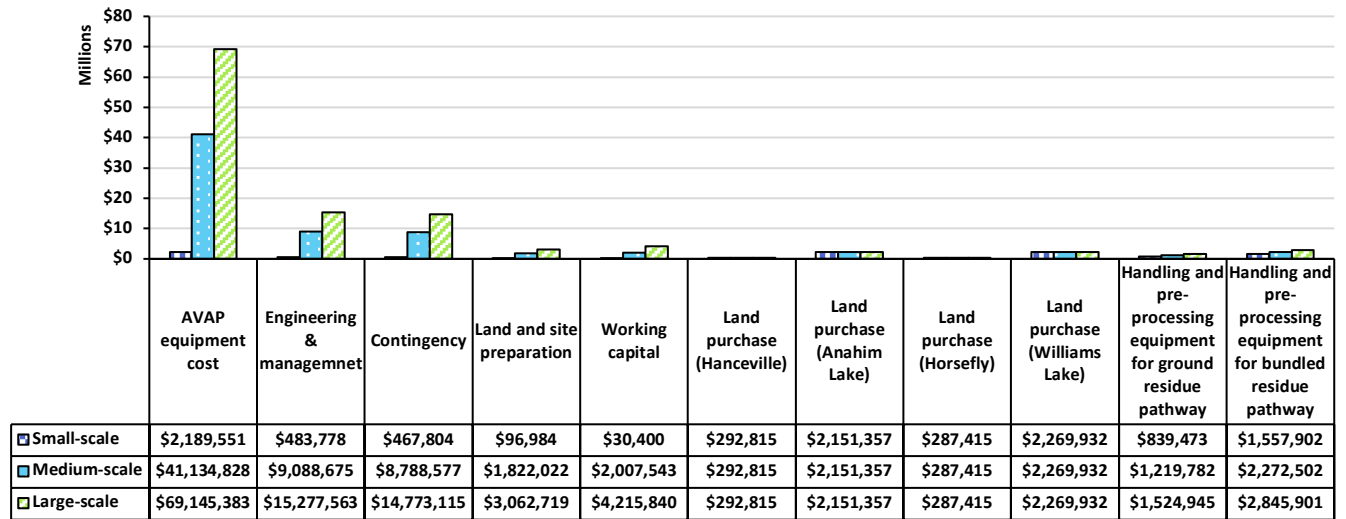


Figure 3-3. Capital investment and initial costs (in millions of CAD) for Cellulose Nanofibrils (CNF) production at different scales.

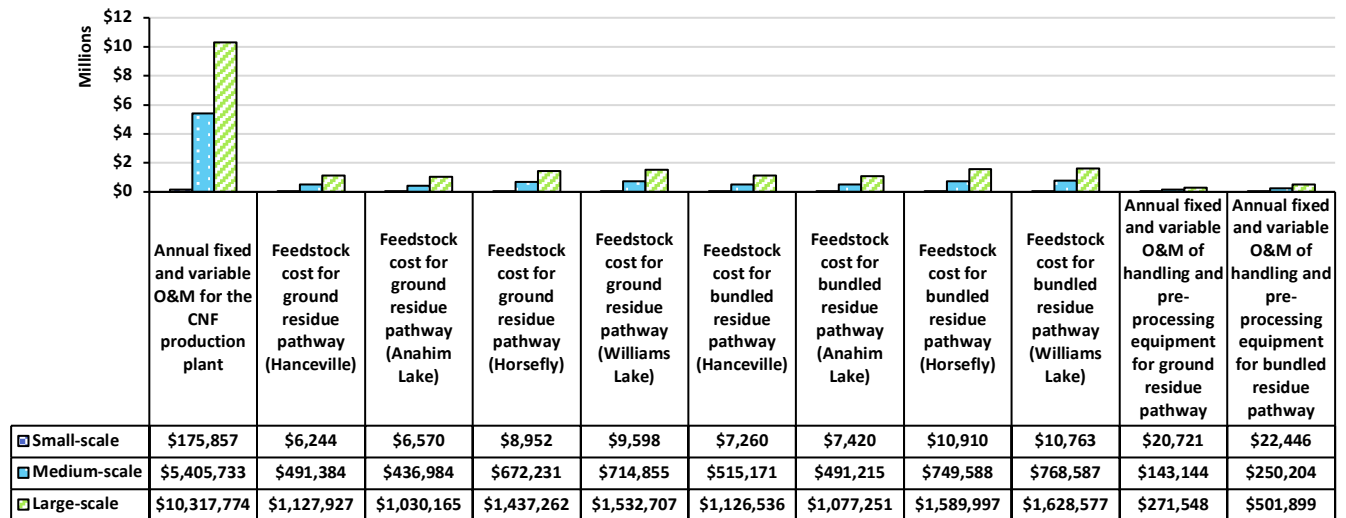


Figure 3-4. Annual operating costs (in millions CAD) for Cellulose Nanofibrils (CNF) production at different production scales.

The revenues from the sale of CNC, CNF, and their co-products (i.e., mixed sugar, lignosulfonate, and lignin) are calculated based on a selling price of 50,000 CAD/tonne for of CNC/CNF (Godfrey et al., 2023). The selling prices of mixed sugar, lignosulfonate, and lignin are estimated at 523 CAD/tonne, 462 CAD/tonne, and 277 CAD/tonne, respectively (Blair, 2020). The annual revenues for each capacity size are presented in Figure 3-5. The outer layer shows the revenues for large-

scale capacity, the middle layer shows the revenues for medium-scale capacity, and the inner layer shows the revenues for small-scale capacity.

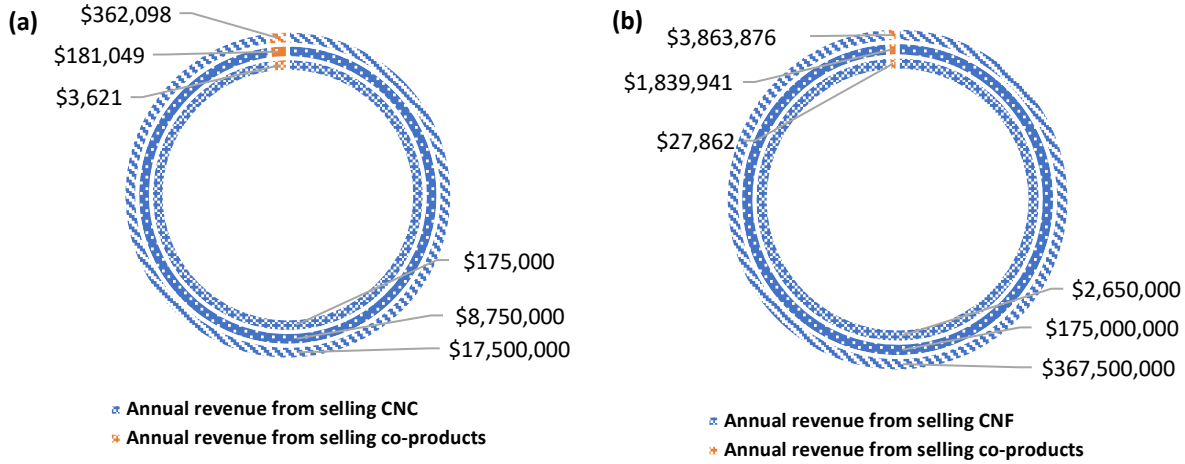


Figure 3-5. (a) Annual revenue from Cellulose Nanocrystal (CNC) sales and its co-products; (b) Annual revenue from Cellulose Nanofibrils (CNF) sales and its co-products.

3.2.3 Economic indicators and cash flow

For the economic analysis, the net present value (NPV) is calculated. In the NPV method, the present worth of all future cash flows are calculated at time 0 taking into account a discount rate (Park, 2007). A positive NPV indicates that the project is acceptable (Park, 2007). The calculation of NPV is shown in Eq. 3-3, where NCF_n represents net cash flow at the end of year n and i is equal to the discount rate. N is the service life of the project.

$$NPV = \sum_{n=0}^N \frac{NCF_n}{(1+i)^n} \quad \text{Eq. 3-3}$$

To compute these values, the net cash flow (NCF) of the bioproduction project at the end of each year is determined over the project's lifetime (i.e., 20 years) using Eq. 3-4.

$$Net\ cash\ flow = Total\ revenues - Total\ costs \quad \text{Eq. 3-4}$$

Total revenues include revenue generated from the sale of the main bio-product and co-products (if any), salvage value of bioproduction technology, salvage value of handling and preprocessing equipment pieces at the biohubs, and the land resale value at the end of the project's lifetime. The land resale value is calculated using Eq. 3-5, where N is the project's lifetime.

$$\text{Land resale value} = \text{Initial land cost} \times (1 + \text{landprice increase rate})^N \quad \text{Eq. 3-5}$$

The components of the total costs include investments, working capital (principal amount and interest), loan payment, feedstock cost, operating and maintenance (O&M) costs, and corporate taxes.

To calculate corporate taxes, the taxable income is determined each year using Eq. 3-6:

$$\begin{aligned} \text{Taxable income in each year} = & \text{Revenues} - (\text{Working capital} + \text{Feedstock cost} + \\ & \text{Operating and maintenance costs}) - (\text{Depreciation of bioproduction technology} \\ & \text{and the handling and preprocessing equipment pieces in that year}) - (\text{Amount} \\ & \text{paid towards the loan interest in that year}) + 50\% \text{ of capital gain on land resale} \\ & \text{value (capital gain is only applied for the final year)} \end{aligned} \quad \text{Eq. 3-6}$$

The corporate tax can be calculated following Eq. 3-7:

$$\text{Corporate tax in each year} = \text{Tax rate} \times \text{Taxable income in each year} \quad \text{Eq. 3-7}$$

3.3 Results and sensitivity analysis

3.3.1 Emission analysis for the output-based pricing system

The summary of emissions per category for CNC and CNF production can be found in Table 3-2 and Table 3-3. Based on these values, the emissions of each production capacity can be calculated. The detailed calculations of the emissions can be found in Appendix C.

Table 3-2. Summary of emissions for Cellulose Nanocrystal (CNC) production using ground and bundled slash pathways.

Pathway	Emission category	GHG emissions (g CO ₂ /odt)	GHG emissions (t CO ₂ / t CNC)
Ground slash pathway	General stationary combustion and electricity	565,860	2.02
	Industrial processes (chemicals for bleaching)	66,914	0.24
	On-site transportation (pre-processing and handling at biohub)	2,881	0.01
	Waste/wastewater	16,863	0.06
	Total	652,518	2.33
Bundled slash pathway	General stationary combustion and electricity	565,860	2.02
	Industrial processes (chemicals for bleaching)	66,914	0.24
	On-site transportation (pre-processing and handling at biohub)	4,853	0.02
	Waste/wastewater	16,863	0.06
	Total	654,490	2.34

Table 3-3. Summary of emissions for Cellulose Nanofibrils (CNF) production using ground and bundled slash pathways.

Pathway	Emission category	GHG emissions (g CO ₂ /odt)	GHG emissions (t CO ₂ / t CNF)
Ground slash pathway	General stationary combustion and electricity	566,493	1.45
	Industrial processes (chemicals for bleaching)	93,202	0.24
	On-site transportation (pre-processing and handling at biohub)	2,881	0.01
	Waste/wastewater	23,487	0.06
	Total	686,063	1.76
Bundled slash pathway	General stationary combustion and electricity	566,493	1.45
	Industrial processes (chemicals for bleaching)	93,202	0.24
	On-site transportation (pre-processing and handling at biohub)	4,853	0.01
	Waste/wastewater	23,487	0.06
	Total	688,035	1.76

Based on the values given in Table 3-2 and Table 3-3, the emissions of each production capacity can be calculated.

3.3.2 Economic analysis without policies

Table 3-4 represents the results of economic analysis for CNC and CNF production without the policies. As shown, all small-scale CNC production scenarios across all locations and pathways are economically infeasible, whereas all CNF production scenarios are feasible.

Table 3-4. Net present value (NPV) of cellulose nanocrystals (CNC) and cellulose nanofibrils (CNF) production scenarios without incorporating any governmental policies in the economic analysis.

Biohub location	Pathway	Production size	CNC production		CNF production	
			Required feedstock amount (odt)	NPV value of the scenario	Required feedstock amount (odt)	NPV value of the scenario
Hanceville	Ground slash	Small-scale	12.5	-\$1,398,279	136	\$11,467,676
		Medium-scale	625	\$42,923,894	8,974	\$1,014,200,317
		Large-scale	1,250	\$91,001,668	18,846	\$2,156,708,116
Anahim Lake		Small-scale	12.5	-\$2,932,348	136	\$10,144,530
		Medium-scale	625	\$41,593,463	8,974	\$1,013,217,282
		Large-scale	1,250	\$89,661,926	18,846	\$2,155,994,578
Horsefly		Small-scale	12.5	-\$1,395,820	136	\$11,454,686
		Medium-scale	625	\$42,839,289	8,974	\$1,013,080,203
		Large-scale	1,250	\$90,814,338	18,846	\$2,154,789,471
Williams Lake		Small-scale	12.5	-\$3,032,338	136	\$10,041,420
		Medium-scale	625	\$41,407,850	8,974	\$1,011,406,059
		Large-scale	1,250	\$89,364,275	18,846	\$2,152,787,042
Hanceville	Bundled slash	Small-scale	12.5	-\$2,768,362	136	\$10,404,226
		Medium-scale	625	\$41,774,212	8,974	\$1,012,044,011
		Large-scale	1,250	\$89,748,749	18,846	\$2,153,737,593
Anahim Lake		Small-scale	12.5	-\$4,305,176	136	\$9,082,112
		Medium-scale	625	\$40,448,522	8,974	\$1,010,871,776
		Large-scale	1,250	\$88,418,489	18,846	\$2,152,722,778
Horsefly		Small-scale	12.5	-\$2,766,720	136	\$10,385,383
		Medium-scale	625	\$41,670,078	8,974	\$1,010,590,973
		Large-scale	1,250	\$89,533,351	18,846	\$2,150,861,068
Williams Lake		Small-scale	12.5	-\$4,405,799	136	\$8,977,048
		Medium-scale	625	\$40,259,298	8,974	\$1,009,063,648
		Large-scale	1,250	\$88,113,883	18,846	\$2,149,212,054

Figure 3-6 shows the scenarios with the highest NPV within different investment bracket. For instance, with an initial capital investment of up to \$10 million, the scenario yielding the highest NPV is small-scale CNF production at Hanceville using the ground slash pathway. This figure can

assist investors in identifying the optimal bioproduction investment decision based on their available investment budget.

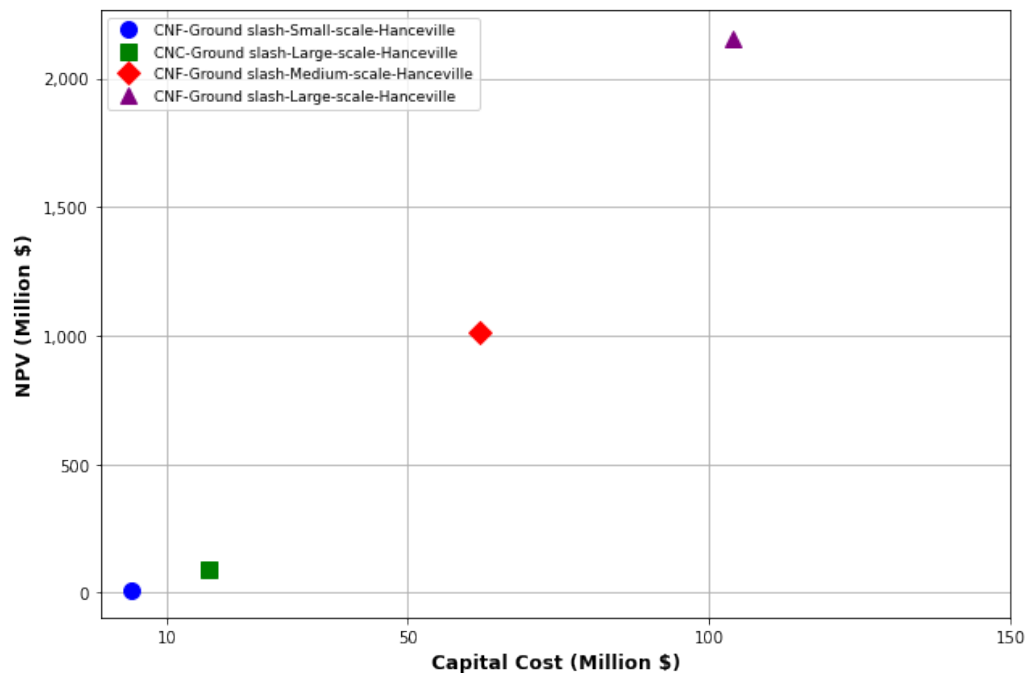


Figure 3-6. Scenarios with highest NPV in each capital investment bracket.

3.3.3 Sensitivity analysis on financial parameters without policy considerations

The results of economic analysis heavily rely on assumptions and input data, which may be uncertain and subject to variations. To account for these variations, sensitivity analysis is performed on key input parameters: feedstock delivered cost, capital investments, selling price, operating and maintenance (O&M) costs, and interest rate after-tax. Each parameter is varied by $\pm 10\%$, $\pm 20\%$, $\pm 30\%$, $\pm 40\%$, and $\pm 50\%$, and the resulting percentage change in NPV is reported.

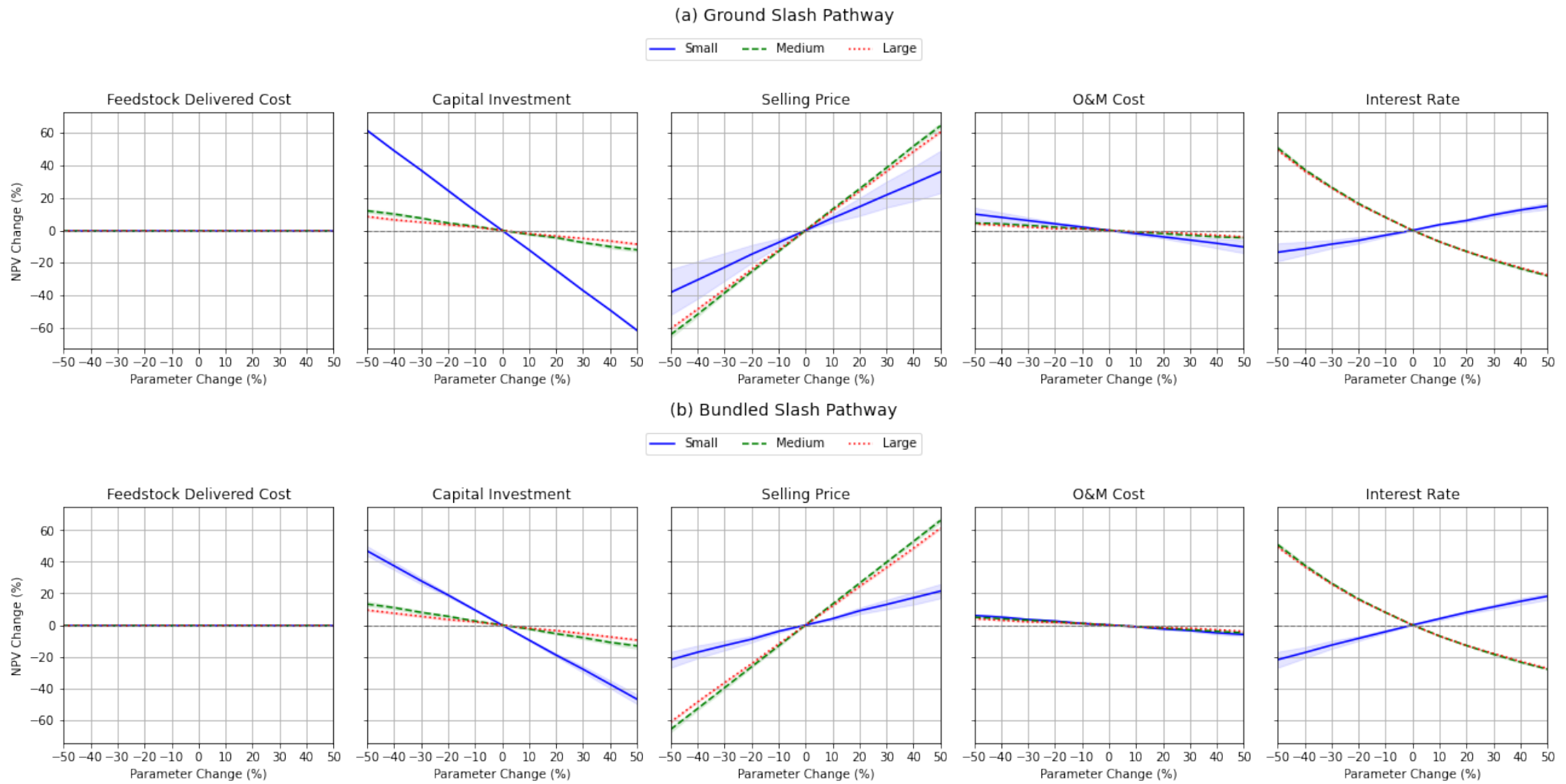


Figure 3-7 (a-b). Sensitivity analysis of net present value (NPV) for CNC production under changes in five key input parameters across three production sizes (small, medium, large). Each subplot represents the percentage change in NPV in response to a variation in a specific parameter. Solid lines indicate the mean response across five biohub locations, and shaded areas represent the minimum and maximum NPV changes observed among the locations.

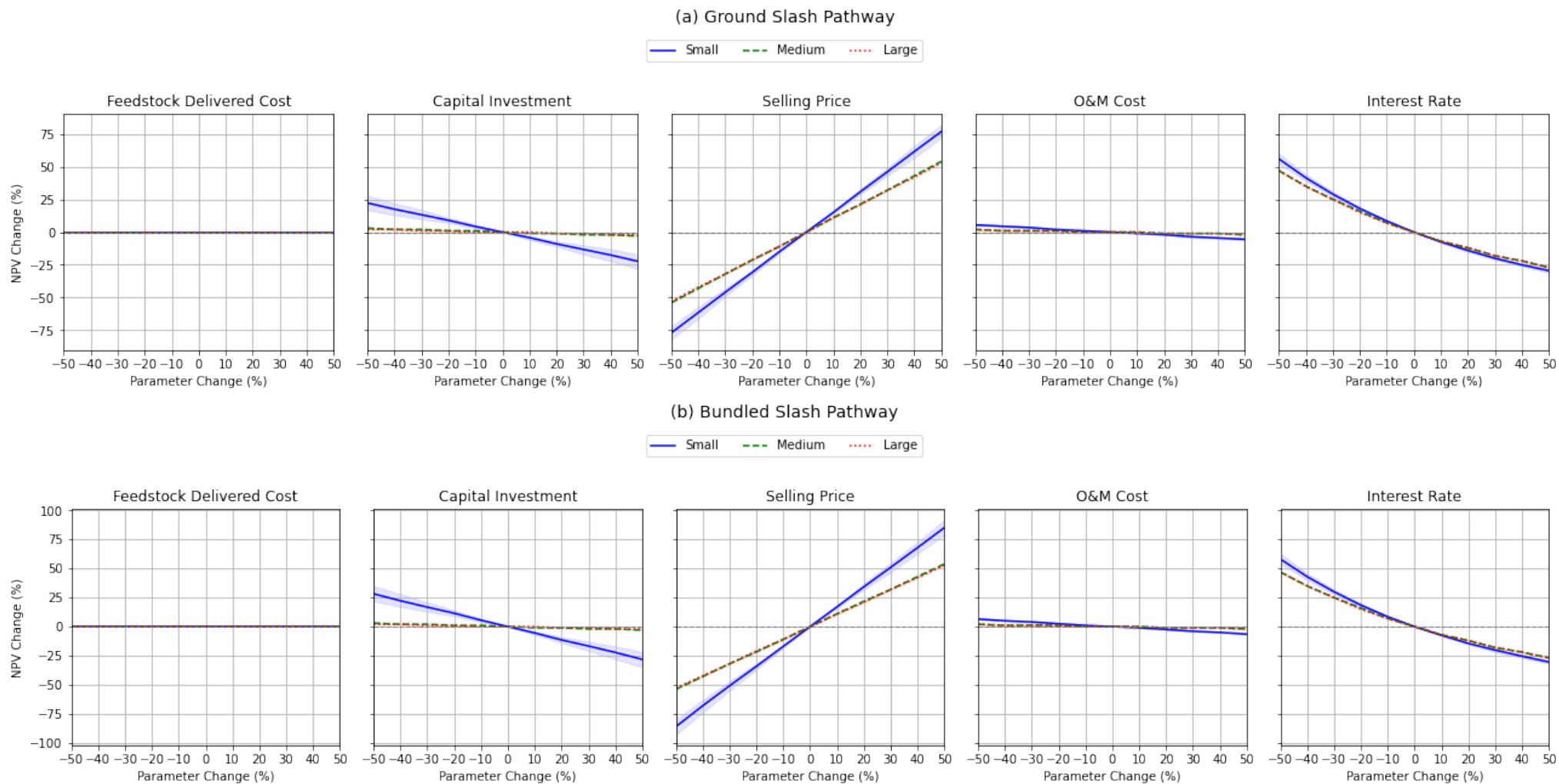


Figure 3-8 (a-b). Sensitivity analysis of net present value (NPV) for CNF production under changes in five key input parameters across three production sizes (Small, Medium, Large). Each subplot represents the percentage change in NPV in response to a variation in a specific parameter. Solid lines indicate the mean response across five biohub locations, and shaded areas represent the minimum and maximum NPV changes observed among the locations.

As shown in Figure 3-7, in the small-scale CNC production (3.5 tonnes/year), across all biohub locations and both ground and bundled slash pathways, capital investment has the greatest impact on NPV, followed by selling price, interest rate, and O&M costs. For medium- (175 tonnes/year) and large-scale (350 tonnes/year) production, selling price and interest rate are the most influential parameters, followed by capital investment and O&M costs. In all CNC scenarios, feedstock delivered cost has the least impact on NPV, as it constitutes a maximum of 2% of total costs. All the small-scale production scenarios remain infeasible despite these parameter variations.

Similarly, Figure 3-8 shows that in small-scale CNF production (53 tonnes/year) across all biohub locations (Hanceville, Anahim Lake, Horsefly, Williams Lake) and both pathways, the selling price has the greatest impact, followed by the interest rate. For medium- (3,500 tonnes/year) and large-scale (7,350 tonnes/year) CNF production, selling price and interest rate remain the dominant factors, with capital investment and O&M costs ranking lower. As with CNC, the feedstock delivered cost has minimal impact in all CNF scenarios. Notably, all CNF scenarios yield positive NPVs, confirming their economic feasibility even in the presence of these variations.

3.3.4 Economic analysis with the policies

Figure 3-9 and Figure 3-10 illustrate the impact of governmental policies on the NPV of the CNC and CNF scenarios. As shown, the policy offering direct capital investment incentives has the most substantial effect on improving the viability of the bioproduction scenarios. However, the small-scale CNC production remains infeasible even under this policy. Other policy interventions also fail to make the small-scale CNC production feasible. This trend is consistent across different locations and supply chain pathways.

For the medium- and large-scale CNC production, feedstock subsidies and enhanced first-year depreciation allowances slightly improve NPVs, while carbon pricing has a negligible positive effect. In the case of CNC, emissions from the biohubs remain below regulatory limits. As a result, these facilities can earn credits and sell them up to the usage limit, providing additional revenue. Nonetheless, this revenue stream does not significantly affect the NPVs, and no previously infeasible scenario becomes feasible. These findings also hold across all modeled locations and pathways.

For CNF, the impact of feedstock subsidies and first-year depreciation allowances is more pronounced in medium- and large-scale production compared to small-scale scenarios. In the small-scale CNF production, only the capital investment incentives have a relatively significant effect on the NPVs; other policies lead to minimal changes. Unlike CNC, CNF production facilities emit above the regulatory limits, requiring them to pay carbon taxes. This increases costs and reduces NPVs. However, this reduction does not make any CNF scenario infeasible. The same general pattern is observed across both supply chain pathways and all locations considered in the analysis.

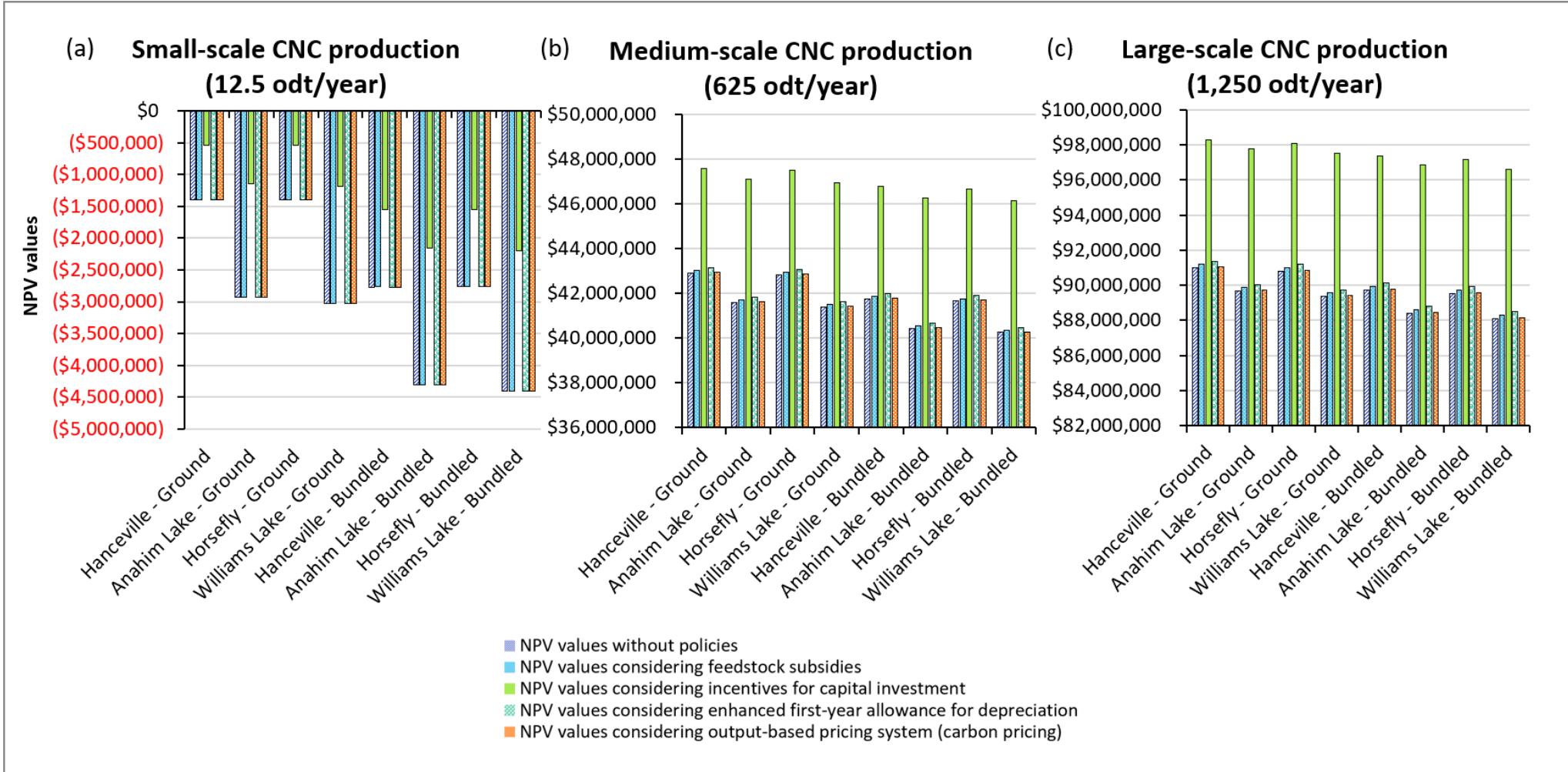


Figure 3-9 (a-c). Comparison of NPV for cellulose nanocrystals (CNC) production under no policy and various policy scenarios.

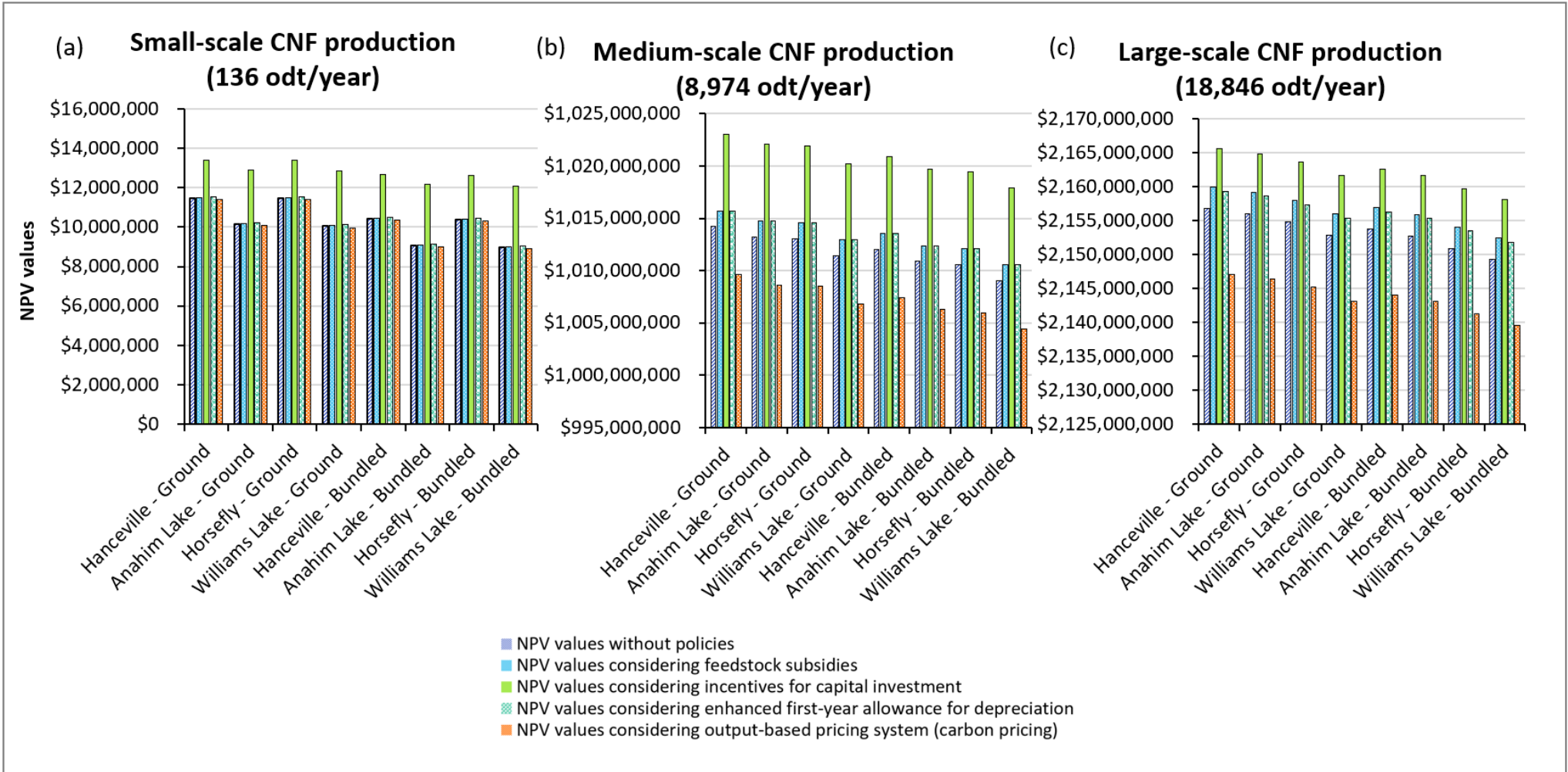


Figure 3-10 (a-c). Comparison of NPV for cellulose nanofibrils (CNF) production under no policy and various policy scenarios.

3.3.5 Sensitivity analysis on governmental policy parameters

As mentioned earlier, feedstock subsidies are applied to reduce the delivered cost of feedstock and encourage the utilization of slash. A subsidy level of \$12/t CO₂-eq, based on the voluntary carbon price (Government of BC, 2024a), was considered. However, this level did not affect the feasibility of any scenario. To further investigate, it is useful to determine the minimum subsidy levels required to make currently infeasible scenarios (i.e., small-scale CNC production) economically viable. This value is determined using the built-in what-if analysis tool in Microsoft Excel, located under the Data tab in the Forecast group.

In addition, the maximum subsidy level that keeps the total subsidy amount below the delivered cost of feedstock, which ensures that the subsidy remains a cost reduction rather than a source of revenue, is calculated. This assessment helps evaluate the practicality of implementing higher subsidy levels. Table 3-5 presents the results of this analysis, which is only performed for small-scale CNC production, as all other scenarios were already feasible.

Table 3-5. Summary of the subsidy analysis for small-scale cellulose nanocrystals (CNC) production under different locations and pathways.

Biohub location	Pathway	Feedstock delivered cost (CAD)	Subsidies (CAD) considering carbon price of \$12/t CO ₂ -eq	Minimum carbon price (CAD/t CO ₂ -eq) to make NPV positive	Carbon price that makes subsidies equal to the feedstock cost
Hanceville	Ground slash	\$574	\$338	\$6,666	\$20
Anahim Lake		\$604	\$338	\$14,101	\$21
Horsefly		\$823	\$338	\$6,653	\$29
Williams Lake		\$870	\$338	\$14,588	\$31
Hanceville	Bundled slash	\$668	\$338	\$12,750	\$24
Anahim Lake		\$683	\$338	\$20,158	\$24
Horsefly		\$1,003	\$338	\$12,740	\$36
Williams Lake		\$990	\$338	\$20,643	\$35

As shown in Table 3-5, the carbon price (i.e., subsidy level) required to make these scenarios feasible is significantly high and impractical, as it far exceeds the level needed for the subsidies to match the feedstock delivery costs. Therefore, no practical subsidy levels can make small-scale CNC productions economically viable.

The other analysis that can be performed is related to the parameters in the BC OBPS system. The results from the output-based pricing system depend on the values used for emission limits, the facility's attributable emissions, and the price of carbon. We estimated the emission limits based on values reported in the literature and used specific emission factors and published data to calculate emissions associated with the production of CNC and CNF. The carbon prices used for both tax payments and credit trading were based on current market values (Government of BC, 2024c), which are subject to change due to the evolving nature of climate policies and carbon markets. Therefore, a sensitivity analysis is also performed on the key parameters of the BC OBPS system to ensure that our results remain reliable under potential variations in these inputs.

Figure 3-11 and Figure 3-12 show the average changes in NPVs of CNC and CNF production across all the biohub locations under different parameter variations. Emission limit, attributable emissions, carbon price for credit sale, and carbon price for carbon tax payments are changed by $\pm 10\%$, $\pm 20\%$, $\pm 30\%$, $\pm 40\%$, and $\pm 50\%$, and the according changes in NPVs are reported.

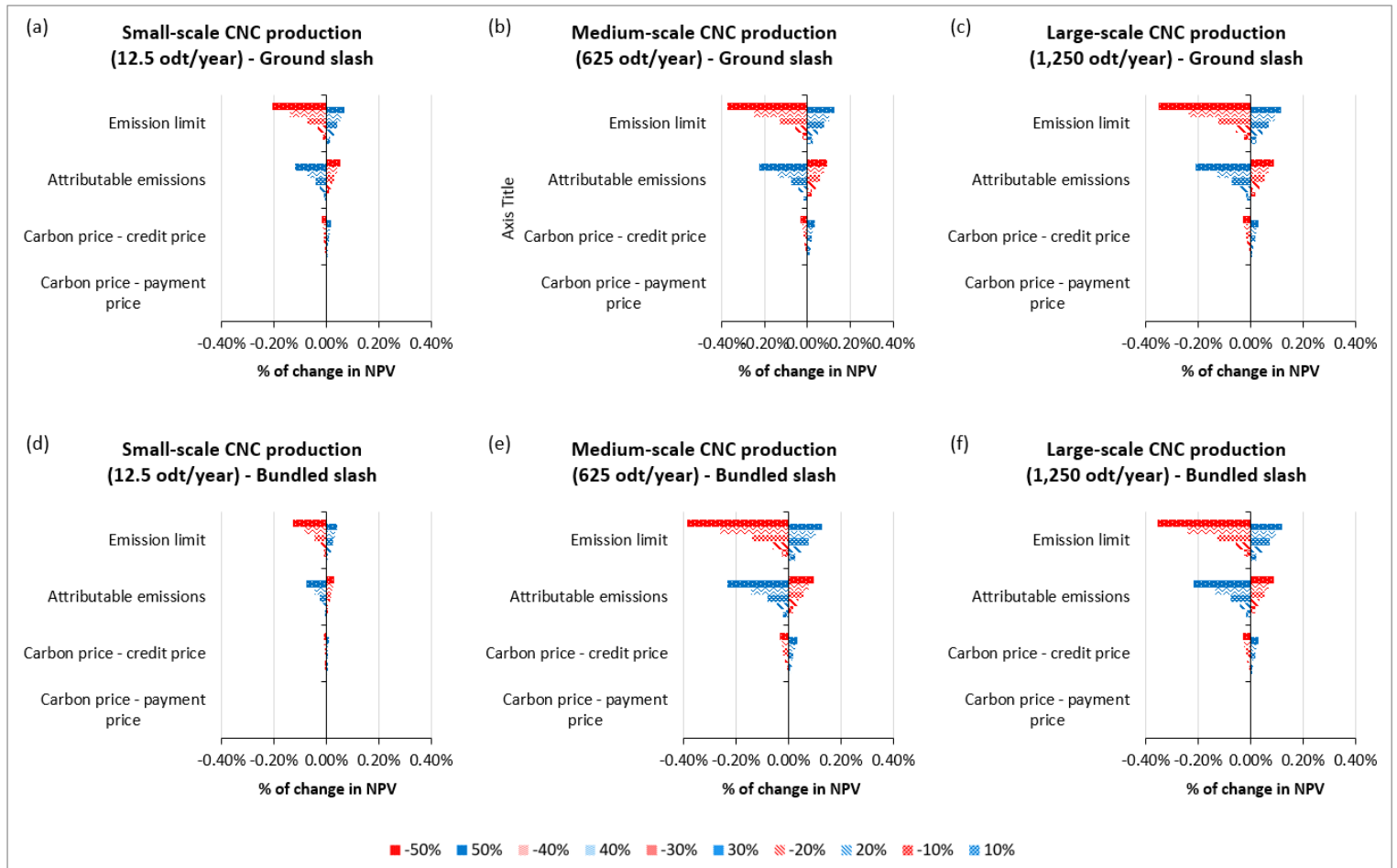


Figure 3-11 (a-f). Sensitivity analysis of average net present value (NPV) changes across all biohub locations in response to variations in output-based pricing system parameters for CNC production at different scales and pathways. (a-c) Results for ground slash supply at small (12.5 odt/year), medium (625 odt/year), and large (1,250 odt/year) production scales, respectively. (d-f) Results for bundled slash supply at small (12.5 odt/year), medium (625 odt/year), and large (1,250 odt/year) production scales, respectively.

As shown in Figure 3-11, the emission limit has higher impact on the CNC production NPVs compared to the other parameters. However, it should be noted that all the changes are below 1% and insignificant. The changes in carbon price for payments is zero, as the emissions from CNC productions in all three small-, medium-, and large-scale were below the emission limit, and there was no carbon tax payment.

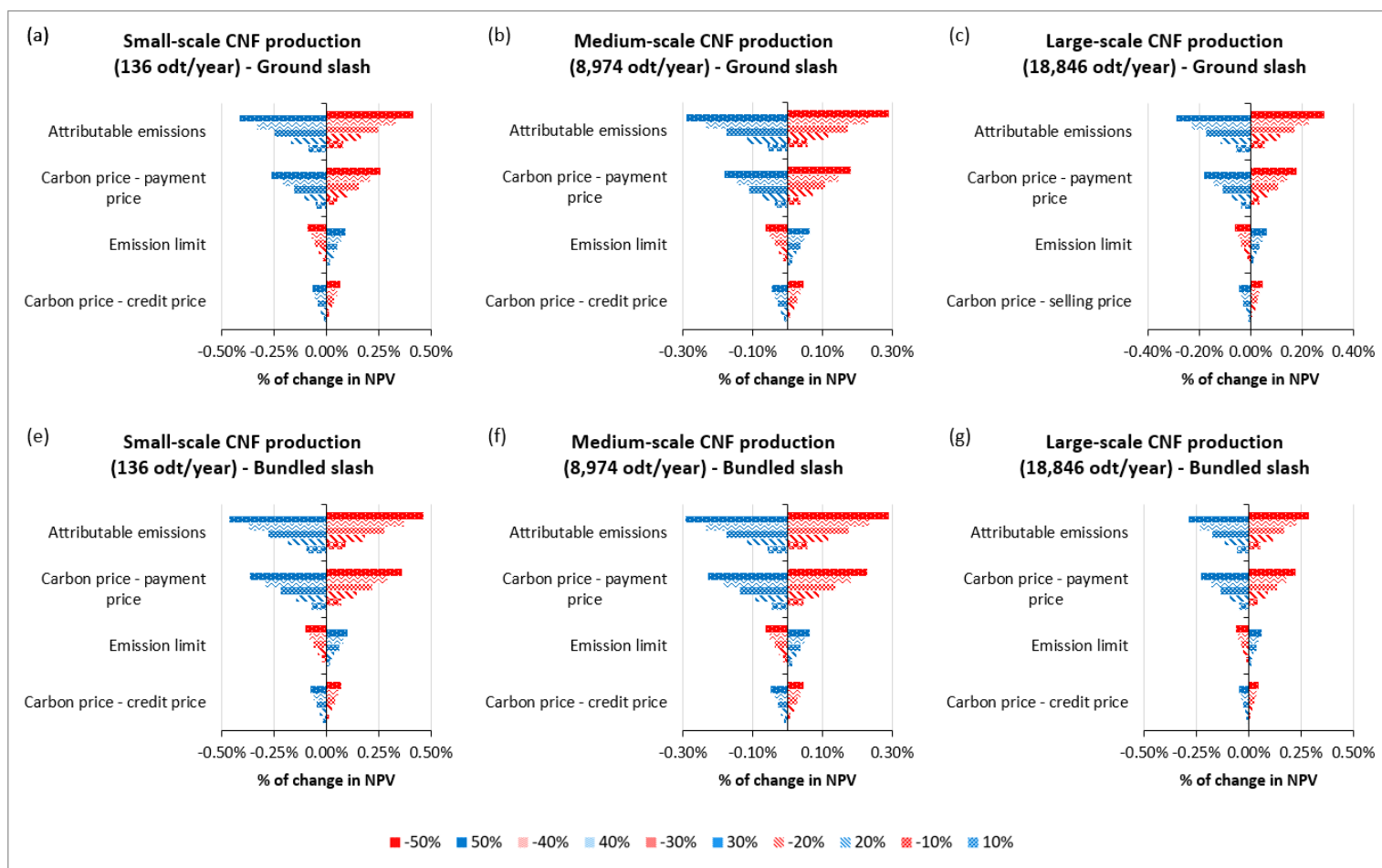


Figure 3-12 (a-f). Sensitivity analysis of average net present value (NPV) changes across all biohub locations in response to variations in output-based pricing system parameters for CNF production at different scales and pathways. (a-c) Results for ground slash supply at small (136 odt/year), medium (8,974 odt/year), and large (18,846 odt/year) production scales, respectively. (d-f) Results for bundled slash supply at small (136 odt/year), medium (8,974 odt/year), and large (18,846 odt/year) production scales, respectively.

As shown in Figure 3-12, the attributable emission limit has higher impact on the CNF production NPVs compared to the other parameters. However, it should be noted that all the changes are below 1% and insignificant. This shows that the increase or decrease in cost due to carbon pricing is negligible.

Overall, the sensitivity analysis showed that even with the variations in the input parameters of the output-based pricing system, the impact of this governmental measure is minimal on the considered bioproduction scenarios.

3.4 Findings and conclusion

In this chapter, the economic viability of producing CNC and CNF from forest residues was evaluated. The analysis also assessed the impact of four governmental policies, including feedstock subsidies, capital incentives, accelerated tax depreciation, and the output-based pricing system (OBPS), across three production scales at four potential biohub locations in the Williams Lake Timber Supply Area, BC.

The results showed that the small-scale CNC production was infeasible through both ground and bundled slash pathways across all locations. The annual small-scale CNC processing capacity of 12.5 odt of forest residues resulted in high per-unit costs due to diseconomies of scale. In contrast, other CNC production scenarios and all CNF production scenarios were feasible. It is worth noting that the small-scale CNF processing capacity is 136 odt of residues per year, which is much higher than that of small-scale CNC production, providing sufficient economies of scale to make CNF production feasible. Similar findings on the importance of production scale have been reported in the literature. For example, Blair and Mabee (2021) reported a decline in the break-even costs of CNC and CNF as production scale increased, highlighting the presence of economies of scale. Similarly, Rajendran et al. (2023a) showed that lower plant capacities, such as 2.5 MT/day, were not economically feasible. Penloglou et al. (2023) identified plant capacity and nanocellulose yield as the most influential factors affecting CNC production costs. For CNF, Lan et al. (2024) found that plant capacity, along with internal rate of return, electricity cost, and pulp consistency, were key drivers of economic outcomes.

In the case evaluated in this study, the sensitivity analysis indicated that variations in the feedstock delivered cost had minimal effect on the economic outcomes of CNC and CNF production scenarios, as feedstock delivered costs accounted for at most 2% of total costs. Although feedstock delivered costs constitute a small portion of total costs, explicitly modeling feedstock logistics remains important to capture spatial feasibility and network configuration, and to quantify their contribution rather than assume it.

In contrast, capital investment costs had a more pronounced influence on NPVs, specifically for small-scale CNC productions. This finding aligns with observations in (Blair & Mabee, 2021), in which capital investment costs were identified as the most influential factor affecting the economic

outcomes of the CNC production. Notably, this effect was more pronounced for small-scale facilities, reflecting higher per-unit costs arising from limited economies of scale. From an investor's perspective, the strong sensitivity to capital costs suggests that financial risk is largely concentrated in upfront expenditures. This highlights the importance of de-risking initial investments, particularly for smaller-scale operations (Holland & Shapira, 2024).

Moreover, the selling prices of CNC and CNF were shown have a relatively noticeable influence on NPVs (an average change of 54% for a 50% change in prices). An increase in the selling price directly translates into higher revenue, and consequently, greater profit margins, thereby improving economic feasibility, while costs remain constant. Therefore, consideration of output-based subsidies per unit of bioproduct sold could be beneficial, as they increase the revenue of bioproducers. Similar governmental interventions were examined in (Ben Daya & Noureldath, 2019), where the effect of government supports were examined by increasing the ethanol price by +10¢ and +15¢ per liter. Their results showed that such price increases led to greater investment in clean production capacities.

Regarding governmental policies, although previous studies have emphasized the importance of government support in enhancing the feasibility of bioproduction (e.g. Ahmadvand & Sowlati, 2023), the findings of this study suggested that not all policy instruments are equally impactful within the study region. Among the interventions considered in this study, only direct incentives toward capital investment improved the NPVs of CNC and CNF productions noticeably as shown in Figure 3-9 and Figure 3-10 by an average of 17%. However, the improvements in NPVs resulting from this intervention were still insufficient to make the small-scale (12.5 odt/year) CNC production scenarios economically feasible. Specifically, providing fundings equivalent to 50% of initial capital investment costs, as outlined in the Investments in Forest Industry Transformation program (Investments in Forest Industry Transformation (IFIT), 2024), was not adequate to achieve economic viability at small scales of CNC production. These results suggested that the production of CNC at small scales within the study region might not be economically justified, even when policy interventions were implemented. A central insight emerging from this comparison is that economic feasibility is fundamentally constrained by scale.

Feedstock subsidies generally had a limited impact on economics of the considered scenarios. This is primarily because feedstock delivery costs accounted for a small portion of total costs (at most 2%). This cost structure has important policy implications. Because feedstock costs in the considered case represented a small fraction of total production costs, primarily due to the regional abundance of residues that incur no cost beyond preprocessing and logistics, subsidies targeting biomass supply are inherently limited in their ability to improve economic feasibility of nanocellulose production in the study region. Results of the sensitivity analysis further confirmed that variations in feedstock costs had minimal influence on NPVs. Although higher subsidy levels could improve NPVs to some extent, the levels required to make small-scale (125 odt/year) CNC production viable were unrealistically high. This highlights the importance of aligning policy instruments with the structural composition of costs rather than assuming that all cost-reduction measures are equally effective.

Similarly, the enhanced first-year depreciation allowance had negligible influence on NPVs, and in some cases even worsened the financial outcomes of already infeasible scenarios. This is because, even though this intervention decreases taxable income in the first few years, there is not enough depreciation remaining for the rest of the planning horizon to bring taxable income to zero. Therefore, when taxable income could have been zero for several years under the usual depreciation method, this measure is unlikely to improve NPV.

The OBPS in BC led to increased NPVs for CNC production scenarios, as emissions from biohubs were lower than the established emission limits, resulting in generation of credits and additional revenue. In contrast, the OBPS reduced NPVs of CNF production scenarios, as emissions exceeded the limit, triggered carbon price payments and thereby increased costs. Overall, however, the OBPS had a minimal impact on NPV as the generated cash flows were relatively small compared to other cost and revenue components. Sensitivity analysis based on a $\pm 50\%$ variation in key OBPS-related parameters, including attributable emissions, emission limits, and carbon prices for both direct payments and credit trading, also showed limited influence on NPVs. The limited impact of the BC OBPS on cash flows suggests that, at currently observed levels, carbon pricing alone is insufficient to act as a transformative economic driver for nanocellulose investments or to stimulate capital-intensive production in the study region without complementary targeted investment support.

In summary, the results showed that while most governmental policies improved the economic outcomes of bioproduction within the study region, their impact was often modest or minimal. Therefore, caution should be exercised when interpreting the impact of policies, and overgeneralizations should be avoided. The effectiveness of policy interventions varies case by case and depends on the specific policy and context. It would be inaccurate to claim that governmental policies are universally essential for the viability of bioproduction; instead, we should specify the type of policies that are beneficial under each condition. As Eversberg et al. (2023) argued, early expectations surrounding bioeconomy policies and their promises of economic growth have been moderated by real-world evidence, suggesting that many government strategies have not delivered the transformative results once anticipated.

Chapter 4: Deterministic Supply Chain Network Design

4.1 Synopsis

In this chapter, a single-objective model is developed to support strategic decision-making in a forest-based biomass supply chain producing different types of bioproducts. The model is formulated as a mixed-integer linear programming (MILP) model that optimizes supply chain decisions over a 20-year planning horizon, including the establishment of bioproduction facilities and the annual flows of biomass and bioproduct production. The objective function maximizes the net present value (NPV) of profit over the planning horizon. In addition, a bi-objective model is developed to incorporate supply chain GHG emissions alongside the NPV. Both models are solved under the considered policy scenarios to evaluate and compare the impact of these policies on supply chain design and decisions.

4.2 Problem description

An overview and simple structure of the supply chain is illustrated in Figure 4-1. The supply chain encompasses a set of biomass supply sources (i.e., cut blocks) ($i \in I$). The biomass is in two types ($f \in F$) of small-diameter non-merchantable logs and residues and can be transported to bioproduction facilities (i.e., biohubs) through different pathways ($w \in W$).

The small-diameter log pathway is only reserved for small-diameter logs; therefore, one biomass type-pathway combination. It should also be noted that small-diameter logs would be eligible for ground and bundled slash pathways as they can be ground or bundled at the roadside with other residues.

At the potential bioproduction facility locations (i.e., biohubs) both pre-processing and conversion activities can occur, and these activities are different based on the selected supply chain pathway. Bioproduction technologies for CNC, CNF, AC, biochar, low-quality and high-quality pellets production can be established at the potential locations in small, medium, or large capacities.

Given this supply chain structure, the problem is formulated as a mixed-integer linear programming (MILP) model. The key components of the proposed model are described below.

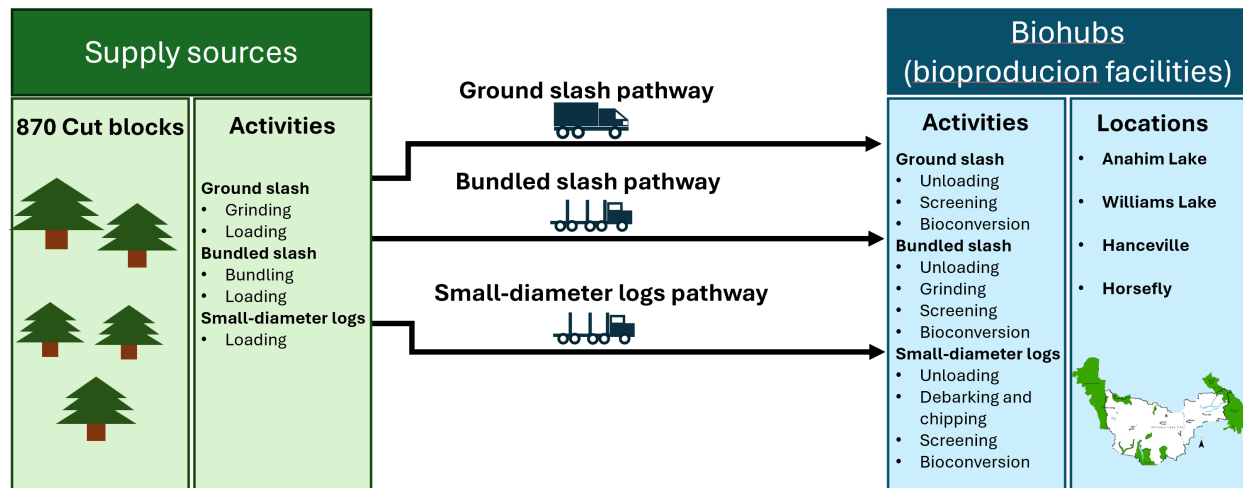


Figure 4-1. The schematic representation of the biomass supply chain, demonstrating activities at supply sources and bioproduction facility (i.e., biohub) locations for each pathway. HA: Hanceville, AL: Anahim Lake, HF: Horsefly, and WL: Williams Lake.

Decision variables

The main decisions of the model include:

1. **Biomass flow:** amount of biomass transported from each cut block to each bioproduction facility (i.e., biohub) using each pathway, for a specific bioproduct, in each period (non-negative decision variable).
2. **Bioproduct production:** amount of each bioproduct produced at each biohub location in each period (non-negative decision variable).
3. **Facility establishment:** whether a bioproduction technology with a given capacity is to be established at a location to produce a specific bioproduct or not (binary decision variable).

Objective function

The main objective function of the model is to **maximize the Net Present Value (NPV)** of the entire supply chain over the planning horizon. The NPV includes discounted revenues from bioproduct sales minus discounted operating, transportation, preprocessing, and investment costs, while accounting for taxes and depreciation.

Constraints

The constraints or the limitations of the problem, including the logical and operational ones, are:

1. **Supply availability:** Biomass transported from each cut block cannot exceed the available biomass in that cut block in each period.
2. **Conversion relationship:** Bioproduct output is based on the amount of biomass input and the conversion yield.
3. **Facility capacity:** Biomass processed at a facility cannot exceed its installed capacity, and is zero, if the facility is not built.
4. **Capacity selection:** At most one capacity of a conversion facility type for a product can be installed at each location.
5. **Minimum utilization:** Installed facilities must operate at a minimum of 70% of their capacity.
6. **Demand limit:** Total production of each bioproduct cannot exceed market demand that was estimated in the Market Analysis section.
7. **Variable domains:** Biomass flows and production quantities are non-negative, and facility establishment decisions are binary.

4.3 Deterministic single-objective model formulation without policies

The notations for the mathematical programming model in the absence of the governmental policies are presented in Table 4-1. The model is developed in a generic form that can incorporate multiple biomass types, supply chain pathways, products, capacity sizes, supply sources, and facility locations.

Table 4-1. Notations of the mathematical programming model without policy considerations.

Indices/Sets	
F	Type of biomass (i.e., residues or small-diameter logs) $f \in F$
W	Supply chain pathways (i.e., ground, bundled, small-diameter logs) $w \in W$
O	Valid type-pathway combinations $o \in (F \times W)$ {residues, small diameter logs}
I	Supply locations (i.e., cut blocks) $i \in I$
J	Bioproduction facility locations (i.e., Hanceville, Anahim Lake, Williams Lake, Horsefly) $j \in J$
C	Capacity sizes for facilities (i.e., small, medium, large) $c \in C$
P	Products (i.e., CNC, CNF, AC, Biochar-wet, Biochar-dry, Pellets-low, Pellets-high) $p \in P$
T	Time periods $t \in T$
Parameters	
KK_{cp}	Processing capacity (odt/year) of capacity size c for product p
PY_p	Production yield for product p (tonne of product/odt of biomass)
PR_p	Selling price of product p (CAD/tonne of product) (CAD)

CC_{cpj}	Capital investment cost of establishing bioproduction facility with capacity size c to produce product p at bioproduction facility location j (CAD)
FC_{cp}	Fixed O&M cost of bioproduction facility with capacity size c to produce product p
VC_p	Variable O&M cost of bioproduction facility producing product p (CAD/odt of biomass)
PC_w	Preprocessing cost of biomass through pathway w at bioproduction facilities (CAD/odt of biomass)
SS_{fijt}	Supply of biomass with type f from cut block i available to be sent to location j in period t
TC_{fwijt}	Transportation and preprocessing cost of biomass from cut block i to location j through pathway w in period t
DM_{pt}	Maximum demand for bioproduct p in period t
TR	Tax rate
α	Discount rate
DP_{cpt}	Present value of depreciation for the technology with capacity size c to produce product p if it was established in period t
Decision variables	
x_{fwijpt}	Amount of biomass flow in type f to be transported through supply chain pathway w from cut block i to location j to produce product p in period t (odt)
y_{jpt}	Amount of product p to be produced at location j in period t (tonne)
q_{jcp}	Binary: 1 if bioproduction facility at location j with capacity size c that produces product p at the beginning of the planning horizon; 0 otherwise
Other economic notations	
PTR	Present value of total revenue
PTC	Present value of total costs
PIC	Present value of investment costs
DEP	Present value of depreciation of established bioproduction technologies

Objective function

Similar to the objective function defined in (Ben Daya & Noureldath, 2019), the objective function in Eq. 4-1, shows maximizing the net present value (NPV) of the supply chain's profit.

$$Max. NPV = Max. (PTR - PTC) - PIC - (PTR - PTC - DEP) \times TR \quad \text{Eq. 4-1}$$

The NPV objective function includes the present value of annual revenues from selling bioproducts (Eq. 4-2); the present value of annual costs (Eq. 4-3), including fixed operating and maintenance (O&M) costs, biomass pre-processing costs, and transportation costs; the present value of investment costs (Eq. 4-4); and the present value of taxes, calculated based on revenues minus total costs and depreciation (Eq. 4-5).

$$PTR = \sum_{t \in T} \sum_{p \in P} \sum_{j \in J} \frac{(PR_p \times y_{jpt})}{(1 + \alpha)^t} \quad \text{Eq. 4-2}$$

$$PTC = \sum_{t \in T} \frac{1}{(1 + \alpha)^t} \quad \text{Eq. 4-3}$$

$$\begin{aligned} & \times \left(\sum_{c \in C} \sum_{p \in P} \sum_{j \in J} FC_{cp} \times q_{jcp} + \sum_{p \in P} \sum_{i \in I} \sum_{j \in J} \sum_{(f,w) \in O} VC_p \times x_{fwijpt} \right. \\ & + \sum_{p \in P} \sum_{i \in I} \sum_{j \in J} \sum_{(f,w) \in O} PC_w \times x_{fwijpt} \\ & \left. + \sum_{p \in P} \sum_{i \in I} \sum_{j \in J} \sum_{(f,w) \in O} TC_{fwijt} \times x_{fwijpt} \right) \end{aligned}$$

$$PIC = \sum_{c \in C} \sum_{p \in P} \sum_{j \in J} CC_{cpj} \times q_{jcp} \quad \text{Eq. 4-4}$$

$$DEP = \sum_{c \in C} \sum_{p \in P} \sum_{j \in J} DP_{cpt} \times q_{jcp} \quad \text{Eq. 4-5}$$

Constraints

The first constraint set in Eq. 4-6 represents the supply constraint. The amount of each biomass type sent from each cut block to each biohub location through any supply chain pathway must not exceed the available supply of that biomass type from that cut block to that location in each period.

$$\sum_{p \in P} \sum_{w \in W} x_{fwijpt} \leq SS_{fijt} \quad \forall t \in T, f \in F, i \in I, j \in J \quad \text{Eq. 4-6}$$

The constraint set in Eq. 4-7 indicates the amount of bioproduct that is produced at each bioproduction facility location at each period based on the yields of each production technology.

$$\sum_{p \in P} \sum_{i \in I} \sum_{(f,w) \in O} PY_p \times x_{fwijpt} = y_{jpt} \quad \forall t \in T, j \in J, p \in P \quad \text{Eq. 4-7}$$

The next constraint set (Eq. 4-8) ensures that flow of biomass into a facility does not exceed its capacity. Moreover, this constraint set ensures that if a bioproduction technology is not established at a location (q_{jcpt}), then the flow of biomass to that location remains zero.

$$\sum_{i \in I} \sum_{(f,w) \in O} x_{fwijpt} \leq \sum_{c \in C} KK_{cp} \times q_{jcp} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 4-8}$$

Eq. 4-9 ensures that only one capacity of a bioproduction technology to produce a specific bioproduct is established at a location. For instance, the AC production facility at Hanceville cannot be established in both small and medium-sized capacities.

$$\sum_{c \in C} q_{jcp} \leq 1 \quad \forall j \in J, p \in P \quad \text{Eq. 4-9}$$

The next constraint set (Eq. 4-10) ensures that if a bioproduction technology is established at a location, then at least 70% of its biomass processing capacity should be used.

$$0.7 \times \sum_{c \in C} KK_{cp} \times q_{jcp} \leq \sum_{i \in I} \sum_{(f,w) \in O} x_{fwijpt} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 4-10}$$

Eq. 4-11 ensures that the total amount of each type of produced bioproducts does not exceed the maximum available demand for that bioproduct in each period.

$$\sum_{j \in J} y_{jpt} \leq DM_{pt} \quad \forall t \in T, p \in P \quad \text{Eq. 4-11}$$

The constraint sets in Eq. 4-12 and Eq. 4-13 determine the non-negativity and the domain of binary and continuous decision variables.

$$y_{jpt}, x_{fwijpt} \geq 0 \quad \forall f \in F, w \in W, i \in I, j \in J, p \in P, t \in T \quad \text{Eq. 4-12}$$

$$q_{jcp} \in \{0,1\} \quad \forall c \in C, i \in I, j \in J, p \in P \quad \text{Eq. 4-13}$$

4.4 Deterministic single objective model formulations with policies

4.4.1 Feedstock subsidies

The mathematical programming model remains unchanged under the feedstock subsidy scenario; only the input data for transportation costs are modified. The transportation cost per odt of slash is reduced by the subsidy amount. Consistent with our previous analyses, feedstock subsidies are calculated as the emissions from slash-pile burning (2.25 t CO₂-eq per odt) multiplied by the carbon price of \$12/t CO₂-eq. If the calculated subsidy exceeds the transportation cost per odt, the

transportation cost is set to zero (assuming the subsidy fully offsets transportation expenses, with no additional cash inflow or revenue credited).

4.4.2 Depreciation (enhanced first-year allowance)

Similar to the feedstock subsidy policy, the mathematical programming formulation remains unchanged under the enhanced first-year allowance policy. The only change would be in the calculation of depreciation (i.e., DEP parameter). According to this policy, 75% of the capital cost of equipment is allowed to be written off as depreciation, if the equipment was acquired and put into use in 2024 (*Technical Guide to Class 43.1 and 43.2*, 2020).

4.4.3 Direct incentives for capital investments

Similar to the feedstock subsidy and enhanced first-year allowance policies, direct incentives for capital investments does not change the mathematical programming formulation, however the input values for capital investments change. To reflect this policy, the initial capital costs (CC_{cpj}) are multiplied by 50%, assuming that 50% of it is covered by the government with a cap of \$10 million.

4.4.4 Output-based pricing system (OBPS)

In this section, the mathematical programming model incorporating the BC OBPS is presented. The necessary modifications to the main model to account for this system are detailed here.

Table 4-2. Additional notations required for the mathematical programming model under the output-based pricing policy.

Additional parameters	
EL_{pt}	Emission limit factors for bioproduct $p \in P$ in period $t \in T$
PO_{wp}	Per odt of emissions from biohub activities to produce one tonne of product $p \in P$ through pathway $w \in W$ (CO ₂ -eq/odt)
CL_t	Credit usage limit in period $t \in T$
CP_t	Price for selling or purchasing credits in period $t \in T$
CT_t	Carbon tax in period $t \in T$
M	A very large number used for logical constraints
Additional decision variables	
e_{jpt}	Excess emissions for a facility at location j that produces product $p \in P$ in period $t \in T$ (t CO ₂)
g_{jpt}	Generated credits for a facility at location j that produces product $p \in P$ in period $t \in T$ (t CO ₂)
c_{jpt}	Purchased credits for a facility at location j that produces product $p \in P$ in period $t \in T$ (t CO ₂)
u_{jpt}	Used credits for a facility at location j that produces product $p \in P$ in period $t \in T$ (t CO ₂)
s_{jpt}	Sold credits for a facility at location j that produces product $p \in P$ in period $t \in T$ (t CO ₂)

b_{jpt}	Banked credits for a facility at location j that produces product $p \in P$ in period $t \in T$ (t CO ₂)
p_{jpt}	Part of the excess emissions that are paid for a facility at location $j \in J$ that produces product $p \in P$ in period $t \in T$ (t CO ₂)
a_{jpt}	Binary accessory variable used to linearize what-if constraints

The revenue term in Eq. 4-2 is modified as shown in Eq. 4-14 to account for the revenue a facility can generate by selling credits obtained when its emissions are lower than the emission limits.

$$PTR = \sum_{t \in T} \sum_{p \in P} \sum_{j \in J} \frac{(PR_p \times y_{jpt}) + (CP_t \times s_{jpt})}{(1 + \alpha)^t} \quad \text{Eq. 4-14}$$

The cost term in Eq. 4-3 is also modified as shown in Eq. 4-15 to account for the costs incurred when a facility's emissions exceed the limit and must be compensated by purchasing credits and/or paying for the excess emissions.

$$PTC = \sum_{t \in T} \frac{1}{(1 + \alpha)^t} \quad \text{Eq. 4-15}$$

$$\times \left(\sum_{c \in C} \sum_{p \in P} \sum_{j \in J} FC_{cp} \times q_{jcpt} + \sum_{p \in P} \sum_{i \in I} \sum_{j \in J} \sum_{(f,w) \in O} VC_p \times x_{fwijpt} \right. \\
+ \sum_{p \in P} \sum_{i \in I} \sum_{j \in J} \sum_{(f,w) \in O} PC_w \times x_{fwijpt} \\
+ \sum_{p \in P} \sum_{i \in I} \sum_{j \in J} \sum_{(f,w) \in O} TC_{fwijt} \times x_{fwijpt} + \sum_{p \in P} \sum_{j \in J} p_{jpt} \times CT_t \\
\left. + \sum_{p \in P} \sum_{j \in J} c_{jpt} \times CP_t \right)$$

The following constraints are also added to the main model. Eq. 4-16 to Eq. 4-23 calculate the excess emissions or the generated credits. Using accessory variables and constraints, if the emissions of a facility ($\sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp}$) exceed the emission limit ($EL_{pt} \times y_{jpt}$), then the difference is defined as excess emissions (e_{jpt}). Conversely, if the emission limit ($EL_{pt} \times y_{jpt}$) is greater than the actual emissions of the facility, the difference is defined as generated credits (g_{jpt}).

In Eq. 4-16, if $\sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} - (EL_{pt} \times y_{jpt})$ is positive, then the accessory variable (a_{jpt}) takes the value of one based on Eq. 4-16. With the accessory variable equal to one, and based on Eq. 4-18 and Eq. 4-19 $\sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} - (EL_{pt} \times y_{jpt})$ becomes equal to the excess emissions (e_{jpt}). Moreover, Eq. 4-20 becomes ineffective. In that case, based on Eq. 4-23, generated credits (g_{jpt}) become zero.

On the contrary, if in Eq. 4-16 $\sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} - (EL_{pt} \times y_{jpt})$ is negative, meaning that emissions are lower than the limit, then the accessory binary variable (a_{jpt}) takes the value of zero based on Eq. 4-17. As a result, Eq. 4-18 and Eq. 4-19 become redundant, and e_{jpt} becomes zero based on Eq. 4-20. In that case, based on Eq. 4-21 and Eq. 4-22, g_{jpt} equals $(EL_{pt} \times y_{jpt}) - \sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp}$, and Eq. 4-23 becomes ineffective.

$$\sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} - (EL_{pt} \times y_{jpt}) \leq M \times a_{jpt} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 4-16}$$

$$\sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} - (EL_{pt} \times y_{jpt}) \geq -M \times (1 - a_{jpt}) \quad \text{Eq. 4-17}$$

$$\forall j \in J, p \in P, t \in T$$

$$e_{jpt} \geq \sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} - (EL_{pt} \times y_{jpt}) \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 4-18}$$

$$e_{jpt} \leq \sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} - (EL_{pt} \times y_{jpt}) + M \times (1 - a_{jpt}) \quad \text{Eq. 4-19}$$

$$\forall j \in J, p \in P, t \in T$$

$$e_{jpt} \leq M \times (a_{jpt}) \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 4-20}$$

$$g_{jpt} \geq (EL_{pt} \times y_{jpt}) - \sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 4-21}$$

$$g_{jpt} \leq (EL_{pt} \times y_{jpt}) - \sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwi jpt} \times PO_{wp} + M \times (a_{jpt}) \quad \text{Eq. 4-22}$$

$$\forall j \in J, p \in P, t \in T$$

$$g_{jpt} \leq M \times (1 - a_{jpt}) \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 4-23}$$

Banked credits are determined using Eq. 4-24 and Eq. 4-25. For the first period (Eq. 4-24), they are calculated as the difference between the generated credits and the sum of the used and sold credits. In the subsequent periods, banked credits are equal to the previous period's banked credits plus the generated credits, minus the used and sold credits.

$$b_{jpt} = g_{jpt} - u_{jpt} - s_{jpt} \quad \forall j \in J, p \in P, t \in \{1\} \quad \text{Eq. 4-24}$$

$$b_{jpt} = b_{jpt-1} + g_{jpt} - u_{jpt} - s_{jpt} \quad \forall j \in J, p \in P, t \in \{2, \dots, T\} \quad \text{Eq. 4-25}$$

Eq. 4-26 specifies that excess emissions must be covered either by using credits, by purchasing credits, or by directly paying for them.

$$e_{jpt} = u_{jpt} + c_{jpt} + p_{jpt} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 4-26}$$

Eq. 4-27 specifies that, according to the guidelines (*Getting Started with the B.C. Output-Based Pricing System, 2024*), a specified portion of excess emissions, up to the defined credit usage limit, may be offset through the use or purchase of credits, whereas any remaining emissions must be compensated by direct payment.

$$u_{jpt} + c_{jpt} \leq CL_t \times (e_{jpt}) \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 4-27}$$

The constraint sets in Eq. 4-28 and Eq. 4-29 determine the non-negativity and domain of binary and continuous decision variables.

$$e_{jpt}, g_{jpt}, c_{jpt}, u_{jpt}, s_{jpt}, b_{jpt}, p_{jpt} \geq 0 \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 4-28}$$

$$a_{jpt} \in \{0,1\} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 4-29}$$

4.4.5 All policies

The mathematical model of this scenario is the same as the model for the output-based pricing system in addition to the input changes of the other policies as discussed under each policy.

4.5 Deterministic bi-objective model

For the bi-objective mathematical programming model, a second objective function is added to the previous single objective model. The second objective function accounts for the CO₂-eq emissions of the supply chain network, encompassing emissions from the activities done at the forest roadside, and transportation, handling, and preprocessing of residues, as well as conversion of residues to bioproducts at the biohubs. These emissions were previously calculated in the emission analysis phase.

The additional parameters needed for the bi-objective model are shown in Table 4-3.

Table 4-3. Additional parameters required for the bio-objective model.

Parameters	
EM'_w	Emissions from roadside activities for pathway w (CO ₂ -eq/odt)
EM''_{ijw}	Emissions from transportation of residues from cut block i to biohub location j through pathway w (CO ₂ -eq/odt)
PO_{wp}	Per odt of emissions from biohub activities to produce one tonne of product $p \in P$ through pathway $w \in W$ (CO ₂ -eq/odt)

Objective function

The second objective function that minimizes the network's emissions over the 20-year planning horizon is shown in Eq. 4-30.

$$\text{Min. Emissions} = \sum_{t \in T} \sum_{p \in P} \sum_{j \in J} \sum_{i \in I} \sum_{(f,w) \in O} x_{fwi j p t} (EM'_w + EM''_{ijw} + PO_{wp}) \quad \text{Eq. 4-30}$$

Constraints

The constraints remain exactly the same as in the single objective model.

The bi-objective optimization model is solved using the augmented ϵ -constraint (AUGMECON) method introduced by Mavrotas (2009). The AUGMECON method is an enhanced version of the classical ϵ -constraint method as it prevents the generation of non-efficient solutions. In this method, one objective function is optimized directly, while the remaining objectives are converted

into constraints whose right-hand sides are systematically varied over their feasible ranges to trace the Pareto front. The right-hand side values include ε values that are bounded by the minimum and maximum objective values obtained through lexicographic optimization and slack or surplus variables to ensure the production of efficient solutions only. In another words, the ε values are equal intervals calculated using the minimum and maximum objective values obtained from lexicographic optimization (Mavrotas, 2009).

In the present problem, NPV objective is treated as the main objective, while the GHG emissions objective is considered as a constraint. The AUGMECON method is utilized to generate Pareto optimal solutions. A Pareto optimum solution is one where no objective can be improved without worsening at least one other objective. It is usually shown for multi-objective optimization models and its useful to show the trade-offs among objectives. In the absence of a decision-maker's opinion, we cannot say if one Pareto solution is better than the other. Each Pareto optimal solution shows an efficient supply chain design alternative under different levels of emissions, enabling us to assess how improvements in economic viability (NPV) may come at the cost of increased emissions, or vice versa. The decision makers could then evaluate these solutions and proceed with the supply chain design with revenues, costs, investments, and emissions that they find more aligned with their policies.

The number of pareto solutions is set to 15 here. Therefore, the bi-objective model is converted into the following model following Mavrotas (2009):

For c in $\{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15\}$ do:

$$Max. NPV + eps \left(\frac{s}{r} \right) \quad \text{Eq. 4-31}$$

Subjected to:

$$-\sum_{t \in T} \sum_{p \in P} \sum_{j \in J} \sum_{i \in I} \sum_{(f,w) \in O} x_{fwijpt} (EM_{cp} + EM'_{ijw} + EM''_{ijw}) = s + \varepsilon \quad \text{Eq. 4-32}$$

$$s \geq 0 \quad \text{Eq. 4-33}$$

for the no-policy, feedstock subsidies, enhanced first-year allowance, and capital investment incentive policy scenarios:

Eq. 4-1 – Eq. 4-13

for the output-based pricing and all-policy scenarios

Eq. 4-1, Eq. 4-4 – Eq. 4-29

Where:

eps = a very small number (10^{-3})

s = slack or surplus, which is a nonnegative variable for the emission objective to ensure that efficient solutions are produced.

$$\varepsilon = lb + \frac{c \times r}{g}$$

lb = lower bound of the emission objective

r = range of emission objective = upper bound - lower bound

g = number of intervals =15

c = counter

4.6 Input parameters of the models

4.6.1 Supply

The FPInterface supply data for Williams Lake TSA is used. This data set included the amount of the biomass of each type (small-diameter logs or other residues) that can be transported from a cut block to each biohub location (Williams Lake, Anahim Lake, Hanceville, and Horsefly), the distance between cut blocks and locations. According to the dataset, 1.7 million odt would be available in 2023 and 12.5 million odt between 2023 to 2032. It is assumed that the supply in the final year remains constant and is repeated for the remaining years of the 20-year planning horizon. However, since the estimates were made in 2012 and the allowable annual cut (AAC) in the TSA was 5.7 million cubic meters, which was later reduced to 2.9 million cubic meters, the biomass supply estimates were adjusted accordingly by 51%. The detailed supply data is provided in Appendix A.4.

The cost delivering each odt of biomass for each cut block-destination was also provided which included harvesting related costs, communication cost of the biomass at the roadsides, and road network costs.

4.6.2 Transportation, preprocessing and handling costs

For the bundling pathway, the per odt cost of delivering bundles transported from each cut block to each location is calculated as below. A seven-axle short log truck is considered for transportation (Lindroos et al., 2011). Details are in the Appendix A.1

$$\text{Delivered cost of biomass for bundled slash pathway} \left(\frac{\$}{\text{odt}} \right) \quad \text{Eq. 4-34}$$

$$\begin{aligned} &= \text{Harvesting related costs} \left(\frac{\$}{\text{odt}} \right) \\ &+ \text{Road network costs} \left(\frac{\$}{\text{odt}} \right) \\ &+ \text{Distance (km)} \\ &\times \frac{\text{Truck transportation cost for bundles} \left(\frac{\$}{\text{hr} - \text{odt}} \right)}{\text{Average transportation speed in Williams Lake TSA} \left(\frac{\text{km}}{\text{hr}} \right)} \\ &+ \text{Truck cost while loading and unloading bundles} \left(\frac{\$}{\text{odt}} \right) \\ &+ \text{Loading cost of bundles using grapple loader} \left(\frac{\$}{\text{odt}} \right) \\ &+ \text{Bundling cost} \left(\frac{\$}{\text{odt}} \right) \end{aligned}$$

For the small-diameter logs pathway, the per odt cost of delivering small diameter logs transported from each cut block to each location is calculated as below. A seven-axle short log truck is considered for transportation (Lindroos et al., 2011). Details are in the Appendices A.1 and A.2.

$$\text{Delivered cost of biomass for small diameter logs pathway} \left(\frac{\$}{\text{odt}} \right) \quad \text{Eq. 4-35}$$

$$\begin{aligned} &= \text{Harvesting related costs} \left(\frac{\$}{\text{odt}} \right) \\ &+ \text{Road network costs} \left(\frac{\$}{\text{odt}} \right) \\ &+ \text{Distance (km)} \\ &\times \frac{\text{Truck transportation cost for logs} \left(\frac{\$}{\text{hr} \cdot \text{odt}} \right)}{\text{Average transportation speed in Williams Lake TSA} \left(\frac{\text{km}}{\text{hr}} \right)} \\ &+ \text{Truck cost while loading and unloading logs} \left(\frac{\$}{\text{odt}} \right) \\ &+ \text{Loading cost of logs using grapple loader} \left(\frac{\$}{\text{odt}} \right) \end{aligned}$$

The per-odt costs of handling biomass via different pathways at the biohubs (i.e., bioproduction facilities) are summarized in Table 4-4 based on the required equipment pieces for each pathway. The detailed calculations are provided in Appendix A.2.

Table 4-4. Preprocessing and handling cost of biomass at the biohubs by supply chain pathway.

Pathway	Required equipment	Total cost of preprocessing and handling at biohub (\$/odt)
Ground slash	Front-end loader; reclaim feeder; screener	\$20
Bundled slash	Front-end loader; reclaim feeder; screener; drop feed hogger, grapple loader	\$32
Small-diameter logs	butt-n-top; loader; reclaim feeder; screener; debarker & chipper	\$37

4.6.3 Bioproduction facilities costs

The bioproduction technology costs, total capital investments per location, fixed and variable operating and maintenance costs used in the optimization can be found in Table 4-5 to Table 4-7. The detailed data is provided in Appendix A.3 and Appendix C.

Table 4-5. Input data for small-scale bioproduction facilities.

Items	AC (Activated Carbon)	Biochar (dry torrefaction)	Biochar (wet torrefaction)	Low quality pellets	High quality pellets	CNC (Cellulose Nanocrystals)	CNF (Cellulose Nanofibrils)
Capacity (odt of biomass)	1,252	50	80	2,778	3,912	13	136
Bioproduction technology installation cost (CAD)	388,341	1,153	4,576	29,616	37,640	412,045	2,189,551
Capital investment for the plant (technology & land) – Hanceville (CAD)	1,647,971	298,313	314,645	322,431	102,718	902,186	3,029,024
Capital investment for the plant (technology & land) - Anahim Lake (CAD)	2,066,046	2,152,510	2,173,187	2,180,973	520,793	2,760,728	6,476,235
Capital investment for the plant (technology & land) - Williams Lake (CAD)	2,419,345	2,271,084	2,291,762	2,299,548	874,092	2,879,303	5,508,049
Capital investment for the plant (technology & land) – Horsefly (CAD)	1,702,481	288,568	856,036	317,031	157,228	896,786	3,525,533
Fixed annual O&M costs (CAD)	14,551	0	0	0	0	24,723	131,373
Variable O&M costs (CAD/per odt)	1,004	18	35	24	24	327	327

Table 4-6. Input data for medium-scale bioproduction facilities.

Items	AC (Activated Carbon)	Biochar (dry torrefaction)	Biochar (wet torrefaction)	Low quality pellets	High quality pellets	CNC (Cellulose Nanocrystals)	CNF (Cellulose Nanofibrils)
Capacity (odt of biomass)	2,504	12,500	20,000	100,000	140,845	625	8,974
Bioproduction technology installation cost (CAD)	630,862	54,988	218,317	363,864	462,443	6,371,230	41,134,828
Capital investment for the plant (technology & land) – Hanceville (CAD)	2,636,495	555,120	1,334,231	656,679	527,521	9,715,197	42,354,610
Capital investment for the plant (technology & land) - Anahim Lake (CAD)	3,054,570	2,206,345	3,192,773	2,515,221	945,596	11,573,739	64,072,219
Capital investment for the plant (technology & land) - Williams Lake (CAD)	3,407,869	2,324,920	3,311,348	2,633,796	1,298,895	11,692,314	63,104,033
Capital investment for the plant (technology & land) – Horsefly (CAD)	2,691,005	342,404	2,599,191	651,279	582,031	9,709,797	61,121,517
Fixed annual O&M costs (CAD)	29,103	-	-	-	-	382,274	2,468,090
Variable O&M costs (CAD/per odt)	1,004	18	35	24	24	327	327

Table 4-7. Input data for large-scale bioproduction facilities.

Items	AC (Activated Carbon)	Biochar (dry torrefaction)	Biochar (wet torrefaction)	Low quality pellets	High quality pellets	CNC (Cellulose Nanocrystals)	CNF (Cellulose Nanofibrils)
Capacity (odt of biomass)	3,756	18,750	30,000	506,944	714,006	1,250	18,846
Bioproduction technology installation cost (CAD)	837,911	73,036	289,969	1,133,473	1,440,556	10,350,094	69,145,383
Capital investment for the plant (technology & land) – Hanceville (CAD)	3,480,438	641,209	1,676,026	1,426,288	1,505,634	15,599,519	70,670,328
Capital investment for the plant (technology & land) - Anahim Lake (CAD)	3,898,512	2,224,392	3,534,568	3,284,830	1,923,709	17,458,061	105,496,897
Capital investment for the plant (technology & land) - Williams Lake (CAD)	4,251,811	2,342,967	3,653,143	3,403,405	2,277,008	17,576,636	104,528,711
Capital investment for the plant (technology & land) – Horsefly (CAD)	3,534,947	360,451	3,209,960	1,420,888	1,560,144	15,594,120	102,546,195
Fixed annual O&M costs (CAD)	43,654	-	-	-	-	621,006	4,148,723
Variable O&M costs (CAD/per odt)	1,004	18	35	24	24	327	327

4.6.4 Bioproduct demands

Based on the market analysis detailed in 0, the estimated demands for the bioproducts are shown in Table 4-8.

Table 4-8. Estimated demand for the bioproducts from 2024 to 2043.

Year	CNC and CNF (Nanocellulose)	Biochar	AC (Activated Carbon)	Pellet
2024	75	2,574	2,140	30067
2025	89	2,894	2,230	30067
2026	106	3,253	2,324	30067
2027	126	3,656	2,422	30067
2028	149	4,109	2,523	30067
2029	177	4,619	2,629	30067
2030	210	5,192	2,740	30067
2031	249	5,835	2,855	30067
2032	296	6,559	2,975	30067
2033	351	7,372	3,100	30067
2034	417	8,287	3,230	30067
2035	495	9,314	3,365	30067
2036	588	10,469	3,507	30067
2037	697	11,768	3,654	30067
2038	828	13,227	3,807	30067
2039	983	14,867	3,967	30067
2040	1,166	16,711	4,134	30067
2041	1,385	18,783	4,308	30067
2042	1,643	21,112	4,489	30067
2043	1,951	23,730	4,677	30067

4.6.5 Emissions

In the optimization models, emissions from roadside activities, transportation, and activities at the bioproduction facilities (i.e., biohubs) are accounted for.

Emissions from roadside activities are summarized in Table 4-9, and the detailed calculations are provided in Section B.1.

Table 4-9. Emissions from roadside activities by the supply chain pathway.

Pathways	Handling and preprocessing activities	Emissions (tonne of CO₂-eq/odt)
Ground slash	Grinding and loading	0.0182
Bundled slash	Bundling and loading	0.0141
Small-diameter logs	loading	0.0018

Emissions from activities at the biohubs, including handling, preprocessing, and conversion, are presented in Table 4-10. The detailed calculations are provided in Sections B.1 and B.3.

Table 4-10. Emissions from activities performed at the bioproduction facilities (i.e, biohubs) including emissions from bioproduction, handling, and preprocessing.

Product	Pathways	Handling and preprocessing activities (equipment)	Emissions (tonne of CO₂-eq/odt)
CNC (Cellulose Nanocrystals)	Ground slash	Loading and unloading (front-end loader); reclaiming (reclaim feeder); screening (screener)	0.6525
	Bundled slash	Unloading bundles (grapple loader or butt-n-top loader); grinding (drop feed hogger); loading and unloading (front-end loader); Reclaiming (reclaim feeder); screening (screener)	0.6545
CNF (Cellulose Nanofibrils)	Ground slash	Loading and unloading (front-end loader); reclaiming (reclaim feeder); screening (screener)	0.6861
	Bundled slash	Unloading bundles (grapple loader or butt-n-top loader); grinding (drop feed hogger); loading and unloading (front-end loader); Reclaiming (reclaim feeder); screening (screener)	0.6880
Biochar (wet torrefaction)	Ground slash	Loading and unloading (front-end loader); reclaiming (reclaim feeder); screening (screener)	0.0488
	Bundled slash	Unloading bundles (grapple loader or butt-n-top loader); grinding (drop feed hogger); loading and unloading (front-end loader); Reclaiming (reclaim feeder); screening (screener)	0.0508
Biochar (dry torrefaction)	Ground slash	Loading and unloading (front-end loader); reclaiming (reclaim feeder); screening (screener)	0.0499
	Bundled slash	Unloading bundles (grapple loader or butt-n-top loader); grinding (drop feed hogger); loading and unloading (front-end loader); Reclaiming (reclaim feeder); screening (screener)	0.0519
Pellets (low quality)	Ground slash	Loading and unloading (front-end loader); reclaiming (reclaim feeder); screening (screener)	0.0058
	Bundled slash	Unloading bundles (grapple loader or butt-n-top loader); grinding (drop feed hogger); loading and unloading (front-end loader); Reclaiming (reclaim feeder); screening (screener)	0.0077
Pellets (high quality)	Small-diameter logs	Unloading logs (grapple loader or butt-n-top loader); debarking and chipping (deparker and chipper); Reclaiming (reclaim feeder); screening (screener)	0.0056
AC (Activated Carbon)	Small-diameter logs	Unloading logs (grapple loader or butt-n-top loader); debarking and chipping (deparker and chipper); Reclaiming (reclaim feeder); screening (screener)	1.3589

Transportation emissions are calculated using the following equations. The corresponding input data are provided in Section B.2.

$$\begin{aligned}
& \text{GHG emission of transportation} \left(t \text{ CO}_2 \text{ eq.} \frac{\text{emissions}}{\text{odt}} \right) \text{ (roundtrip)} \\
& = \text{fuel consumption} \left(\frac{\text{Liter of diesel}}{\text{km}} \right) \times 2 \text{ Distance between cutblocks and biohubs (km)} \\
& \times \frac{1}{\text{Capacity of trucks(odt)}} \times \text{emission factor of diesel} \left(\frac{t \text{ CO}_2 \text{ eq. emissions}}{\text{Liter of diesel}} \right)
\end{aligned}
\tag{Eq. 4-36}$$

$$\begin{aligned}
& \text{GHG emission of trucks when loading and unloading} \left(t \text{ CO}_2 \text{ eq.} \frac{\text{emissions}}{\text{odt}} \right) \\
& = \text{fuel consumption} \left(\frac{\text{Liter of diesel}}{\text{km}} \right) \\
& \times \text{average speed in Williams Lake TSA} \left(\frac{\text{km}}{\text{hour}} \right) \\
& \times \text{Loading and unloading time (hour)} \times \frac{1}{\text{Capacity of trucks (odt)}} \\
& \times \text{emission factor of diesel} \left(\frac{t \text{ CO}_2 \text{ eq. emissions}}{\text{Liter of diesel}} \right)
\end{aligned}
\tag{Eq. 4-37}$$

4.7 Results of the deterministic single objective models

All the mathematical programming models in this study are run using the AIMMS 24.5.14 software and are solved using CPLEX 22.1 solver on an Intel ® core ™ i7-11700 CPU @ 2.50 GHz processor with 16.0 GB RAM.

4.7.1 Supply chain network designs

The proposed facilities for each scenario are illustrated in Figure 4-2 to Figure 4-5. The type and number of facilities recommended under the no-policy, feedstock subsidy, and enhanced first-year allowance scenarios are identical (Figure 4-2). This indicates that these policies have a relatively limited influence on facility establishment decisions, but affect supply chain costs, although not significantly.

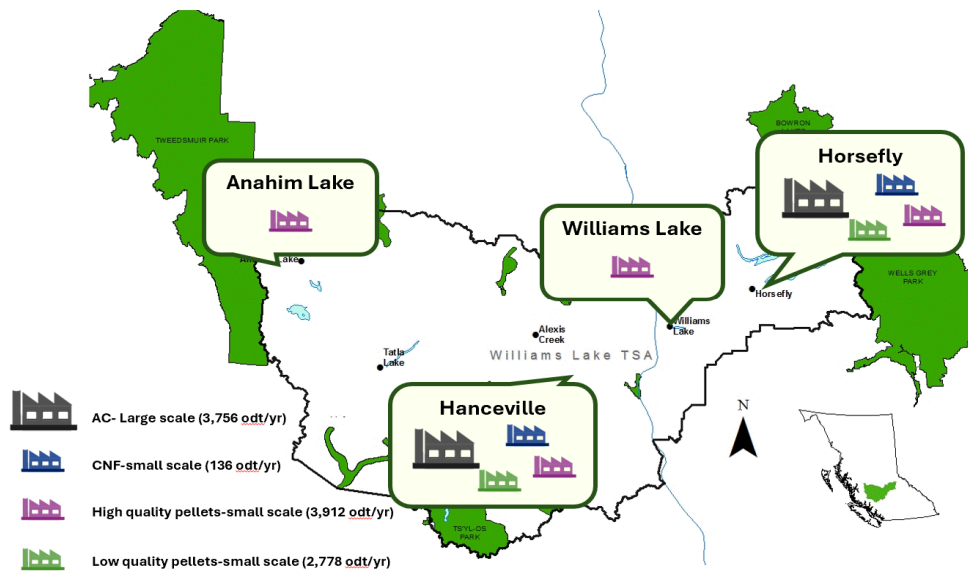


Figure 4-2. Suggested facilities to be established under the enhanced first-year allowance, feedstock subsidies, and no-policy scenarios.

Under the direct incentives for capital investments policy, expectedly, more plants are recommended to be established as shown in Figure 4-3. Majority of the facilities are recommended to be established in Hanceville due to the largest biomass availability in this location compared to other locations.

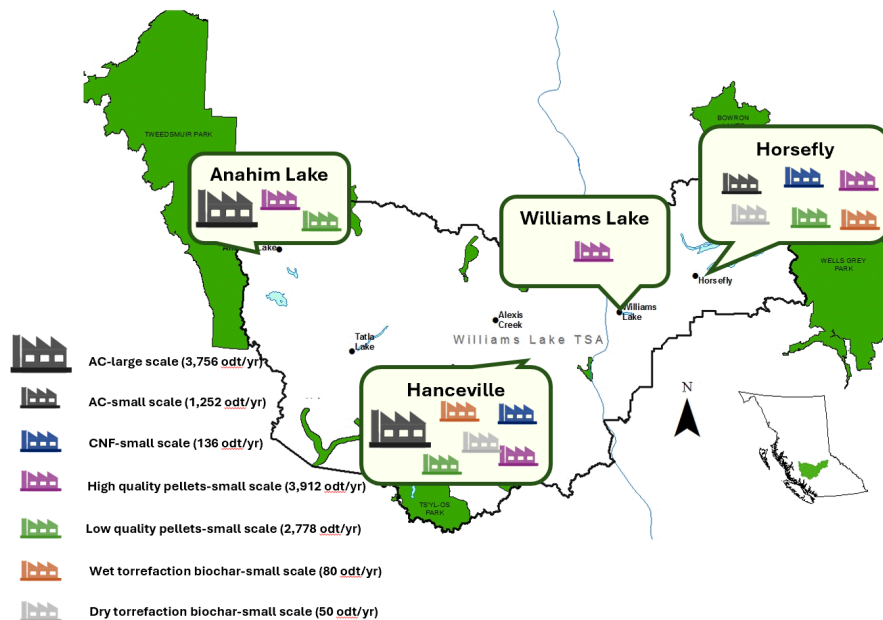


Figure 4-3. Suggested facilities to be established under the direct incentives for capital investments policy.

Figure 4-4 demonstrates the effect of implementing an output-based pricing system on facility establishment decisions. This policy leads to a reduced number of recommended facilities and results in the exclusion of AC facilities. The absence of AC plant establishment can be attributed to its substantially higher emission intensity (1.36 t CO₂-eq/odt of input biomass) as discussed in the emission analysis phase, making AC plants less economically attractive once carbon penalties are applied.

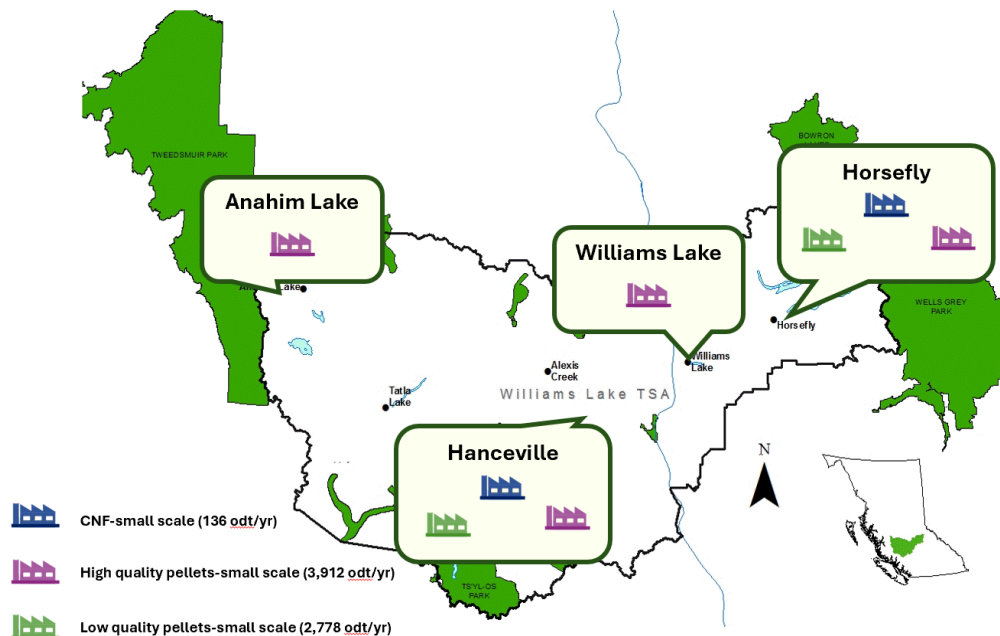


Figure 4-4. Suggested facilities to be established under the output-based pricing policy.

As shown in Figure 4-5, when all policies are taken into account simultaneously, 16 facilities are proposed to be established, similar to those in the direct incentives for capital investment policy. Majority of the facilities are established in Hanceville and Horsefly due to the lower land prices and large biomass availability.

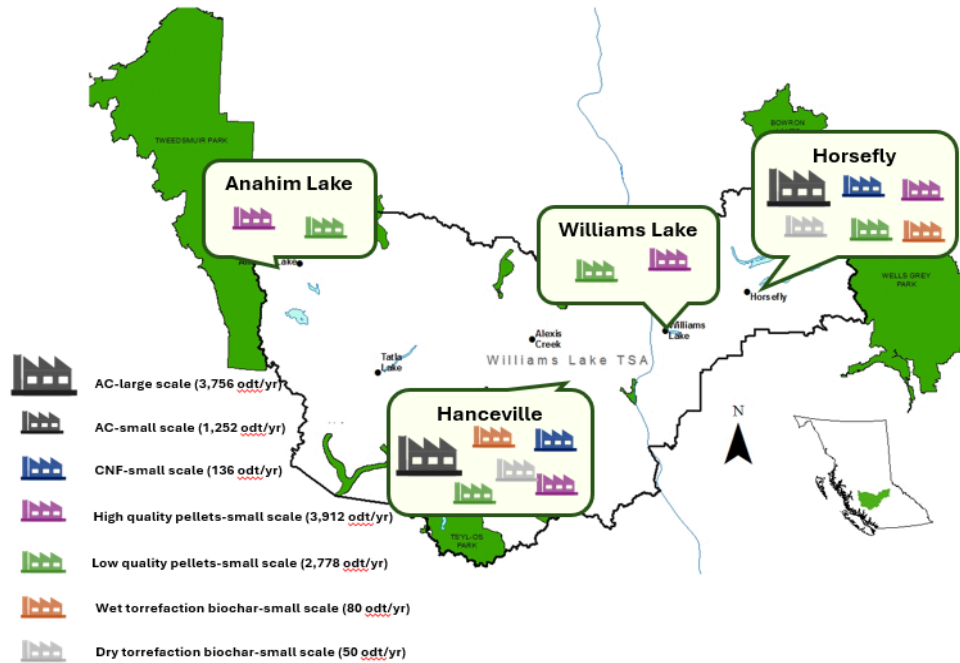


Figure 4-5. Suggested facilities to be established under all-policy scenario.

4.7.2 Computational characteristics and supply chain financials

The number of decision variables, binary variables, constraints, and solution time under each policy scenario are shown in Table 4-11. Expectedly, the number of decision variables and constraints are similar under the no-policy, feedstock subsidies, enhanced first-year allowance, and direct incentives for capital investments as the mathematical programming formulation for these scenarios is identical and the differences of these policies were in the input data. The mathematical model of the output-based pricing policy, however, includes more constraints and decision variables.

Table 4-11. Number of constraints and variables, and solution time of the deterministic single objective mathematical models under the policy scenarios.

Indicators	Without policies	Feedstock subsidies	Enhanced first-year allowance (depreciation)	Direct incentives for capital investments	Output-based pricing	All policies
Constraints	142,114	142,114	142,114	142,114	148,274	148,274
Decision variables	1,531,850	1531850	1,531,850	153,1850	1,536,330	1,536,330
Binary variables	84	84	84	84	644	644
Solution time (sec.)	18.91	18.53	24.39	16.25	32.59	25.75

The PV (present value) of revenue, required investments, costs, NPV, and emissions associated with the proposed supply chain network design under different scenarios are shown in Table 4-12.

Table 4-12. Results of the deterministic single objective model under different policy scenarios.

Indicators	Without policies	Feedstock subsidies	Enhanced first-year allowance (depreciation)	Direct incentives for capital investments	Output-based pricing	All policies
Present value (PV) of revenue	\$167,034,974	\$167,034,974	\$167,034,974	\$179,646,061	\$84,493,998	\$176,718,954
Investment cost	\$16,366,143	\$16,366,143	\$16,366,143	\$5,457,070	\$9,350,758	\$5,515,445
Present value (PV) of operating and maintenance (O&M) costs	\$106,751,014	\$100,127,967	\$106,751,014	\$117,120,551	\$33,733,036	\$110,726,440
Net present value (NPV)	\$28,845,703	\$33,680,528	\$29,075,305	\$41,474,099	\$28,585,419	\$44,109,514
Present value (PV) of government costs	NA	\$6,623,047	\$229,599	\$16,371,209	NA	\$24,738,487
Present value (PV) of government revenues	\$15,072,114 (corporate tax)	\$16,860,337 (corporate tax)	\$14,842,512 (corporate tax)	\$15,594,341 (corporate tax)	\$12,824,784 (corporate tax) \$186,585 (carbon tax)	\$16,367,555 (corporate tax) \$4,587,229 (carbon tax)
Emissions (tonne of CO ₂ -eq)	213,905	213,905	213,905	241,214	10,938	217,847

The PV of revenues, investment costs, and emissions in feedstock subsidies, enhanced first-year allowance (depreciation), and no-policy scenarios are the same. However, the PV of O&M costs under the feedstock subsidies policy is lower than that in the no-policy and enhanced first-year allowance scenarios, leading to higher NPV. Moreover, since depreciations and subsequently the tax savings are higher under the enhanced first-year allowance policy, the NPV under this policy is higher than that in the no-policy scenario. However, the difference is not substantial, and this minimal impact aligns with findings from the economic feasibility analysis considering the policies, in which enhanced first-year allowance was shown to provide only marginal changes to bioproduction feasibility.

Direct incentives for capital investments policy resulted in the highest NPV (\$41 million). This high NPV is primarily driven by low capital investment costs, the establishment of a large number of facilities, and increased revenue resulting from high production volumes. Higher production volumes have also resulted in the highest emissions for the network.

The output-based pricing system has resulted in the lowest investment and operational costs, driven by fewer facility establishments. However, revenues are also lower, leading to the lowest NPV, but close to no-policy scenario. Moreover, the emissions are the lowest under this scenario compared to those in other scenarios.

The model under all policies achieves the highest NPV (\$44 million). Since the facility establishments are similar to those in the direct incentives for capital investment policy, the investment costs and revenues of these two scenarios are close to each other. However, the operating and maintenance costs of the all-policy scenario is lower than that of the direct incentive policy due to the feedstock subsidies received from the government. Additionally, the network under the all-policy scenario results in lower emissions due to the output-based policy consideration.

From the government's perspective, the policy scenarios exhibit varying cost–revenue dynamics. In the no-policy case, government revenues are generated solely through corporate tax payments, amounting to approximately \$15 million, with no direct government expenditures. Feedstock subsidies incur a government cost of \$6.6 million; however, government revenue increases due to higher corporate tax revenues of \$16.9 million, partially offsetting the subsidy cost. The enhanced first-year allowance does not impose direct government costs; however, corporate tax revenues decline to \$14.8 million due to accelerated depreciation and reduced taxable income. This reduction in corporate tax revenues represents forgone government revenue and can therefore be regarded as an implicit cost of this policy. Direct incentives for capital investments result in the highest government cost at \$16.4 million, while corporate tax revenues remain comparable to the no-policy case at \$15.6 million, indicating limited fiscal recovery of the incentive. Under the output-based pricing policy, government revenues consist of both corporate tax (\$12.8 million) and carbon tax (\$0.19 million); however, total revenues are lower due to significantly reduced emissions and lower taxable profits. When all policies are implemented simultaneously,

government costs increase to \$8.0 million, while total government revenues rise to \$20.9 million, driven by combined corporate and carbon tax revenues, suggesting a more balanced fiscal outcome compared to individual policy instruments.

4.7.3 Biomass and pathway utilization

The amount of biomass utilized under each policy scenario compared with the total available supply at each location is shown Figure 4-6. As shown, the biomass used in feedstock subsidy and enhanced first-year allowance scenarios are equal to the scenario where no policy is considered. Under these two policy scenarios, the number and type of facilities suggested to be established are identical. The only difference between these two scenarios and the no-policy scenario is the costs, which are reduced through the policies. Therefore, the required biomass to be used in the feedstock subsidy, enhanced first-year allowance, and no policy scenarios are the same.

The direct capital-investment incentive scenario results in the highest biomass utilization, as it encourages the establishment of a greater number of facilities. In contrast, under the output-based pricing system, fewer facilities are recommended for establishment, which consequently reduces the total amount of utilized biomass. Moreover, when all policies are simultaneously implemented, the amount of biomass utilized is the highest compared with that in other policy scenarios.

Figure 4-6 also shows that the amount of biomass transported and utilized at each biohub location is significantly lower than the total available biomass. This indicates that the biomass utilization and bioproduct productions are limited by the available demand rather than supply.

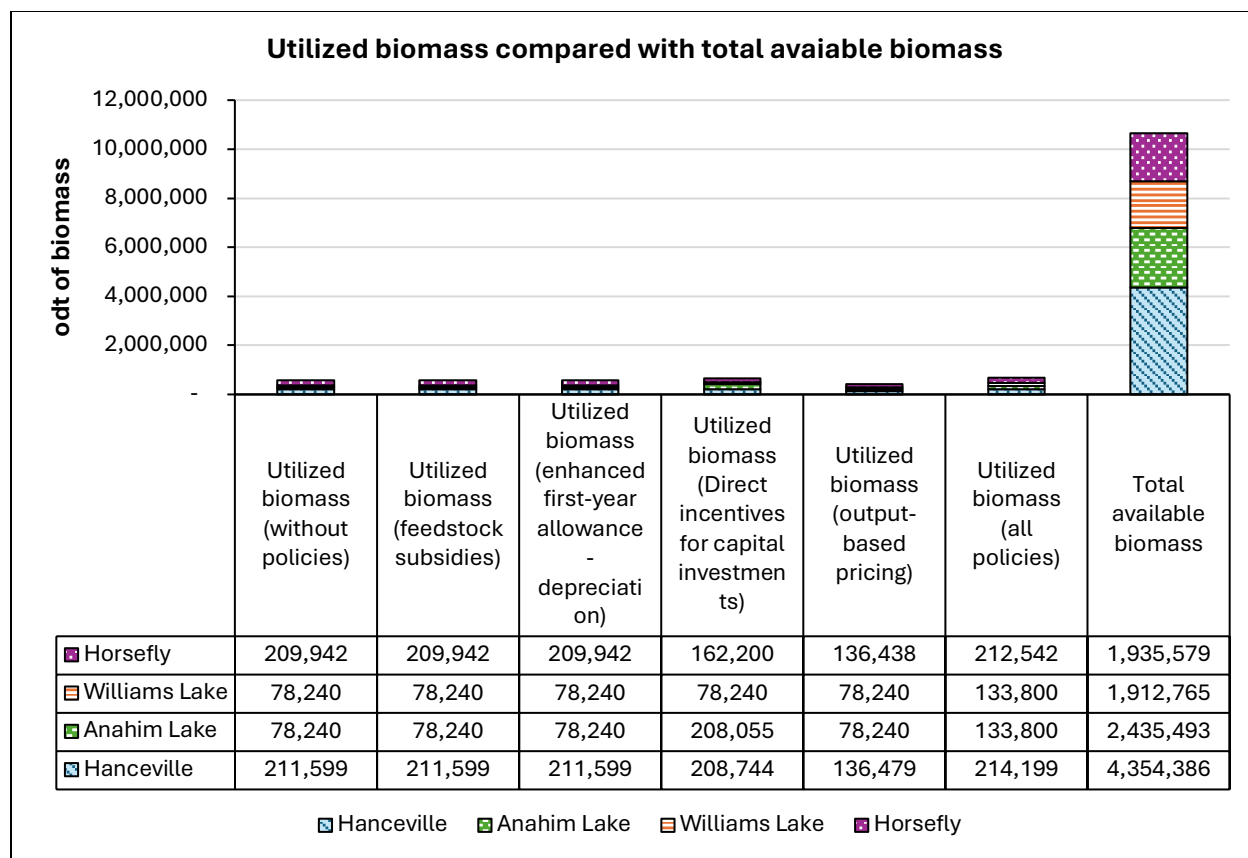


Figure 4-6. Utilized biomass (odt) under each policy at each location compared with the total available biomass supply for each location over the 20-year planning horizon (deterministic single objective model).

Figure 4-7 shows the supply chain pathway selection under the policy scenarios. Most of the biomass was transported through the small-diameter log pathways. Moreover, the bundled slash pathway was not selected under any of the scenarios due to its relatively higher transportation costs.

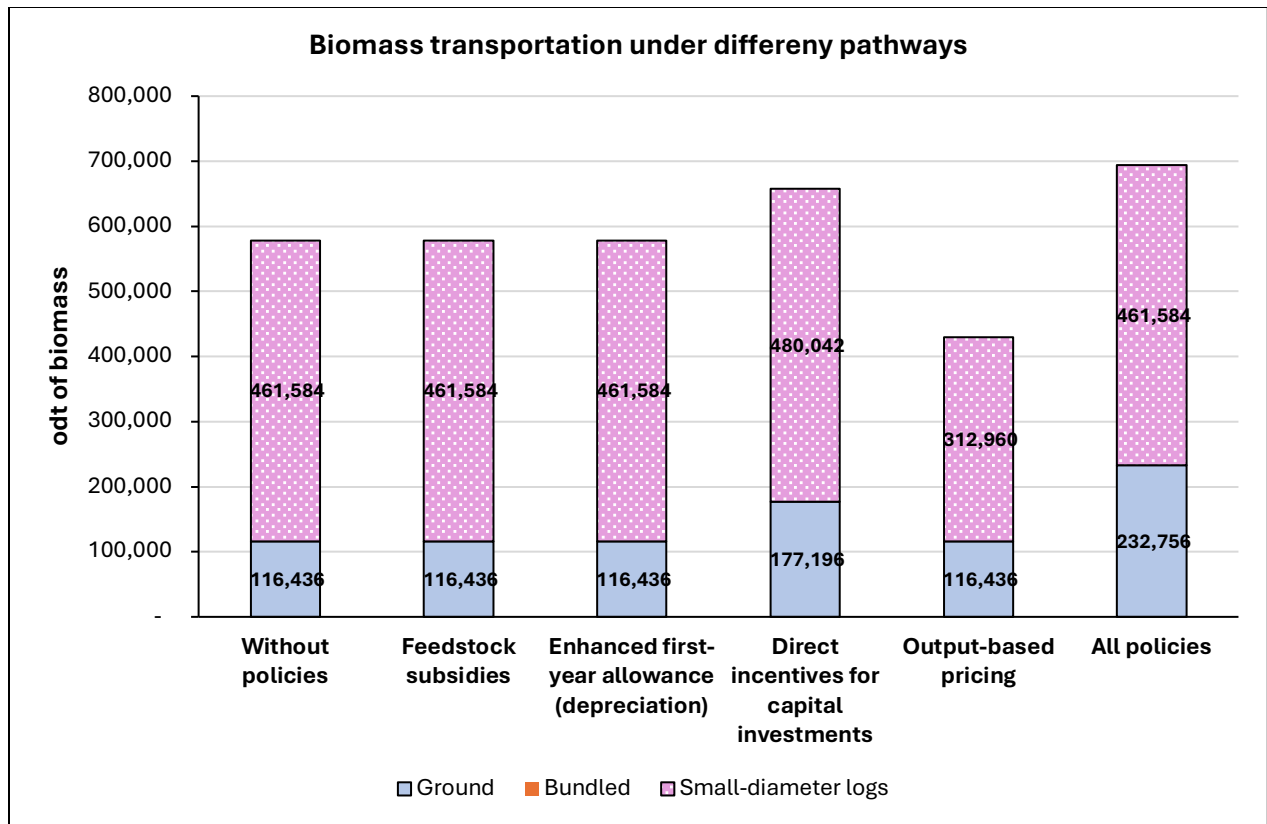


Figure 4-7. Amount of biomass (odt) transported through different supply chain pathways under each policy scenario over the 20-year planning horizon.

4.7.4 Bioproduct production amounts

Production amounts under different policies can be found in Table 4-13 to Table 4-16. As the biomass transported to biohubs, and the number and type of facilities are identical under no-policy, feedstock subsidy and enhanced first-year allowance scenarios, the production level of bioproducts under these scenarios are also identical.

Table 4-13. Bioproduction amount (yield of technologies × input biomass) at each facility under no-policy, feedstock subsidies, and enhanced first-year allowance scenarios (deterministic single objective model).

Location	Bioproduct	Capacity (biomass processing)	Years (tonne of product)																			
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Hanceville	CNF (Cellulose Nanocrystal)	Small (136 odt/yr)	38	52	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53
	AC (Activated Carbon)	Large (3,756 odt/yr)	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202
	Low-quality pellets	Small (2,778 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Anahim Lake	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Williams Lake	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Horsefly	CNF (Cellulose Nanocrystal)	Small (136 odt/yr)	37	37	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53
	AC (Activated Carbon)	Large (3,756 odt/yr)	938	1028	1122	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202
	Low-quality pellets	Small (2,778 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000

Table 4-14. Bioproduction amount (yield of technologies × input biomass) at each facility under output-based pricing policy (deterministic single objective model).

Location	Bioproduct	Production scale	Years (tonne of product)																			
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Hanceville	CNF (Cellulose Nanocrystal)	Small (136 odt/yr)	38	52	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53
	Low-quality pellets	Small (2,778 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Anahim Lake	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Williams Lake	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Horsefly	CNF (Cellulose Nanocrystal)	Small (136 odt/yr)	37	37	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53
	Low-quality pellets	Small (2,778 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000

Table 4-15. Bioproduction amount (yield of technologies × input biomass) at each facility under direct incentives for capital investment policy (deterministic single objective model).

Location	Bioproduct	Production scale	Years (tonne of products)																			
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Hanceville	CNF (Cellulose Nanocrystal)	Small (136 odt/yr)	38	52	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53
	Biochar (wet torrefaction)	Small (80 odt/yr)	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40
	Biochar (dry torrefaction)	Small (50 odt/yr)	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40
	AC (Activated Carbon)	Large (3,756 odt/yr)	841	841	842	939	1041	1027	1137	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202
	Low-quality pellets	Small (2,778 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Anahim Lake	AC (Activated Carbon)	Large (3,756 odt/yr)	1019	1108	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202
	Low-quality pellets	Small (2,778 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Williams Lake	Low-quality pellets	Small (2,778 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Horsefly	CNF (Cellulose Nanocrystal)	Small (136 odt/yr)	37	37	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53
	AC (Activated Carbon)	Small (1,252 odt/yr)	280	280	280	280	280	401	401	401	401	401	401	401	401	401	401	401	401	401	401	401
	Biochar (dry torrefaction)	Small (50 odt/yr)	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40
	Low-quality pellets	Small (2,778 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000

Table 4-16. Bioproduction amount (yield of technologies × input biomass) at each facility under all policies (deterministic single objective model).

Location	Bioproduct	Production scale	Years (tonne of products)																			
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Hanceville	CNF (Cellulose Nanocrystal)	Small (136 odt/yr)	38	52	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53
	Biochar (wet torrefaction)	Small (80 odt/yr)	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40
	Biochar (dry torrefaction)	Small (50 odt/yr)	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40
	AC (Activated Carbon)	Large (3,756 odt/yr)	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202
	Low-quality pellets	Small (2,778 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Anahim Lake	Low-quality pellets	Small (2,778 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Williams Lake	Low-quality pellets	Small (2,778 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Horsefly	CNF (Cellulose Nanocrystal)	Small (136 odt/yr)	37	37	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53
	AC (Activated Carbon)	Large (3,756 odt/yr)	938	1028	1122	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202	1202
	Biochar (wet torrefaction)	Small (80 odt/yr)	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40
	Biochar (dry torrefaction)	Small (50 odt/yr)	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40
	Low-quality pellets	Small (2,778 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
	High-quality pellets	Small (3,912 odt/yr)	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000

4.7.5 Output-based pricing system trading

The results regarding the emission trading under the output-based pricing policy are presented in Figure 4-8 and Figure 4-9. For pellet production facilities, emissions remain below the emission limits, leading to the generation of credits. According to the model, these credits are banked during the first four years and subsequently sold each year thereafter.

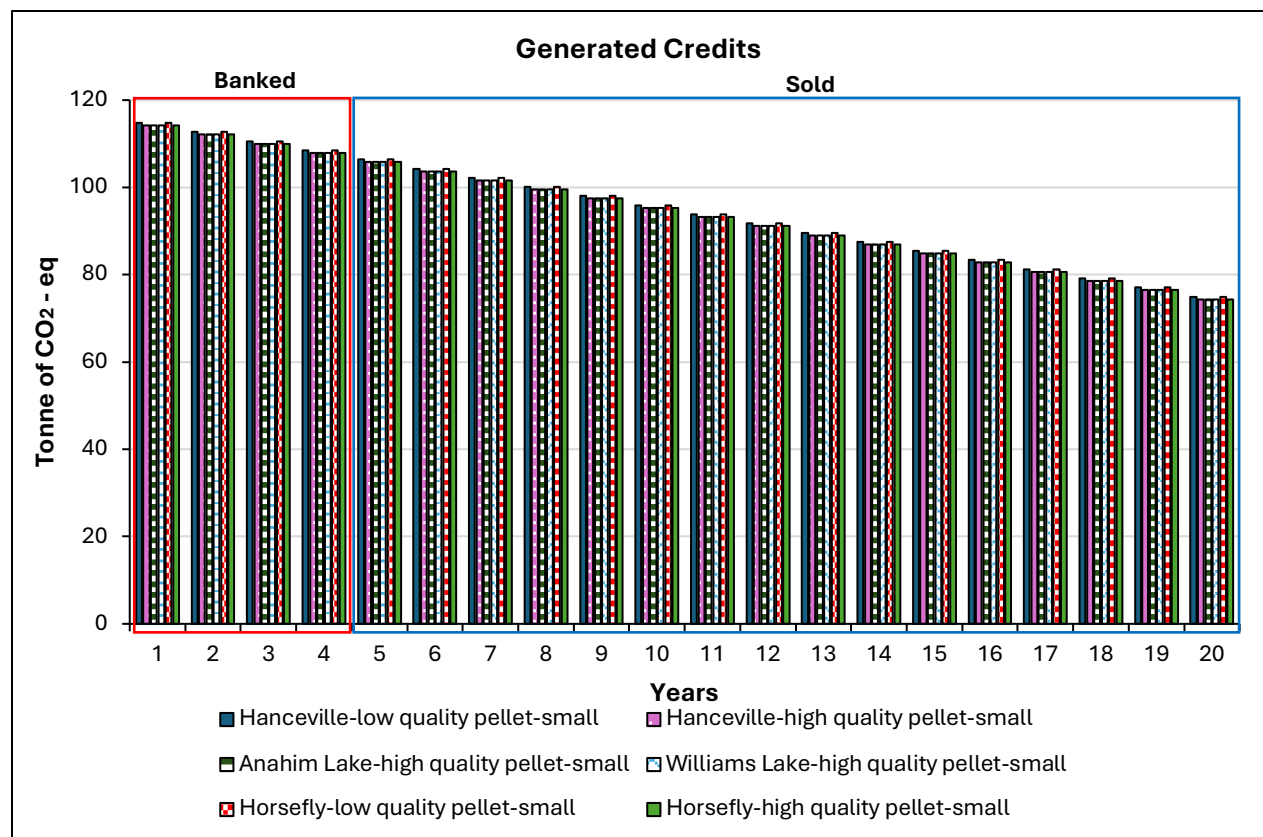


Figure 4-8. Generated credits and decisions regarding banking them or selling them in pellets production facilities under the output-based pricing policy.

For the CNF production in Hanceville and Horsefly, the emissions are above the limits. Therefore, excess emissions are calculated as shown in Figure 4-9. To compensate for excess emissions, part of it (up to the defined credit usage limits) is covered by purchasing credits and the rest are directly paid for.

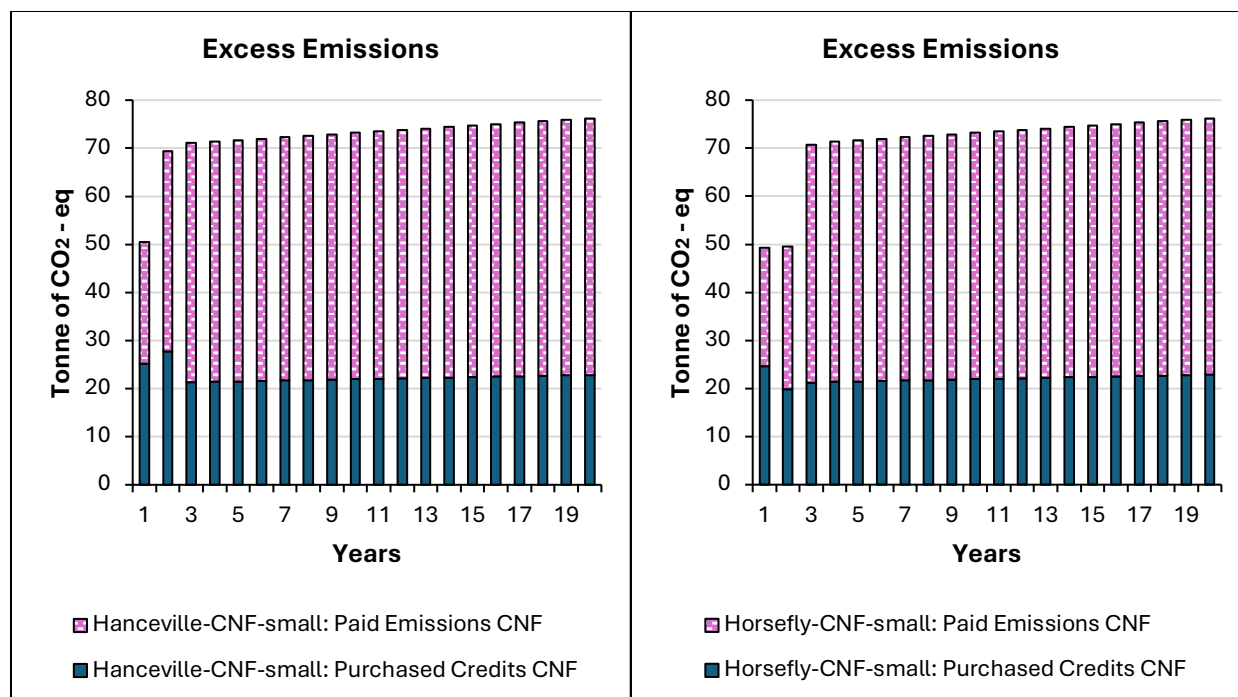


Figure 4-9. Excess emissions for CNF (cellulose nanofibrils) production facilities under the output-based pricing policy.

The emission trading under the all-policy scenario, where feedstock subsidies, enhanced first-year allowance, direct incentives for capital investments, and output-based pricing policies are simultaneously considered, can be seen in Figure 4-10 and Figure 4-11. For pellet production and biochar (dry torrefaction) facilities, emissions remain below the emission limits, leading to the generation of credits. For biochar (wet torrefaction) facilities, emissions remain below the emission limits until year 13, and exceed the emission limits thereafter. According to the model, the generated credits are banked during the first four years and subsequently sold each year thereafter.

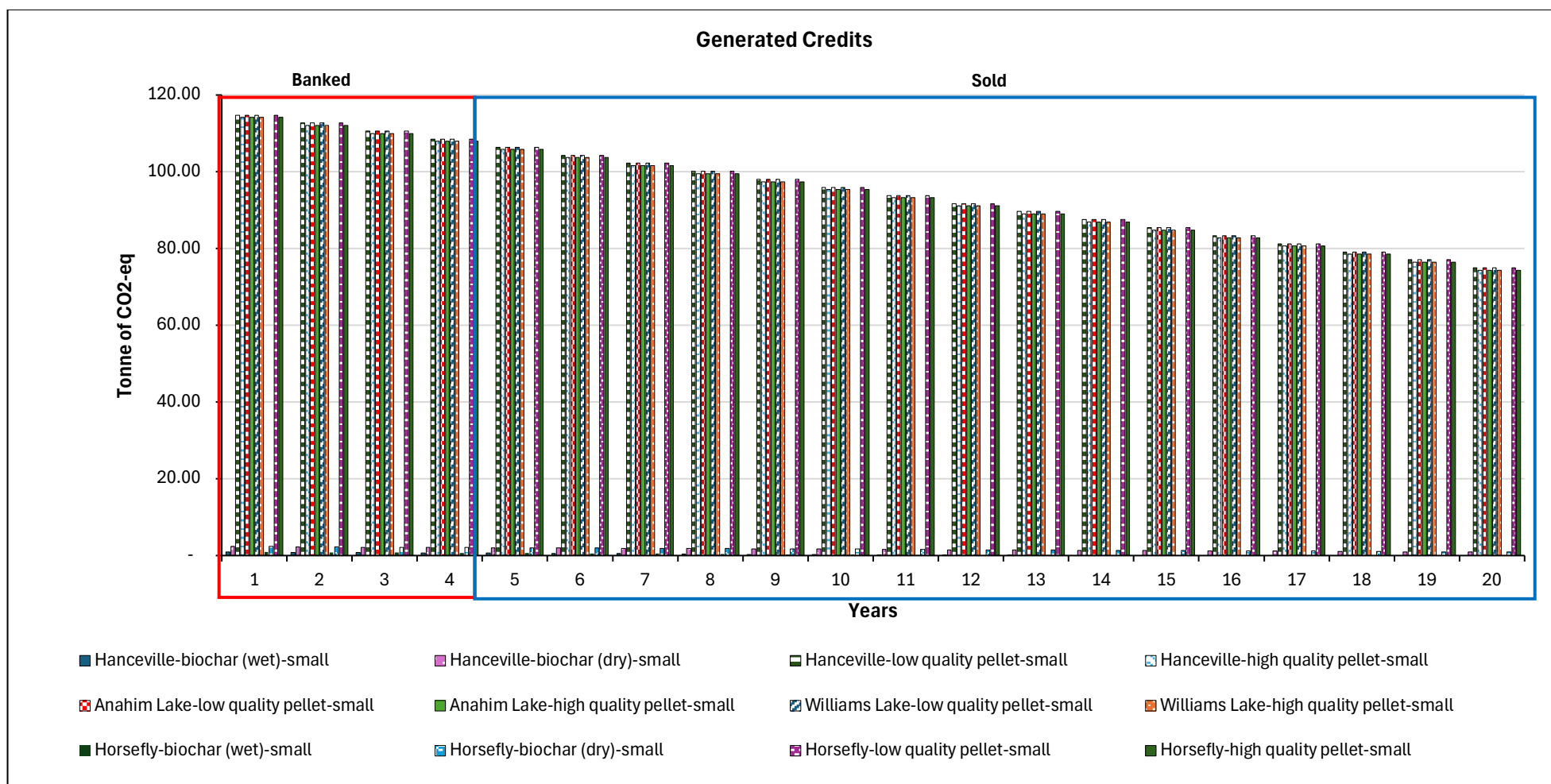


Figure 4-10. Generated credits and decisions regarding banking them or selling them in pellets and biochar production facilities under all-policy scenario.

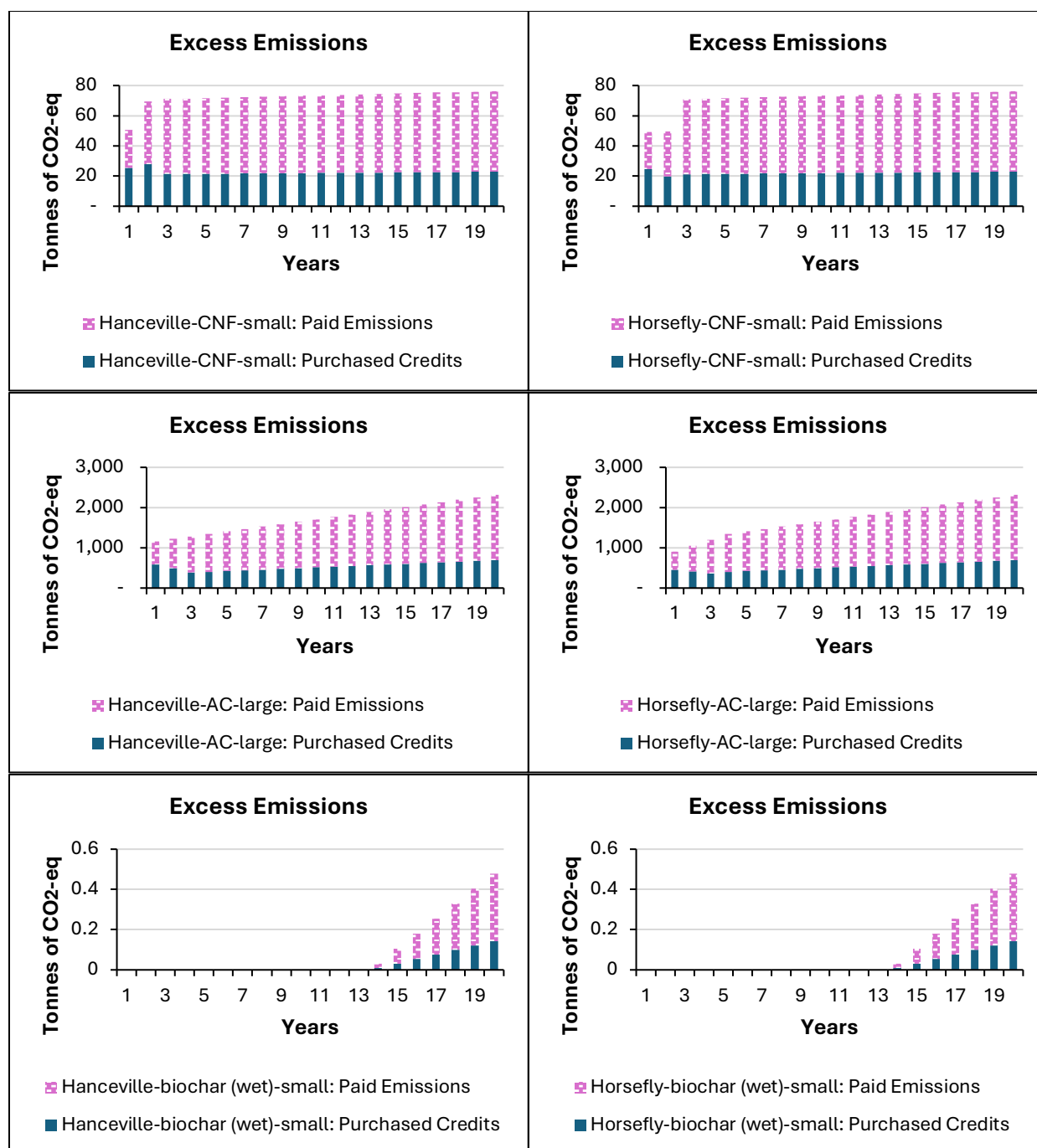


Figure 4-11. Excess emissions for CNF (cellulose nanofibrils), AC (activated carbon), and biochar (wet torrefaction) production facilities under the all-policy scenario.

For the CNF and AC production in Hanceville and Horsefly, the emissions are above the limits. For biochar (wet torrefaction) production in Hanceville and Horsefly, the emissions are above the emission limits from year 14. Therefore, excess emissions are calculated as shown in Figure 4-11.

To compensate for excess emissions, part of it (up to the defined credit usage limits) is covered by purchasing credits and the rest are directly paid for.

4.7.6 Sensitivity analysis

The sensitivity analysis is performed for the all-policy model, where all policies are assumed to be implemented simultaneously. As described in Table 4-17, the sensitivity analysis is focused on capital investment costs, feedstock delivered costs, variable O&M cost, fixed O&M costs, preprocessing costs of ground slash pathway, preprocessing costs of bundled slash pathway, preprocessing costs of small-diameter logs pathway, discount rate after-tax, emission limits, attributable emission, carbon tax, selling or purchasing price of carbon credits, and maximum demand for bioproducts. These parameters are varied by $\pm 10\%$, $\pm 20\%$, $\pm 30\%$, $\pm 40\%$, and $\pm 50\%$ change, and the resulting percentage change in NPV of the supply chain is reported. Each parameter change is done one at a time.

Table 4-17. Parameters in the optimization model and their definitions.

Item	Definition
Capital investment cost	Costs of bioproduction facility investments, land and storage expenses, and the acquisition of preprocessing and handling equipment at the biohubs.
Variable operating & maintenance (O&M) costs	Variable operational and maintenance expenses at biohubs, including raw material costs, labor, utilities, maintenance, etc.
Fixed operating & maintenance (O&M) costs	Fixed operational and maintenance expenses at biohubs, including maintenance, insurance, overhead, etc.
Preprocessing costs of small diameter logs pathway	Preprocessing and handling costs at biohubs related to equipment pieces required for small-diameter logs pathway, including butt-n-top loader, reclaim feeder, screener, and debarker & chipper.
Preprocessing costs of bundled slash pathway	Preprocessing and handling costs at biohubs related to equipment pieces required for bundled slash pathway, including butt-n-top loader, reclaim feeder, screener, drop feed hogger, and grapple loader.
Preprocessing costs of ground slash pathway	Preprocessing and handling costs at biohubs related to equipment pieces required for ground slash pathway, including front-end loader, reclaim feeder, and screener.
Feedstock delivered cost for ground slash pathway	Costs of grinding at the cut blocks and transportation to biohubs, including the waiting time of trucks for loading and unloading
Feedstock delivered cost	Costs of biomass transportation to biohubs, including the waiting time of trucks for loading and unloading
Discount rate after-tax	The rate that is used to adjust the after-tax cash flow values to a present value.
Max demand	Maximum estimated demand for bioproducts.
Attributable emissions	Emissions from preprocessing, transportation, and handling of residues, and conversion of feedstock at biohubs.

Item	Definition
Emission limit	Emission limit in output-based pricing system, indicating whether attributable emissions were above or below the limit, leading to excess emissions or generated carbon credits.
Carbon tax	The price for CO ₂ -eq emissions.
Sale/purchase credit price	The price for selling or purchasing carbon credits.

The results of the sensitivity analysis can help us determine the parameters that has significant influence on the NPV and emissions of the supply chain network, and account for the uncertainty of such parameters.

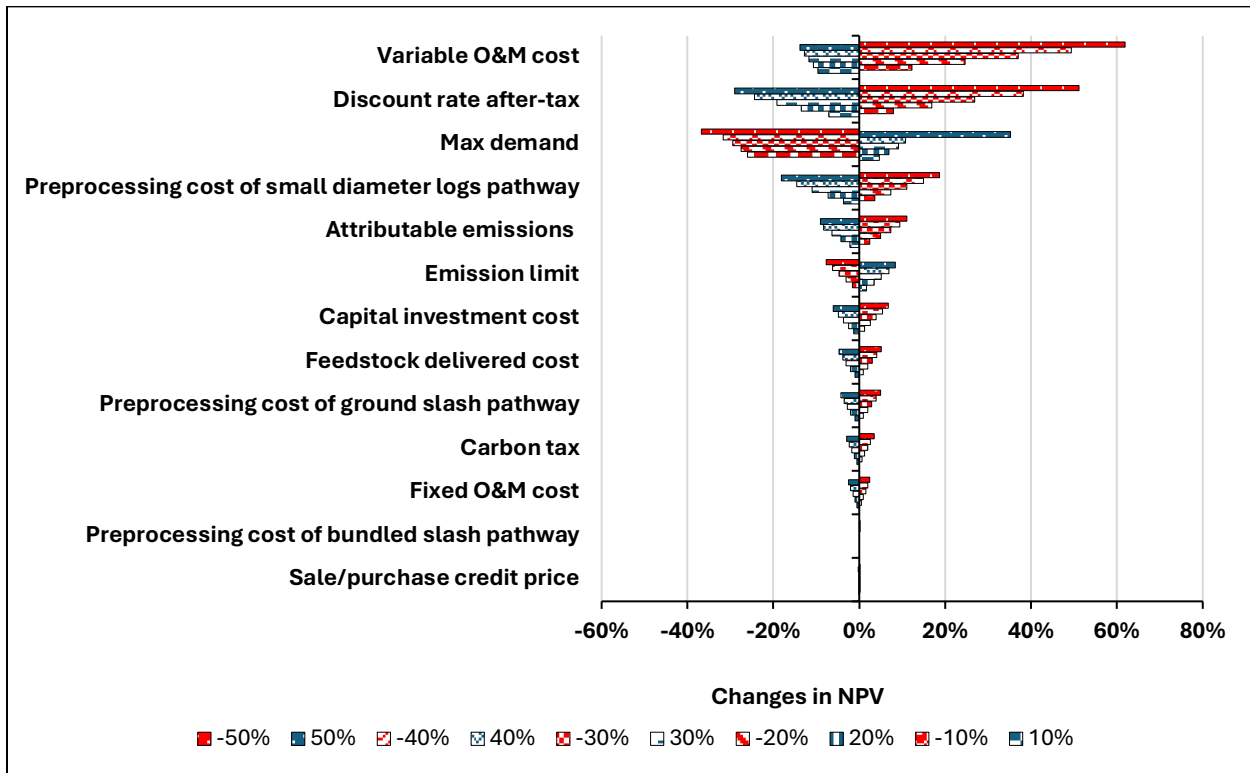


Figure 4-12. Changes in NPV (net present value) obtained by solving a single-objective NPV profit-maximization model under the all-policy scenario, for each input parameter variation.

As shown in Figure 4-12, variable O&M cost and discount rate are the most influential parameters. A 50% reduction in variable O&M cost increases NPV by 62%, while a 50% increase in this parameter reduces NPV by approximately 15%. Similarly, lowering the discount rate by 50% improves NPV by approximately +50%, whereas higher discount rates decrease NPV (around -30% at +50% increase in the discount rate).

The maximum demand has a limited impact. Reductions in the demand decrease NPV (up to -37% at -50%), while higher demand increases NPV ($+35\%$ at $+50\%$), indicating that market access and demand realization could enhance the economic viability.

Preprocessing costs associated with the small-diameter logs pathway have small, but higher impacts compared with the preprocessing costs of other types of pathways. A 50% reduction/increase in the preprocessing costs of small-diameter logs pathway results in approximately 19% reduction/increase in the NPV. The impact of preprocessing costs of other pathways are negligible. This can be explained by the results of the previous section, where it was shown that the majority of residues are transported through small-diameter logs pathway, while ground slash pathway was selected for much lower portion and bundled slash pathway was not selected at all.

Policy- and environment-related parameters, including attributable emissions and emission limits, have small effects. Changes in attributable emissions by $+50\%$ and -50% result in NPV variations within -9% to $+11\%$, respectively. Tighter emission limits reduce NPV, while relaxed limits improve it, with magnitudes remaining within approximately $\pm 8\%$.

The capital investment cost and feedstock delivered cost exhibit negligible sensitivity (generally within $\pm 7\%$), indicating that the optimal network design is relatively robust to uncertainties in upfront capital and feedstock prices under the all-policy scenario. Other carbon-pricing parameters, including carbon tax and the price of selling or purchasing carbon credits, have the lowest impacts, at approximately from 0% to 3%.

4.8 Results of the deterministic bi-objective model

Figure 4-13 illustrates the Pareto trade-off between the net present value (NPV) of profit and greenhouse gas (GHG) emissions under the considered policy scenarios, and compares the effects of different policies. The Pareto fronts reveal that emissions and NPV are largely aligned rather than conflicting.

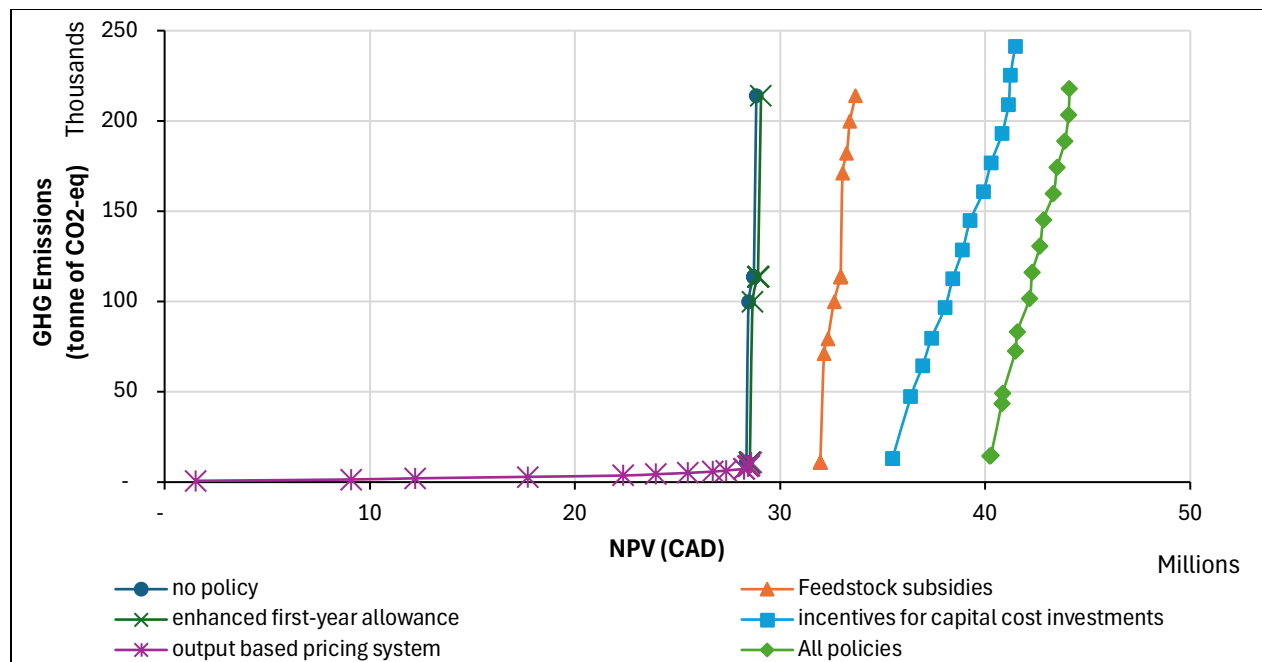


Figure 4-13. Pareto-optimal solutions showing the trade-off between NPV (net present value) and total greenhouse gas (GHG) emissions for the supply chain network under the considered policy scenarios (deterministic bi-objective model).

It should be noted that as mentioned in the previous section, although the AUGMECON method was set to generate 15 Pareto-optimal solutions under each policy scenario; several ϵ values under each policy scenario resulted in identical Pareto-optimal solutions due to the flat regions of the Pareto frontier. Therefore, those duplicates are removed from the Pareto-optimal solutions and only the unique ones are shown for each policy scenario.

For each policy scenario, three optimal solutions from the Pareto-optimal fronts are selected and shown in more details. These solutions are the end points and one middle solution.

4.8.1 No-policy scenario

Figure 4-14 shows the Pareto front generated for the no-policy scenario.

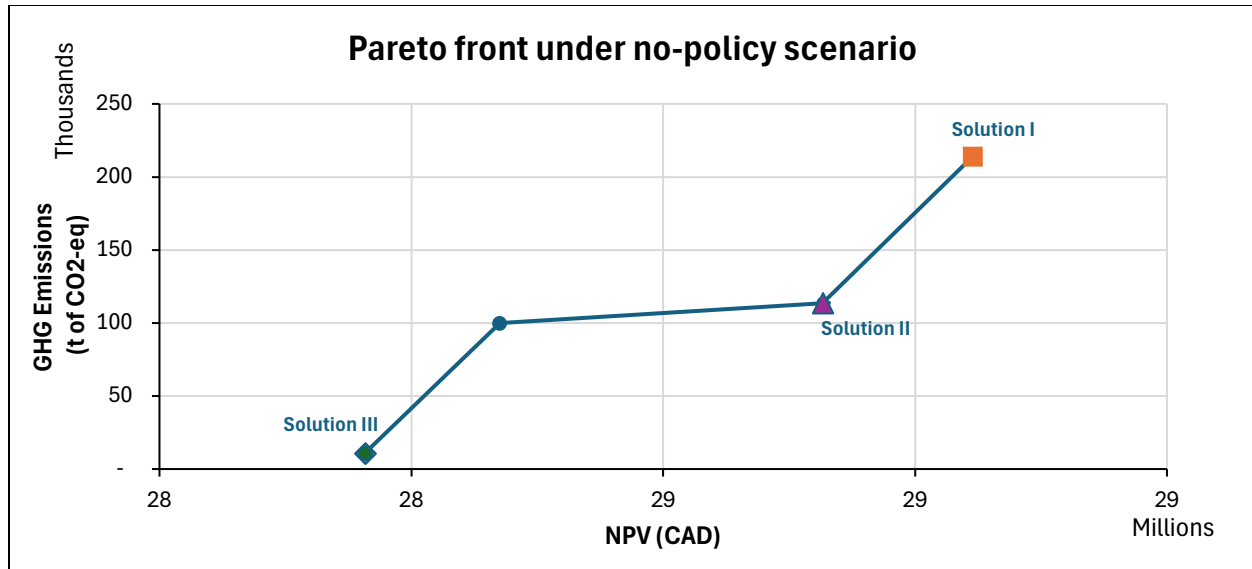


Figure 4-14. Pareto-optimal solutions illustrating changes in NPV (net present value) as the emission constraint varies under the no-policy scenario (deterministic bi-objective model).

As shown in Table 4-18, Solution I, which matches the solution obtained from the associated deterministic single-objective model presented in the previous section (where NPV was maximized without emission minimization), suggests establishing 10 facilities to produce AC, CNF, and pellets. When emission levels are reduced by approximately 47% in Solution II ($\epsilon = 114,083$), one AC production facility is excluded from the supply chain network and NPV reduces by 0.4%. Lowering emissions by 93% in Solution III ($\epsilon = 14,260$) leads to the elimination of the two AC production facilities from the network and a 1.7% reduction in the NPV. This outcome is driven by the high emissions intensity of AC production, as shown in the earlier emissions analysis.

Table 4-18. Prescribed bioproduction facility establishments under the no-policy scenario for three Pareto-optimal solutions (deterministic bi-objective model).

Location	Bioproduct	Capacity	Solution I ($\epsilon = 213,905$)	Solution II ($\epsilon = 114,083$)	Solution III ($\epsilon = 14,260$)
Hanceville	AC (Activated Carbon)	Large (3,756 odt/year)	✓	✓	-
	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	✓	✓
	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓
Anahim Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
Williams Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	✓

Location	Bioproduct	Capacity	Solution I ($\epsilon = 213,905$)	Solution II ($\epsilon = 114,083$)	Solution III ($\epsilon = 14,260$)
Horsefly	AC (Activated Carbon)	Large (3,756 odt/year)	✓	-	-
	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	✓	✓
	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓

As illustrated in Figure 4-15, Solution I shows the highest emissions (214 thousand tonnes of CO₂-eq) and NPV (\$29 million) for the suggested supply chain design. In Solution II, where emissions are lower at 114 thousand tonnes of CO₂-eq, one AC facility is eliminated from the proposed supply chain compared to Solution I, however, NPV remains at approximately \$29 million. In Solution III, where two AC production facilities are eliminated from the suggested network compared to Solution I, emissions are at the lowest level of 11 thousand tonnes of CO₂-eq, while NPV decreases to approximately the same at \$28 million. It should be noted that while there is no significant difference between NPVs of profits of the three solutions, the PV of revenues, PV of total operating and maintenance (O&M) costs, PVs of investment costs and the design of the supply chain networks are substantially varied.

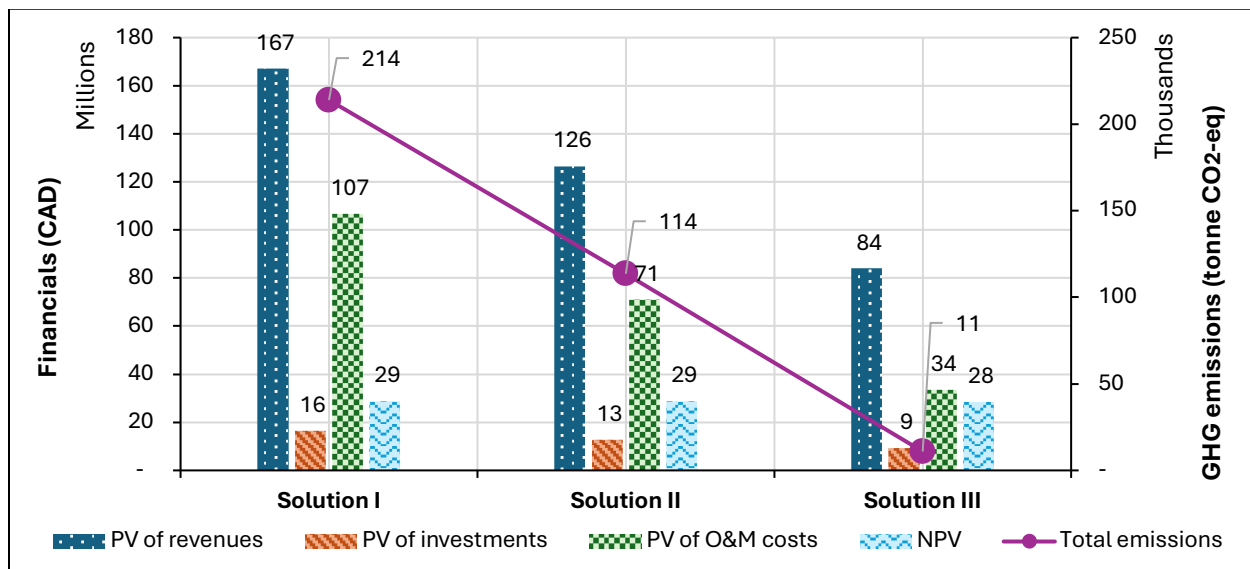


Figure 4-15. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the no-policy scenario for three Pareto-optimal solutions (deterministic bi-objective model).

4.8.2 Feedstock subsidies

Figure 4-16 is the Pareto front generated for the feedstock subsidy scenario.

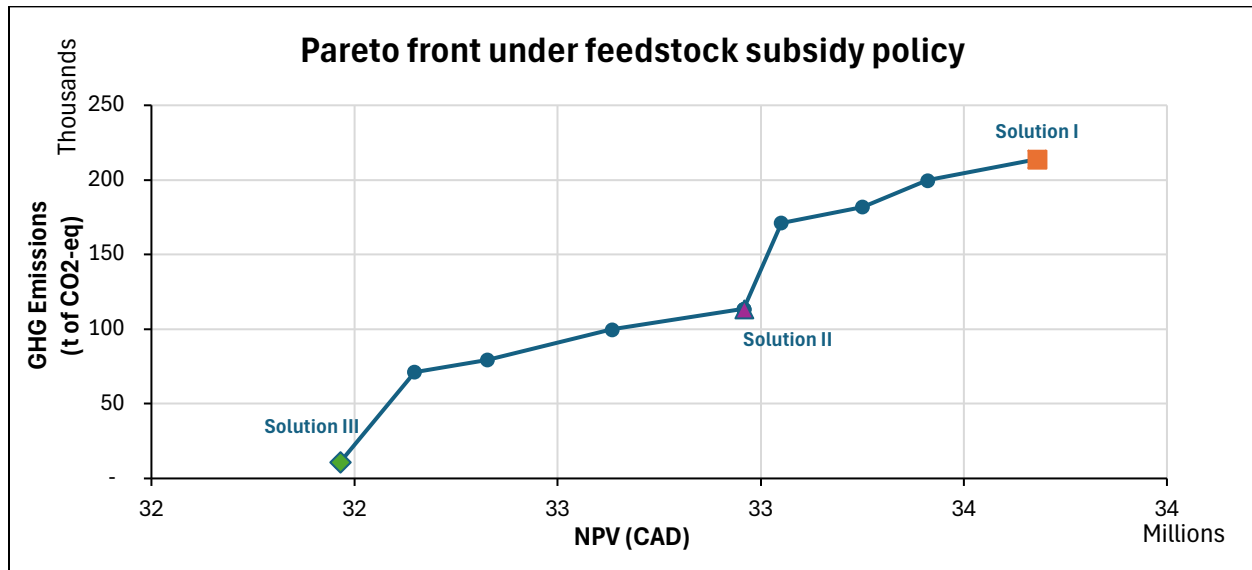


Figure 4-16. Pareto-optimal solutions illustrating changes in NPV (net present value) as emission constraint varies under the feedstock subsidy scenario (deterministic bi-objective model).

The proposed supply chain networks under the three solutions are the same as those in the no-policy scenario. As shown in Table 4-19, Solution I, which matches the solution obtained from the associated single-objective model presented in the previous section (where NPV was maximized without emission minimization), suggests establishing 10 facilities to produce AC, CNF, and pellets. When emission levels are reduced by approximately 47% in Solution II ($\epsilon = 114,083$), one AC facility is excluded from the supply chain network, and NPV reduces by 2.4%. Lowering emissions by 93% in Solution III ($\epsilon = 14,260$) results in the elimination of the two AC production facilities from the network and a 5.1% reduction in the NPV. This outcome is driven by the high emissions intensity of AC production, as shown in the earlier emissions analysis.

Table 4-19. Bioproduction facility establishments under the feedstock subsidy scenario for three Pareto-optimal solutions (deterministic bi-objective model).

Location	Bioproduct	Capacity	Solution I ($\epsilon = 213,905$)	Solution II ($\epsilon = 114,083$)	Solution III ($\epsilon = 14,260$)
Hanceville	AC (Activated Carbon)	Large (3,756 odt/year)	✓	✓	-
	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	✓	✓
	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓
Anahim Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
Williams Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
Horsefly	AC (Activated Carbon)	Large (3,756 odt/year)	✓	-	-
	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	✓	✓
	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓

Solution I shows the highest emissions (214 thousand tonnes of CO₂-eq) and NPV (\$34 million), as shown in Figure 4-17. In Solution II, where emissions are lower at 114 thousand tonne of CO₂-eq, one AC production facility is eliminated from the proposed supply chain network, leading to an NPV of approximately \$33 million. In Solution III, where two AC production facilities are eliminated from the suggested network, emissions are at the lowest level of 11 thousand tonnes of CO₂-eq and NPV reduces to approximately \$32 million. It should be noted that while there is no significant difference between NPVs of profits of the three solutions, the PV of revenues, PV of total operating and maintenance (O&M) costs, PVs of investment costs and the design of the supply chain networks are substantially varied.

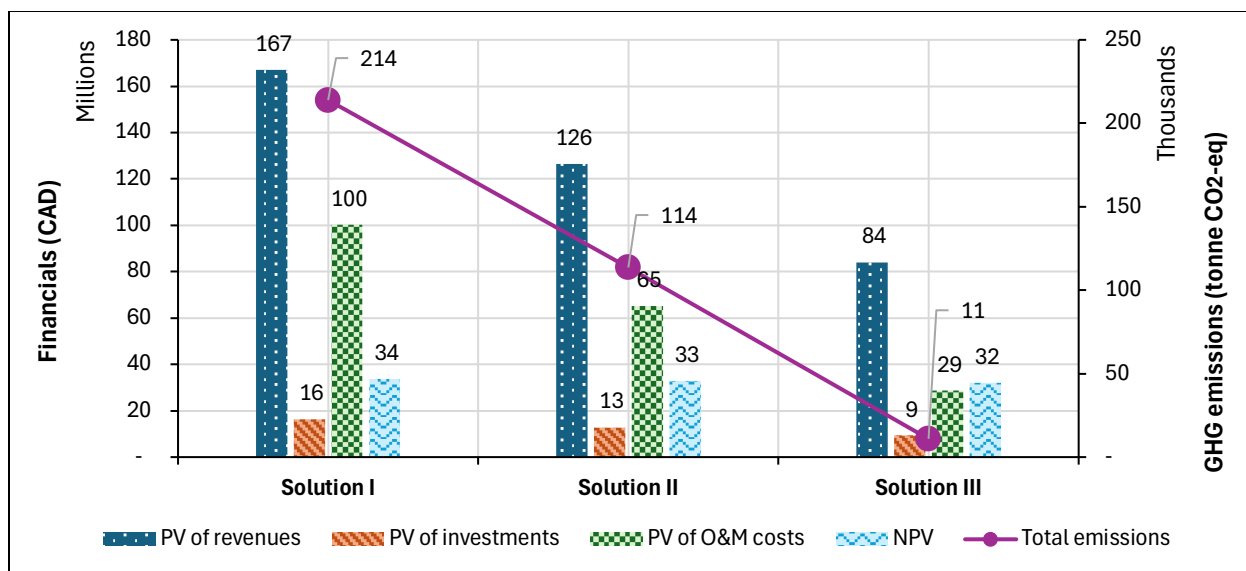


Figure 4-17. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the feedstock subsidy scenario for three Pareto-optimal solutions (deterministic bi-objective model).

4.8.3 Depreciation (enhanced first-year allowance) policy scenario

Figure 4-18 is the Pareto front generated for the enhanced first-year allowance policy scenario.

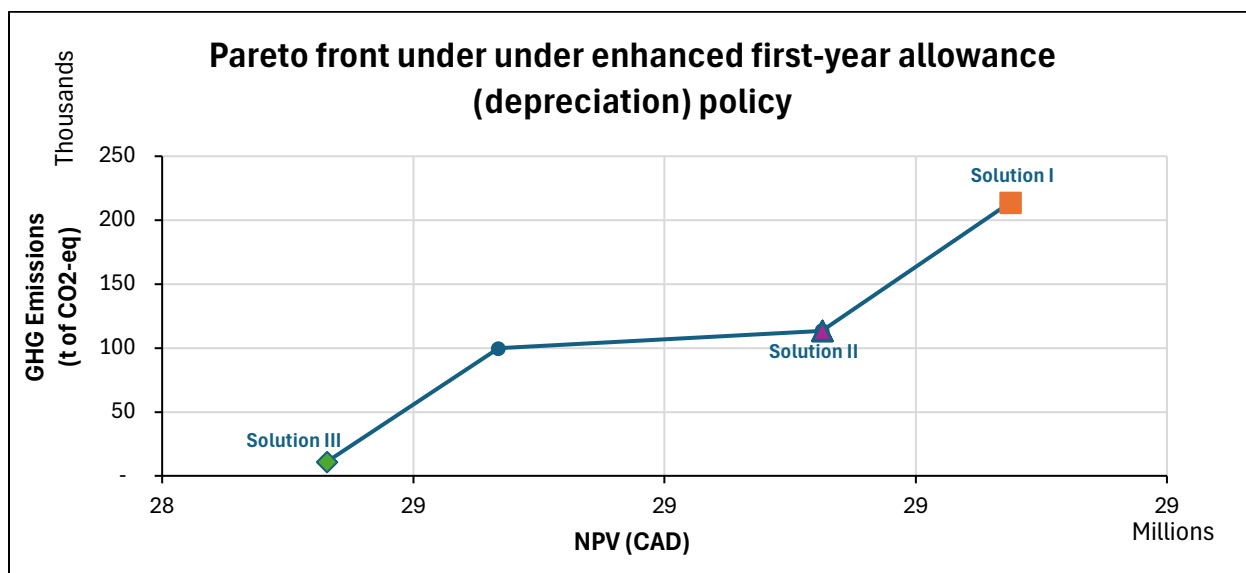


Figure 4-18. Pareto-optimal solutions illustrating changes in NPV (net present value) as emissions vary under the enhanced first-year allowance scenario (deterministic bi-objective model).

The proposed supply chain networks under the three solutions are the same as those in the no-policy scenario. As shown in Table 4-20, Solution I, which matches the solution obtained from the associated single-objective model presented in the previous section (where NPV was maximized without emission minimization), suggests establishing 10 facilities to produce AC, CNF, and pellets. When emission levels are reduced by approximately 47% in Solution II ($\epsilon = 114,083$), one AC facility is excluded from the supply chain network and NPV reduces by 0.5%. Lowering emissions by 93% in Solution III ($\epsilon = 14,260$) results in the elimination of the two AC production facilities from the network and a 1.9% reduction in the NPV. This outcome is driven by the high emissions intensity of AC production, as shown in the earlier emissions analysis.

Table 4-20. Bioproduction facility establishments under the enhanced first-year allowance scenario for three Pareto-optimal solutions (deterministic bi-objective model).

Location	Bioproduct	Capacity	Solution I ($\epsilon = 213,905$)	Solution II ($\epsilon = 114,083$)	Solution III ($\epsilon = 14,260$)
Hanceville	AC (Activated Carbon)	Large (3,756 odt/year)	✓	✓	-
	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	✓	✓
	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓
Anahim Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
Williams Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
Horsefly	AC (Activated Carbon)	Large (3,756 odt/year)	✓	-	-
	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	✓	✓
	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓

As shown in Figure 4-19, under this policy scenario, the NPV variations are very small. The NPVs of profit in Solutions I, II, and III are approximately \$29 million. However, the emissions, revenues, costs, and the design of the supply chain networks are significantly different. The values under this policy are very similar to the results obtained from no-policy scenario. Solution I shows the highest emissions at 241 thousand tonne of CO₂-eq. In solution II, emissions are lower at 114 thousand tonne of CO₂-eq, and in Solution III, it reaches its lowest level at 11 thousand tonne of CO₂-eq.

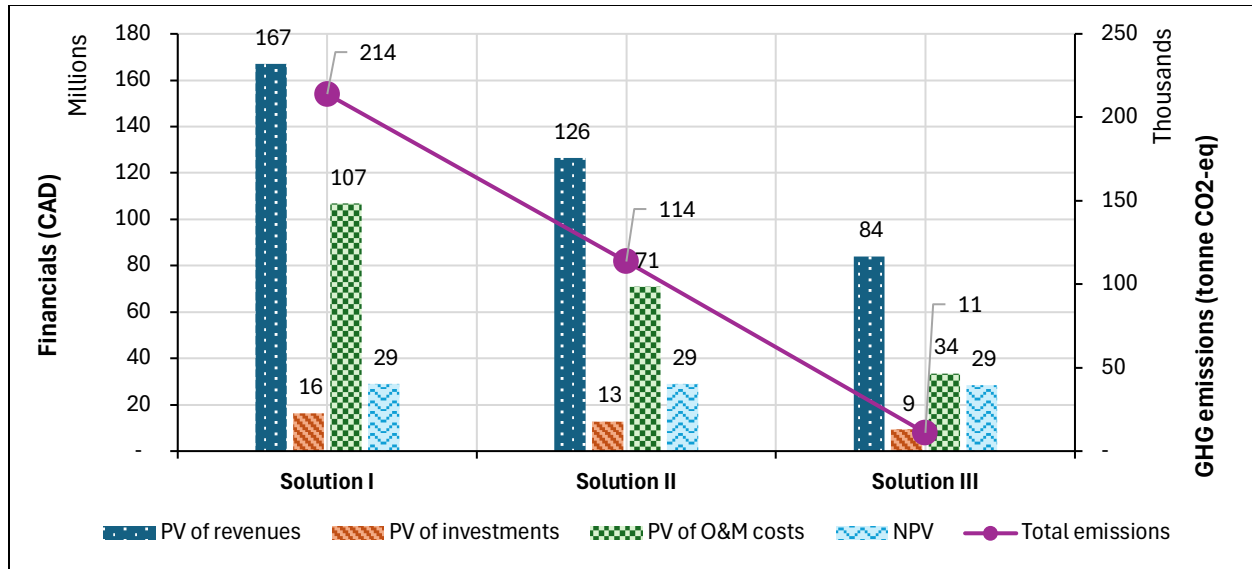


Figure 4-19. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the enhanced first-year allowance scenario for three Pareto-optimal solutions (deterministic bi-objective model).

4.8.4 Direct incentives for capital investment policy scenario

Figure 4-20 is the Pareto front generated for the direct incentives for capital investments scenario.

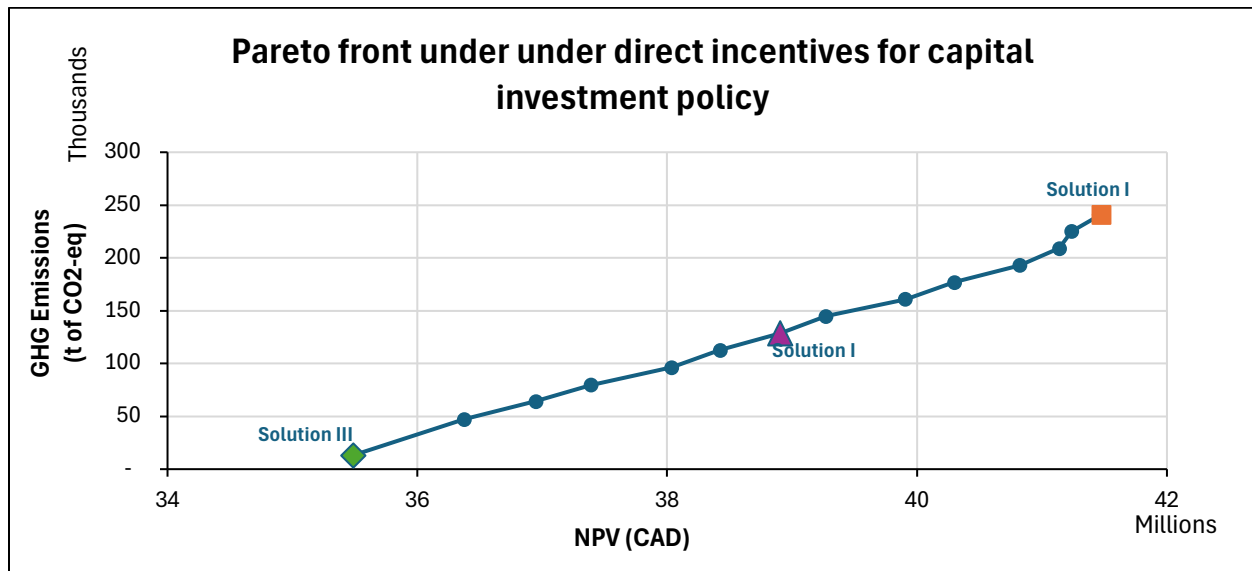


Figure 4-20. Pareto-optimal solutions illustrating changes in NPV (net present value) as emissions vary under the direct incentives for capital investments policy scenario (deterministic bi-objective model).

As shown in Table 4-21, Solution I, which is the same as the solution obtained from the associated single objective model (where NPV was maximized without emission minimization), suggests establishing 16 facilities to produce AC, CNF, biochar and pellets. When emission levels are reduced by approximately 47% in solution II ($\epsilon = 128,647$), one AC and one pellet production facilities are excluded from the supply chain network and NPV reduces by 6.2%. Lowering emissions by 93% in solution III ($\epsilon = 16,081$) results in the elimination of three AC production facilities from the network and a 14.4% reduction in the NPV. This outcome is driven by the high emissions intensity of AC production, as shown in the earlier emissions analysis.

Table 4-21. Bioproduction facility establishments under the direct incentives for capital investments policy scenario for three Pareto-optimal solutions (deterministic bi-objective model).

Location	Bioproduct	Capacity	Solution I ($\epsilon = 241,213$)	Solution II ($\epsilon = 128,647$)	Solution III ($\epsilon = 16,081$)
Hanceville	AC (Activated Carbon)	Large (3,756 odt/year)	✓	✓	-
	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	✓	✓
	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓
	Biochar (wet torrefaction)	Small (80 odt/yr)	✓	✓	✓
	Biochar (dry torrefaction)	Small (50 odt/yr)	✓	✓	✓
Anahim Lake	AC (Activated Carbon)	Large (3,756 odt/yr)	✓	-	-
	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	-	✓
Williams Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
Horsefly	AC (Activated Carbon)	Small (1,252 odt/yr)	✓	✓	-
	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	✓	✓
	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓
	Biochar (wet torrefaction)	Small (80 odt/yr)	✓	✓	✓
	Biochar (dry torrefaction)	Small (50 odt/yr)	✓	✓	✓

Solution I shows the highest emissions (241 thousand tonnes CO₂-eq) and NPV (\$40 million), as depicted in Figure 4-21. In solution II, where emissions are lower at 129 thousand tonnes of CO₂-eq, one AC and one pellet production facilities are excluded from the suggested supply chain network, leading to an NPV of approximately \$39 million. In solution III, where three AC production facilities are eliminated from the suggested network, emissions are at the lowest level

of 13 thousand tonnes of CO₂-eq, and NPV decreases to approximately \$35 million. It should be noted that while there is no significant difference between NPVs of profits of the three solutions, the PV of revenues, PV of total operating and maintenance (O&M) costs, PVs of investment costs and the design of the supply chain networks are substantially varied.

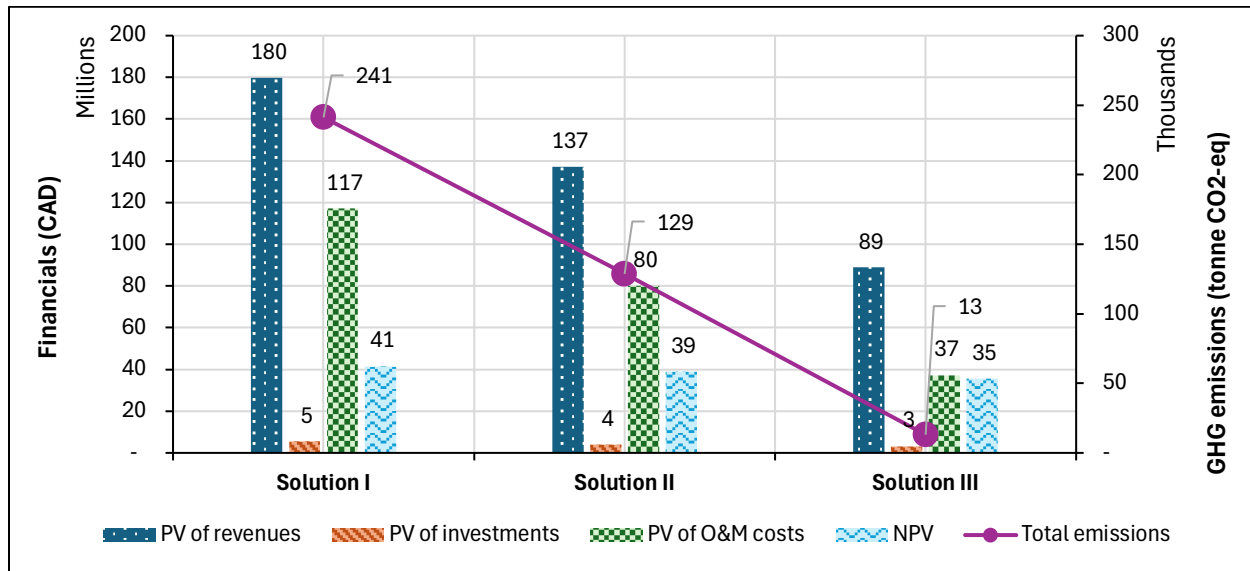


Figure 4-21. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the capital investments policy scenario for three Pareto-optimal solutions (deterministic bi-objective model).

4.8.5 Output-based pricing system policy scenario

Figure 4-22 is the Pareto front generated for the output-based pricing policy scenario.

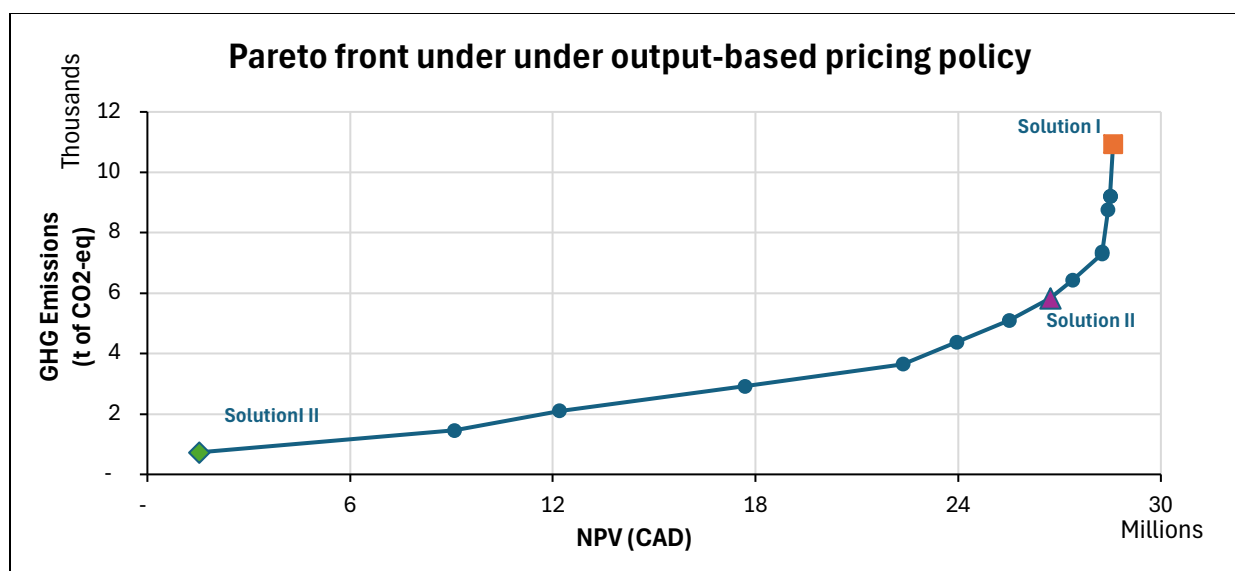


Figure 4-22. Pareto-optimal solutions illustrating changes in NPV (net present value) as emissions vary under the output-based pricing policy scenario (deterministic bi-objective model).

As shown in Table 4-22, solution I which is the same as the solution obtained from the associated single objective model where NPV was maximized without any emission minimization considerations, suggests establishing eight facilities to produce CNF and pellets. When emission levels are reduced by approximately 47% in Solution II ($\epsilon = 5,834$), three pellet production facilities are excluded from the supply chain network and NPV reduces by 6.5%. Lowering emissions by 93% in Solution III ($\epsilon = 729$) results in establishment of only one pellet production facility and a 94.7% reduction in the NPV.

Table 4-22. Bioproduction facility establishments under the direct incentives for the output-based pricing policy scenario for three Pareto-optimal solutions (deterministic bi-objective model).

Location	Bioproduct	Capacity	Solution I ($\epsilon = 10,938$)	Solution II ($\epsilon = 5,834$)	Solution III ($\epsilon = 729$)
Hanceville	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	✓	-
	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	-	-
Anahim Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	-
Williams Lake	High quality pellets	Small (3,912 odt/year)	✓	-	-
Horsefly	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	✓	-
	High quality pellets	Small (3,912 odt/year)	✓	✓	-
	Low quality pellets	Small (2,778 odt/year)	✓	-	-

Solution I shows the highest Emissions (11 thousand tonnes of CO₂-eq) and NPV (\$29 million), as depicted in Figure 4-23. In solution II, where emissions are lower at 6 thousand tonnes of CO₂-eq, three pellet production facilities are excluded from the supply chain network, leading to an NPV of approximately \$27 million. In Solution III, only one facility is established, emissions are at the lowest level of one thousand tonne of CO₂-eq, and NPV decreases to approximately \$2 million.

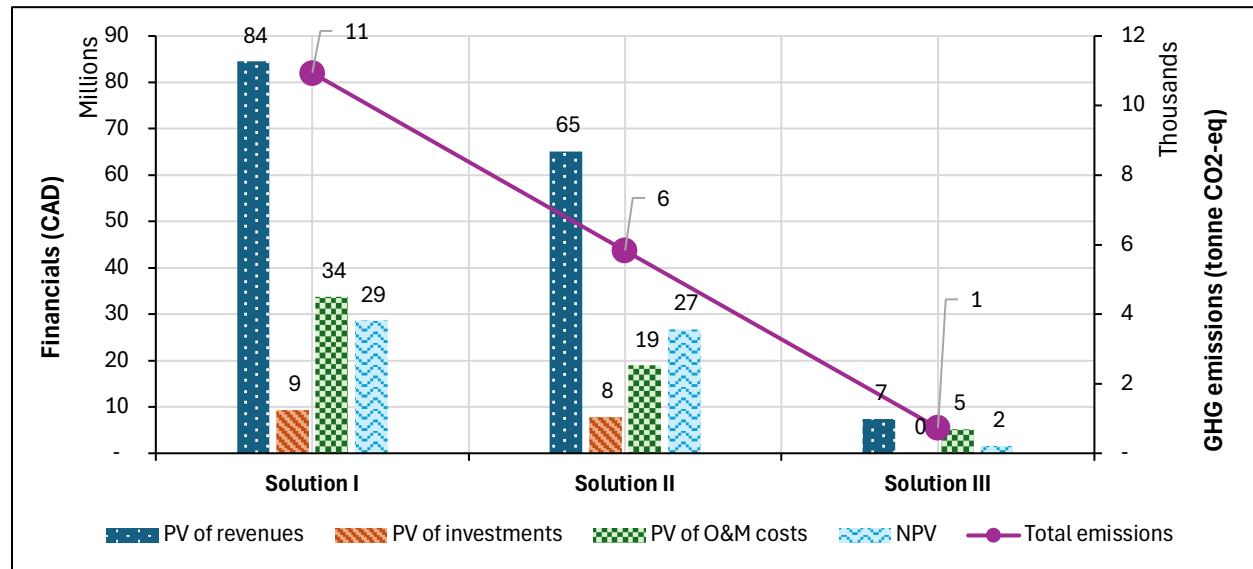


Figure 4-23. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the direct incentives the output-based pricing policy scenario for three Pareto-optimal solutions (deterministic bi-objective model).

4.8.6 All-policy scenario

Figure 4-24 is the Pareto front generated for the scenario where all the policies are implemented.

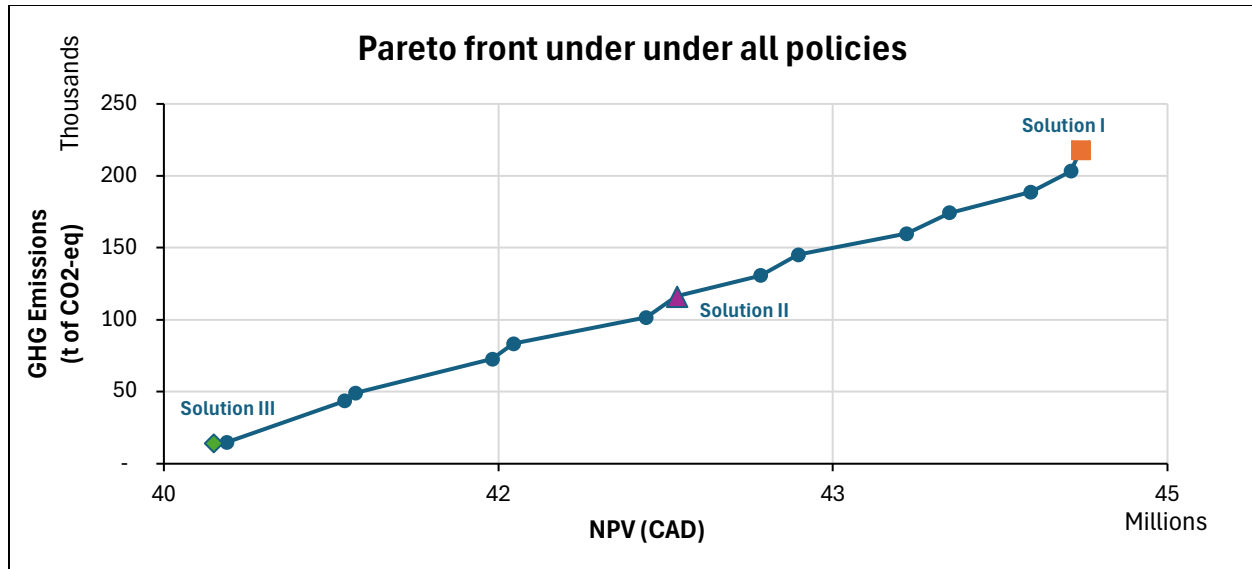


Figure 4-24. Pareto-optimal solutions illustrating changes in NPV (net present value) as emissions vary under the scenario where all policies are implemented deterministic bi-objective model (deterministic bi-objective model).

As shown in Table 4-23, Solution I, which is the same as the solution obtained from the associated single objective model where NPV was maximized without any emission minimization considerations, suggests establishing 16 facilities to produce AC, CNF, biochar and pellets. When emission levels are reduced by approximately 47% in Solution II ($\epsilon = 116,185$), one AC is excluded from the supply chain network and NPV reduces by 4.1%. Lowering emissions by 93% in Solution III ($\epsilon = 14,523$) results in the elimination of two AC, one pellet, and one biochar production facilities from the network and a 8.8% reduction in the NPV.

Table 4-23. Bioproduction facility establishments under the scenario where all policies are implemented for three Pareto-optimal solutions (deterministic bi-objective model).

Location	Bioproduct	Capacity	Solution I ($\epsilon = 217,847$)	Solution II ($\epsilon = 116,185$)	Solution III ($\epsilon = 14,523$)
Hanceville	AC (Activated Carbon)	Large (3,756 odt/year)	✓	✓	-
	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	✓	✓
	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓
	Biochar (wet torrefaction)	Small (80 odt/yr)	✓	✓	✓
	Biochar (dry torrefaction)	Small (50 odt/yr)	✓	✓	✓
Anahim Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓

Location	Bioproduct	Capacity	Solution I ($\epsilon = 217,847$)	Solution II ($\epsilon = 116,185$)	Solution III ($\epsilon = 14,523$)
Williams Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓
Horsefly	AC (Activated Carbon)	Large (3,756 odt/year)	✓	-	-
	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	✓	✓
	High quality pellets	Small (3,912 odt/year)	✓	✓	-
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓
	Biochar (wet torrefaction)	Small (80 odt/yr)	✓	✓	✓
	Biochar (dry torrefaction)	Small (50 odt/yr)	✓	✓	

Solution I shows the highest emissions (218 thousand tonnes of CO₂-eq) and NPV (\$44 million), as depicted in Figure 4-25. In solution II, where emissions are lower at 116 thousand tonnes of CO₂-eq, the NPV decreases to approximately \$42 million. In Solution III, emissions are at the lowest level of 15 thousand tonnes of CO₂-eq, and NPV decreases to approximately \$40 million.

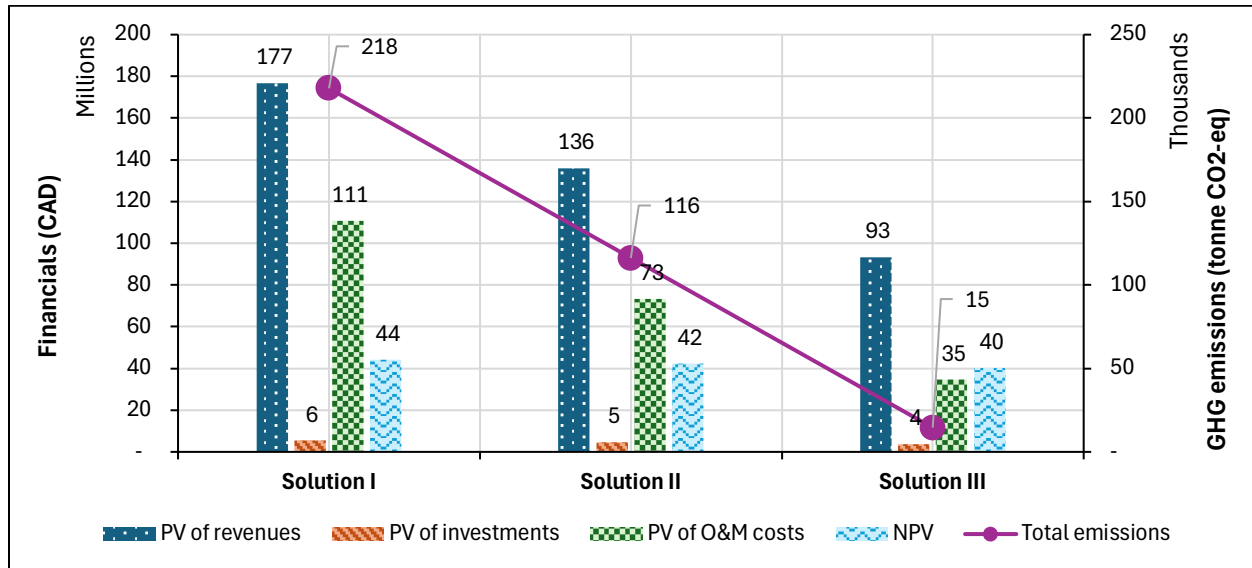


Figure 4-25. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the scenario where all policies are implemented for three Pareto-optimal solutions (deterministic bi-objective model).

4.9 Conclusion

In this chapter, the results of the mathematical programming model developed to optimize the design of a biomass supply chain network in the Williams Lake TSA were presented. According to the results, a total of 10 facilities were recommended for establishment, producing AC, CNF,

and pellets across four biohub locations (Hanceville, Anahim Lake, Williams Lake, and Horsefly), resulting in an NPV of \$28.8 million. The same number and types of facilities were recommended under the feedstock subsidy and enhanced first-year allowance policies, with higher NPVs of \$33.7 million and \$29.1 million, respectively, as these policies provide cost savings for the network. Direct incentives for the capital investment policy noticeably altered the network design, recommending the establishment of 16 facilities producing AC, CNF, pellets, and biochar, resulting in an NPV of \$41.5 million. The output-based pricing system generated the lowest NPV (\$28.6 million) due to additional emission-related costs, and it also resulted in fewer facilities (eight facilities in total) being established, leading to lower overall emissions (10,938 tonne of CO₂-eq). When all policies were simultaneously taken into account, 16 facilities were recommended to establish for producing AC, CNF, pellets, and biochar, resulting in an NPV of \$44 million. This network also resulted in total emissions of 217,847 CO₂-eq, which ranged between no-policy (213,905 CO₂-eq) and output-based pricing policy (10,938 CO₂-eq) emissions.

The results of the presented bio-objective model showed that across all policy scenarios higher NPVs were generally associated with higher emissions. However, the slopes of the curves indicated that reducing emissions did not lead to substantial reductions in the supply chain's NPV.

Under the no-policy and enhanced first-year allowance scenarios, a 47% reduction in emissions resulted in less than a 1% reduction in the NPV, while a 93% reduction in emissions led to less than a 2% reduction in the NPV. Similarly, under the feedstock subsidy policy, 47% and 93% reductions in emissions resulted in approximately 2% and 5% reductions in the NPV, respectively.

In the all-policy scenario, a 47% reduction in emissions corresponded to a 4% reduction in the NPV, while a 93% reduction led to a 9% reduction. The capital investment policy exhibits a steeper slope, with the NPV decreasing by approximately 6% and 14% for 47% and 93% emission reductions, respectively.

The output-based pricing policy showed the most pronounced sensitivity of the NPV to emission reductions, due to the direct linkage between emissions and the profit objective through the carbon tax. Under this policy, a 47% reduction in emissions resulted in approximately a 7% reduction in the NPV, while a 93% reduction in emissions led to a 95% reduction in the NPV.

Moreover, the results of the bi-objective model showed that the no-policy and enhanced first-year allowance scenarios exhibited nearly identical NPVs of profits (approximately \$29 million) across a wide range of emission levels. This indicates that depreciation incentives alone do not significantly influence either the economic performance or the emissions outcomes of the optimal supply chain networks identified by the optimization models.

Feedstock subsidies and capital investment incentives shifted the Pareto frontier toward higher NPVs of profits. Under the feedstock subsidy scenario, the optimization model yielded NPVs of profits in the range of \$32 to \$34 million, while under the capital investment incentive scenario, NPVs of profits ranged from \$35 to \$40 million. These policies primarily reduced costs and/or encourage the establishment of more facilities and higher production levels, without directly constraining or penalizing emissions. When all policies were considered simultaneously, the optimization model resulted in even higher NPVs of profits, ranging from \$40 to \$44 million. As illustrated in Figure 4-13, the Pareto frontier shifted to the right, reflecting improved economic performance.

Overall, the results highlighted that financial incentives in the form of feedstock subsidies, enhanced depreciation allowances, and capital investment incentives improve economic performance, albeit only marginally in the case of depreciation allowances. In contrast, the optimization model under the carbon pricing policy (output-based pricing system) steered the supply chain toward designs with lower NPVs of profits (ranging from \$1.5 to \$29 million) and lower emissions (from approximately 11 to one thousand tonnes of CO₂-eq), as shown in Figure 4-13.

The generated Pareto fronts support decision making by illustrating how changes in emission constraint correspond to changes in supply chain network design and NPV. By comparing Pareto optimum solutions, decision makers can identify network configurations that achieve emission reductions with only modest reductions in profit, enabling the selection of economically viable and environmentally improved designs.

While the results of the techno-economic analyses showed that the impact of majority of policies on individual bioproduction facilities was insignificant, and there were a few policy scenarios that

could render the infeasible bioproduction facilities feasible, the results of this phase showed that the policies impacted the optimum network design and the overall NPV of the supply chain.

It should also be noted that the results of the mathematical programming models and the suggested supply chain network designs heavily rely on the input data and assumptions regarding the readiness, availability, and costs of the bioproduction technologies at the considered scales. The input data for the economic feasibility studies were derived from available studies and documents, and cost assumptions were made based on existing formulations that estimate cost increases with scale, regardless of the commercialization status of those scales. Considering that these input data may be subject to uncertainty, the next chapter treats the government policy-related parameters and those identified through sensitivity analysis as having a significant impact on NPV as uncertain parameters, and evaluates the supply chain network design and related decisions under such uncertainties.

Chapter 5: Non-deterministic Supply Chain Network Design

5.1 Synopsis

In this chapter, the non-deterministic models are presented. The sensitivity analysis revealed that variable O&M costs, the after-tax discount rate, and the maximum demand for bioproducts exert the greatest influence on the net present value (NPV) of the supply chain profit.

Although the discount rate significantly affected the NPV, treating it as an uncertain parameter would introduce nonlinearity into the model, as the discount rate appears in the denominator of the discounting term. Moreover, the results indicated that the positive impact on NPV due to the reduction in the discount rate was stronger than the negative impact on NPV caused by increasing it. Under a worst-case perspective, lower or higher discount rates would not represent significant adverse conditions. Therefore, the discount rate is excluded from the uncertainty analysis.

One of the primary objectives of this study is to assess how uncertainties in policy-related parameters influence supply chain network design decisions and the selection and establishment of bioproduct facilities. Accordingly, policy-related parameters are modeled as uncertain. These include:

- The percentage of capital investment covered by government support
- The subsidy level applied to delivered feedstock costs
- The percentage of initial investment eligible for enhanced first-year depreciation
- Emission limits
- Carbon tax levels under the output-based pricing system
- Carbon credit prices under the output-based pricing system

In addition to these policy parameters, the two most influential parameters identified in the sensitivity analysis (variable O&M costs, and maximum product demand) are also treated as uncertain.

5.2 Possibilistic chance constraint programming

The single-objective model for the all-policy scenario incorporating these uncertain parameters can therefore be formulated as follows:

Table 5-1. Notations of the non-deterministic mathematical programming model without policy considerations.

Indices/Sets	
F	Type of biomass (i.e., residues or small-diameter logs) $f \in F$
W	Supply chain pathways (i.e., ground, bundled, small-diameter logs) $w \in W$
O	Valid type-pathway combinations $o \in (F \times W)$ {residues, small diameter logs}
I	Supply locations (i.e., cut blocks) $i \in I$
J	Bioproduction facility locations (i.e., Hanceville, Anahim Lake, Williams Lake, Horsefly) $j \in J$
C	Capacity sizes for facilities (i.e., small, medium, large) $c \in C$
P	Products (i.e., CNC, CNF, AC, Biochar-wet, Biochar-dry, Pellets-low, Pellets-high) $p \in P$
T	Time periods $t \in T$
Parameters	
KK_{cp}	Processing capacity (odt/year) of capacity size c for product p
PY_p	Production yield for product p (tonne of product/odt of biomass)
PR_p	Selling price of product p (CAD/tonne of product) (CAD)
FC_{cp}	Fixed O&M cost of bioproduction facility with capacity size c to produce product p
PC_w	Preprocessing cost of biomass through pathway w at bioproduction facilities (CAD/odt of biomass)
SS_{fijt}	Supply of biomass with type f from cut block i available to be sent to location j in period t
TR	Tax rate
α	Discount rate
PO_{wp}	Per odt of emissions from producing one tonne of product $p \in P$ through pathway $w \in W$
M	A very large number used for logical constraints
Uncertain parameters	
$\widetilde{CC}_{cpj}$	Uncertain capital investment cost of establishing bioproduction facility with capacity size c to produce product p at bioproduction facility location j (CAD) accounting for the covered portion by the government – uncertain parameter
$\widetilde{VC}_p$	Uncertain variable O&M cost of bioproduction facility producing product p (CAD/odt of biomass)
$\widetilde{TC}_{fwijt}$	Uncertain transportation and preprocessing cost of biomass from cut block i to location j through pathway w in period t accounting for the feedstock subsidies
$\widetilde{DM}_{pt}$	Uncertain maximum demand for bioproduct p in period t
$\widetilde{DP}_{cpt}$	Present value of uncertain depreciation for the technology with capacity size c to produce product p if it was established in period t
$\widetilde{EL}_{pt}$	Uncertain emission limit factors for bioproduct $p \in P$ in period $t \in T$
$\widetilde{CP}_t$	Uncertain price for selling or purchasing credits in period $t \in T$
$\widetilde{CT}_t$	Uncertain carbon tax in period $t \in T$
Decision variables	
x_{fwijpt}	Amount of biomass flow in type f to be transported through supply chain pathway w from cut block i to location j to produce product p in period t (odt)
y_{jpt}	Amount of product p to be produced at location j in period t (tonne)
q_{jcp}	Binary: 1 if bioproduction facility at location j with capacity size c that produces product p at the beginning of the planning horizon; 0 otherwise
e_{jpt}	Excess emissions for a facility at location j that produces product $p \in P$ in period $t \in T$ (t CO ₂)

g_{jpt}	Generated credits for a facility at location j that produces product $p \in P$ in period $t \in T$ (t CO ₂)
c_{jpt}	Purchased credits for a facility at location j that produces product $p \in P$ in period $t \in T$ (t CO ₂)
u_{jpt}	Used credits for a facility at location j that produces product $p \in P$ in period $t \in T$ (t CO ₂)
s_{jpt}	Sold credits for a facility at location j that produces product $p \in P$ in period $t \in T$ (t CO ₂)
b_{jpt}	Banked credits for a facility at location j that produces product $p \in P$ in period $t \in T$ (t CO ₂)
p_{jpt}	Part of the excess emissions that are paid for a facility at location $j \in J$ that produces product $p \in P$ in period $t \in T$ (t CO ₂)
a_{jpt}	Binary accessory variable used to linearize what-if constraints
Other economic notations	
PTR	Present value of total revenue
PTC	Present value of total costs
PIC	Present value of investment costs
DEP	Present value of depreciation of established bioproduction technologies

The model description is the same as that presented in Section 4.4.

Objective function

$$Max. NPV = Max. (PTR - PTC) - PIC - (PTR - PTC - DEP) \times TR \quad \text{Eq. 5-1}$$

$$PTR = \sum_{t \in T} \sum_{p \in P} \sum_{j \in J} \frac{(PR_p \times y_{jpt}) + (\widetilde{CP}_t \times s_{jpt})}{(1 + \alpha)^t} \quad \text{Eq. 5-2}$$

$$PTC = \sum_{t \in T} \frac{1}{(1 + \alpha)^t} \quad \text{Eq. 5-3}$$

$$\begin{aligned} & \times \left(\sum_{c \in C} \sum_{p \in P} \sum_{j \in J} FC_{cp} \times q_{jcpt} + \sum_{p \in P} \sum_{i \in I} \sum_{j \in J} \sum_{(f,w) \in O} \widetilde{VC}_p \times x_{fwijpt} \right. \\ & + \sum_{p \in P} \sum_{i \in I} \sum_{j \in J} \sum_{(f,w) \in O} PC_w \times x_{fwijpt} \\ & + \sum_{p \in P} \sum_{i \in I} \sum_{j \in J} \sum_{(f,w) \in O} T\widetilde{C}_{fwijt} \times x_{fwijpt} + \sum_{p \in P} \sum_{j \in J} p_{jpt} \times \widetilde{CT}_t \\ & \left. + \sum_{p \in P} \sum_{j \in J} c_{jpt} \times \widetilde{CP}_t \right) \\ PIC &= \sum_{c \in C} \sum_{p \in P} \sum_{j \in J} \widetilde{CC}_{cpj} \times q_{jcp} \quad \text{Eq. 5-4} \end{aligned}$$

$$DEP = \sum_{c \in C} \sum_{p \in P} \sum_{j \in J} \widetilde{DP}_{cpt} \times q_{jcp} \quad \text{Eq. 5-5}$$

Constraints

$$\sum_{p \in P} \sum_{w \in W} x_{fwijpt} \leq SS_{fijt} \quad \forall t \in T, f \in F, i \in I, j \in J \quad \text{Eq. 5-6}$$

$$\sum_{p \in P} \sum_{i \in I} \sum_{(f,w) \in O} PY_p \times x_{fwijpt} = y_{jpt} \quad \forall t \in T, j \in J, p \in P \quad \text{Eq. 5-7}$$

$$\sum_{i \in I} \sum_{(f,w) \in O} x_{fwijpt} \leq \sum_{c \in C} KK_{cp} \times q_{jcp} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-8}$$

$$\sum_{c \in C} q_{jcp} \leq 1 \quad \forall j \in J, p \in P \quad \text{Eq. 5-9}$$

$$0.7 \times \sum_{c \in C} KK_{cp} \times q_{jcp} \leq \sum_{i \in I} \sum_{(f,w) \in O} x_{fwijpt} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-10}$$

$$\sum_{j \in J} y_{jpt} \leq \widetilde{DM}_{pt} \quad \forall t \in T, p \in P \quad \text{Eq. 5-11}$$

$$\sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} - (\widetilde{EL}_{pt} \times y_{jpt}) \leq M \times a_{jpt} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-12}$$

$$\sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} - (\widetilde{EL}_{pt} \times y_{jpt}) \geq -M \times (1 - a_{jpt}) \quad \text{Eq. 5-13}$$

$$\forall j \in J, p \in P, t \in T$$

$$e_{jpt} \geq \sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} - (\widetilde{EL}_{pt} \times y_{jpt}) \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-14}$$

$$e_{jpt} \leq \sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} - (\widetilde{EL}_{pt} \times y_{jpt}) + M \times (1 - a_{jpt}) \quad \text{Eq. 5-15}$$

$$\forall j \in J, p \in P, t \in T$$

$$e_{jpt} \leq M \times (a_{jpt}) \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-16}$$

$$g_{jpt} \geq (\widetilde{EL}_{pt} \times y_{jpt}) - \sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-17}$$

$$g_{jpt} \leq (\widetilde{EL}_{pt} \times y_{jpt}) - \sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} + M \times (a_{jpt}) \quad \text{Eq. 5-18}$$

$$\forall j \in J, p \in P, t \in T$$

$$g_{jpt} \leq M \times (1 - a_{jpt}) \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-19}$$

$$b_{jpt} = g_{jpt} - u_{jpt} - s_{jpt} \quad \forall j \in J, p \in P, t \in \{1\} \quad \text{Eq. 5-20}$$

$$b_{jpt} = b_{jpt-1} + g_{jpt} - u_{jpt} - s_{jpt} \quad \forall j \in J, p \in P, t \in \{2, \dots, T\} \quad \text{Eq. 5-21}$$

$$e_{jpt} = u_{jpt} + c_{jpt} + p_{jpt} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-22}$$

$$u_{jpt} + c_{jpt} \leq CL_t \times (e_{jpt}) \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-23}$$

$$e_{jpt}, g_{jpt}, c_{jpt}, u_{jpt}, s_{jpt}, b_{jpt}, p_{jpt}, y_{jpt}, x_{fwijpt} \geq 0 \quad \text{Eq. 5-24}$$

$$\forall f \in F, w \in W, i \in I, j \in J, p \in P, t \in T$$

$$a_{jpt}, q_{jcp} \in \{0,1\} \quad \forall c \in C, i \in I, j \in J, p \in P \quad \text{Eq. 5-25}$$

$$y_{jpt}, x_{fwijpt} \geq 0 \quad \forall f \in F, w \in W, i \in I, j \in J, p \in P, t \in T \quad \text{Eq. 5-26}$$

Uncertainty in the present study stems primarily from incomplete or imprecise information regarding policy-related parameters, rather than from stochastic variability supported by reliable historical data. For this reason, possibility theory (Dubois & Prade, 2012) provides a more appropriate modeling framework than probability-based approaches to deal with such epistemic uncertainty in this study. The literature suggests that optimization models involving epistemic uncertainty can be addressed through possibilistic chance constraint programming, a methodological extension of possibilistic programming (Sarkar et al., 2025).

Possibilistic chance constraint programming is based on mathematical foundations, including the expected value of fuzzy numbers and the application of possibility and necessity measures, which help decision makers to control the confidence level of constraint satisfaction (Pishvae et al.,

2012a). The possibility measure evaluates to what extent an event is possible, while necessity measure evaluates to what extent an event is certain (Inuiguchi et al., 2003). Mousazadeh et al. (2015) also indicate that the possibility measure reflects an optimistic attitude of a decision maker, while the necessity measure indicates a pessimistic attitude of the decision maker. We follow the necessity measure to be more conservative. These measures are used to derive the crisp counterpart model, which represents the deterministic equivalent of the possibilistic optimization model at specified confidence levels, allowing the model to be solved using commercial optimization software.

Here, we assume that the uncertain parameters follow trapezoidal possibility distributions defined by four characteristic points (Figure 5-1). The possibility degree of $\tilde{f}$ (uncertain parameter) is equal to one within the core interval $[f_2, f_3]$, representing the most plausible values. Between $[f_1, f_2]$ and $[f_3, f_4]$, the possibility degree decreases linearly, and outside the interval $[f_1, f_4]$, the possibility is zero. In other words, the true value of $\tilde{f}$ is assumed to lie within the range $[f_1, f_4]$, with higher plausibility assigned to values closer to the core interval. If f_2 and f_3 are equal, then the trapezoidal possibility distribution is reduced to triangular possibility distribution.

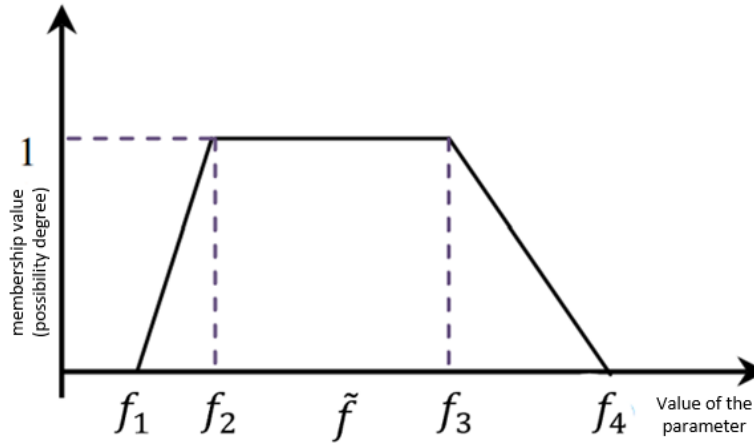


Figure 5-1. Trapezoidal possibility distributions of uncertain parameter $\tilde{f}$.

Such an uncertain parameter ($\tilde{f}$) in a mathematical model can appear as a coefficient in the objective function:

$$\text{Max } z = \tilde{f}x \quad \text{Eq. 5-27}$$

According to the possibilistic chance constraint programming, the uncertain coefficients in the objective function would be replaced by their expected value, which is defined as below (Pishvae et al., 2012b):

$$E[\tilde{f}] = \frac{f_1 + f_2 + f_3 + f_4}{4} \quad \text{Eq. 5-28}$$

It can also appear in the constraints, as shown below, where x is a decision variable and r is a parameter.

$$\tilde{f}x \leq r \quad \text{Eq. 5-29}$$

For $\tilde{f}x \leq r$, the possibility (Pos) and necessity (Nec) of $\tilde{f}x \leq r$ can be illustrated as shown in Figure 5-2.

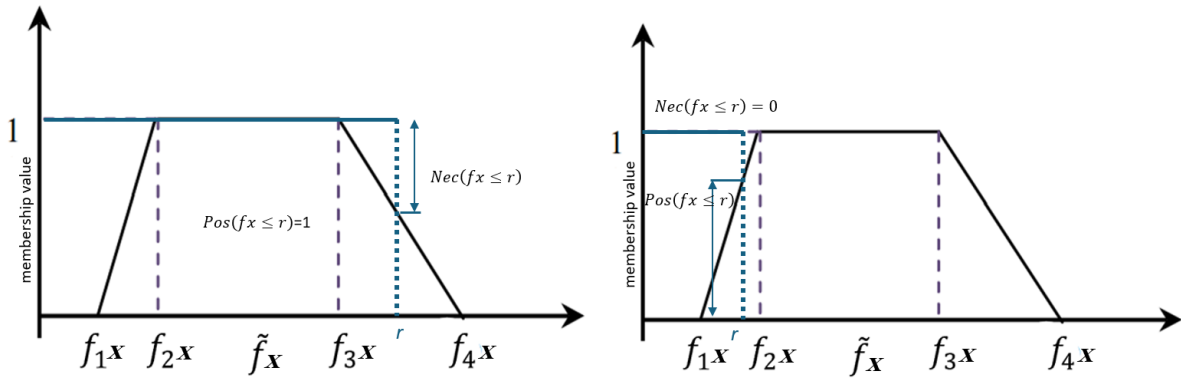


Figure 5-2. Possibility and necessity degrees of $\tilde{f}x \leq r$ following (Inuiguchi & Ramík, 2000).

Considering the trapezoidal possibility distribution, the possibility and necessity of $\tilde{f}x \leq r$ could be written as follows (Inuiguchi & Ramík, 2000):

$$Pos\{\tilde{f}x \leq r\} = \begin{cases} 1, & f_2 \leq r \\ \frac{r - f_1x}{f_2x - f_1x}, & f_1 \leq r \leq f_2 \\ 0, & f_1 \geq r \end{cases} \quad \text{Eq. 5-30}$$

$$Nec\{\tilde{f}x \leq r\} = \begin{cases} 1, & f_4 \leq r \\ \frac{r - f_3x}{f_4x - f_3x}, & f_3 \leq r \leq f_4 \\ 0, & f_3 \geq r \end{cases} \quad \text{Eq. 5-31}$$

The uncertain parameter can also appear in the constraints, as shown below, where x is a decision variable and r is a parameter.

$$\tilde{f}x \geq r$$

Eq. 5-32

For $\tilde{f}x \geq r$, the possibility (Pos) and necessity (Nec) of $\tilde{f}x \geq r$ can be illustrated as shown in Figure 5-3.

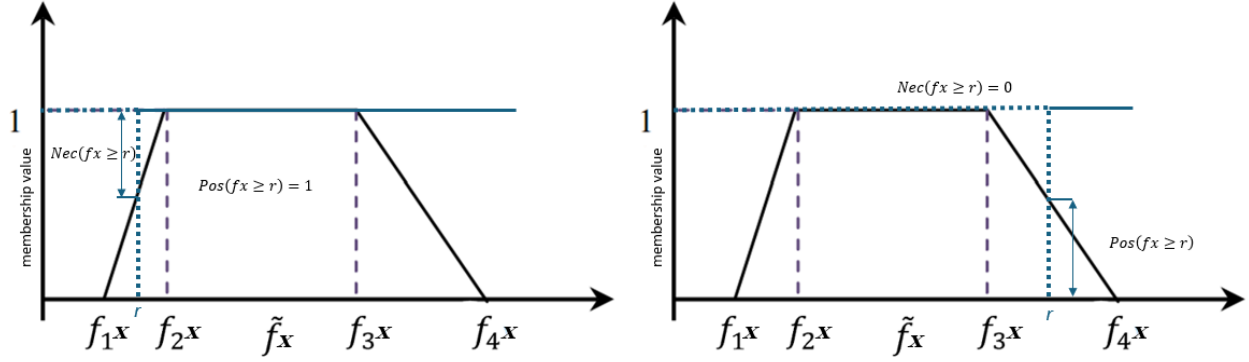


Figure 5-3. Possibility and necessity degrees of $\tilde{f}x \leq r$ following (Inuiguchi & Ramík, 2000).

Considering the trapezoidal possibility distribution, the possibility and necessity of $\tilde{f}x \leq r$ could be written as follows (Inuiguchi & Ramík, 2000):

$$Pos\{\tilde{f}x \geq r\} = \begin{cases} 1, & r \leq f_3 \\ \frac{f_4x - r}{f_4x - f_3x}, & f_3 \leq r \leq f_4 \\ 0, & r \geq f_4 \end{cases} \quad \text{Eq. 5-33}$$

$$Nec\{\tilde{f}x \geq r\} = \begin{cases} 1, & r \leq f_1 \\ \frac{f_2x - r}{f_2x - f_1x}, & f_1 \leq r \leq f_2 \\ 0, & f_3 \geq r \end{cases} \quad \text{Eq. 5-34}$$

Therefore, considering confidence levels (α, β) , which represent the minimum acceptable necessity that a constraint is satisfied, the constraints $Nec\{\tilde{f}x \geq r\} \geq \alpha$ and $Nec\{\tilde{f}x \leq r\} \geq \beta$ could be written as follows:

$$Nec\{\tilde{f}x \geq r\} = \frac{f_2 - r}{f_2 - f_1} \geq \alpha \rightarrow f_2 - r \geq \alpha f_2 - \alpha f_1 \rightarrow r \leq \alpha f_1 + f_2(1 - \alpha) \quad \text{Eq. 5-35}$$

$$Nec\{\tilde{f}x \leq r\} = \frac{r - f_3}{f_4 - f_3} \geq \beta \rightarrow r - f_3 \geq \beta f_4 - \beta f_3 \rightarrow r \geq \beta f_4 + f_3(1 - \beta) \quad \text{Eq. 5-36}$$

If r were an uncertain parameter instead of f , the same approach as in Eq. 70 and Eq. 71 would be applied. When treating the constraints it is important which side of the inequality the uncertain parameter appears on.

The uncertain parameter can also appear in an equality constraint, like the two cases below, where y is a variable:

$$\tilde{f}x = r \quad \text{Eq. 5-37}$$

$$\tilde{f}x = r y \quad \text{Eq. 5-38}$$

Regarding the equality constraints, the necessity measure cannot be used to derive the crisp counterpart of the model. This is because enforcing necessity on both sides would require the constraints $r \leq \alpha f_1 + f_2(1 - \alpha)$ and $r \geq \alpha f_4 + f_3(1 - \alpha)$ or $r y \leq \alpha f_1 + f_2(1 - \alpha)$ and $r y \geq \alpha f_4 + f_3(1 - \alpha)$ to hold simultaneously, which would make Eq. 64 infeasible, and in Eq. 66 it would force the decision variables to take trivial values (i.e., zero) in order to satisfy both bounds. To address this issue, (Torabi et al., 2016), used the *Me* measure, which combines the possibility and necessity measures to provide an integrated optimistic-pessimistic view. This measure is defined as follows, where θ represents the decision maker's degree of optimism-pessimism.

$$Me(\tilde{f}x \leq r) = Nec(\tilde{f}x \leq r) + \theta (Pos(\tilde{f}x \leq r) - Nec(\tilde{f}x \leq r)) \quad \text{Eq. 5-39}$$

$$Me(\tilde{f}x \geq r) = Nec(\tilde{f}x \geq r) + \theta (Pos(\tilde{f}x \geq r) - Nec(\tilde{f}x \geq r)) \quad \text{Eq. 5-40}$$

Therefore, for $\tilde{f}x \leq r$ and $\tilde{f}x \geq r$ the *Me* measure can be written as below:

$$Me\{\tilde{f}x \leq r\} = \begin{cases} 0, & r \leq f_1 \\ \theta \frac{r - f_1x}{f_2x - f_1x}, & f_1 \leq r \leq f_2 \\ \theta, & f_2 \leq r \leq f_3 \\ \theta + (1 - \theta) \frac{r - f_3x}{f_4x - f_3x}, & f_3 \leq r \leq f_4 \\ 1, & r \geq f_4 \end{cases} \quad \text{Eq. 5-41}$$

$$Me\{\tilde{f}x \geq r\} = \begin{cases} 1, & r \leq f_1 \\ \theta + (1 - \theta) \frac{f_2x - r}{f_2x - f_1x}, & f_1 \leq r \leq f_2 \\ \theta, & f_2 \leq r \leq f_3 \\ \theta \frac{f_4x - r}{f_4x - f_3x}, & f_3 \leq r \leq f_4 \\ 0, & r \geq f_4 \end{cases} \quad \text{Eq. 5-42}$$

Torabi et al. (2016) stated that the only interval in which $Me\{\tilde{f}x \leq r\} = Me\{\tilde{f}x \geq r\}$ holds is when $f_2x \leq r \leq f_3x$. Therefore, for equality constraints, they propose the following equivalence to derive the crisp counterpart:

$$\tilde{f}x \approx r \Leftrightarrow f_2x \leq r \leq f_3x \quad \text{Eq. 5-43}$$

Similarly, for $\tilde{f}x \approx ry$, the following equivalence can be written to derive the crisp counterpart:

$$\tilde{f}x \approx ry \Leftrightarrow f_2x \leq ry \leq f_3x \quad \text{Eq. 5-44}$$

5.3 Uncertain parameters

The lowest level represents a 50% decrease from the values used in the deterministic model, the midpoint is equal to the deterministic value, and the highest level represents a 50% increase relative to the deterministic value.

$$\widetilde{VC}_p = (VC_p^{(1)}, VC_p^{(2)}, VC_p^{(3)}, VC_p^{(4)}) = (0.5VC_p, VC_p, VC_p, 1.5VC_p) \quad \text{Eq. 5-45}$$

$$\widetilde{CT}_t = (CT_t^{(1)}, CT_t^{(2)}, CT_t^{(3)}, CT_t^{(4)}) = (0.5CT_t, CT_t, CT_t, 1.5CT_t) \quad \text{Eq. 5-46}$$

$$\widetilde{CP}_t = (CP_t^{(1)}, CP_t^{(2)}, CP_t^{(3)}, CP_t^{(4)}) = (0.5CP_t, CP_t, CP_t, 1.5CP_t) \quad \text{Eq. 5-47}$$

$$\widetilde{DM}_{pt} = (DM_{pt}^{(1)}, DM_{pt}^{(2)}, DM_{pt}^{(3)}, DM_{pt}^{(4)}) = (0.5DM_{pt}, DM_{pt}, DM_{pt}, 1.5DM_{pt}) \quad \text{Eq. 5-48}$$

The feedstock subsidies are deducted from the transportation costs. If this results in negative transportation costs, they are set equal to zero. This adjustment modifies the transportation cost parameters in the input data.

$$\begin{aligned} \widetilde{TC_{fwijt}} &= (TC_{fwijt}^{(1)}, TC_{fwijt}^{(2)}, TC_{fwijt}^{(3)}, TC_{fwijt}^{(4)}) \\ &= (TC_{fwijt} - 0.5(12 \times 2.25), TC_{fwijt} - 12 \times 2.25, TC_{fwijt} \\ &\quad - 12 \times 2.25, TC_{fwijt} - 1.5(12 \times 2.25)) \end{aligned} \quad \text{Eq. 5-49}$$

For capital investment costs, the government-covered portion is considered uncertain. The lowest level assumes that 25% of the original investment cost is covered, the midpoint assumes 50% coverage (as considered in the deterministic model), and the highest level assumes 75% coverage. However, the covered amount is subject to a \$10 million cap. If the calculated covered amount exceeds this cap, \$10 million is deducted from the original capital investment cost. If the covered amount is below the cap, only the calculated covered amount is deducted. The remaining value is then used as the effective capital investment cost in the mathematical model.

Therefore, the capital cost can be written as follows. Note that if the cap is reached, only the capped amount will be deducted from the original capital cost.

$$\begin{aligned} \widetilde{CC_{cpj}} &= (CC_{cpj}^{(1)}, CC_{cpj}^{(2)}, CC_{cpj}^{(3)}, CC_{cpj}^{(4)}) \\ &= (CC_{cpj} - 0.25CC_{cpj}, CC_{cpj} - 0.5CC_{cpj}, CC_{cpj} - 0.5CC_{cpj}, CC_{cpj} \\ &\quad - 0.75CC_{cpj}) \end{aligned} \quad \text{Eq. 5-50}$$

For the depreciation calculations, the deterministic model assumes that 75% of the capital cost can be written off as depreciation. Accordingly, $DP_{cpt}^{(2)}$ and $DP_{cpt}^{(3)}$ are calculated based on this assumption. $DP_{cpt}^{(1)}$ is calculated assuming that 50% of the capital cost can be written off as depreciation, while $DP_{cpt}^{(4)}$ is calculated assuming that 100% of the capital cost can be written off as depreciation.

$$\widetilde{DP_{cpt}} = (DP_{cpt}^{(1)}, DP_{cpt}^{(2)}, DP_{cpt}^{(3)}, DP_{cpt}^{(4)}) \quad \text{Eq. 5-51}$$

5.4 Non-deterministic single objective model

Following the possibilistic chance constraint programming approach, the crisp counterpart formulation for the single-objective all-policy scenario can be formulated as below. Please note

that as Eq. 5-65, Eq. 5-66, Eq. 5-68, and Eq. 5-69 are inherently equality constraints; therefore, they were treated as suggested for equality constraints.

$$Max. NPV = Max. (PTR - PTC) - PIC - (PTR - PTC - DEP) \times TR \quad \text{Eq. 5-52}$$

$$PTR = \sum_{t \in T} \sum_{p \in P} \sum_{j \in J} \frac{(PR_p \times y_{jpt}) + \left(\frac{CP_t^{(1)} + CP_t^{(2)} + CP_t^{(3)} + CP_t^{(4)}}{4} \times s_{jpt} \right)}{(1 + \alpha)^t} \quad \text{Eq. 5-53}$$

$$PTC = \sum_{t \in T} \frac{1}{(1 + \alpha)^t} \quad \text{Eq. 5-54}$$

$$\begin{aligned} & \times \left(\sum_{c \in C} \sum_{p \in P} \sum_{j \in J} FC_{cp} \times q_{jcpt} \right. \\ & + \sum_{p \in P} \sum_{i \in I} \sum_{j \in J} \sum_{(f,w) \in O} \frac{VC_p^{(1)} + VC_p^{(2)} + VC_p^{(3)} + VC_p^{(4)}}{4} \times x_{fwijpt} \\ & + \sum_{p \in P} \sum_{i \in I} \sum_{j \in J} \sum_{(f,w) \in O} PC_w \times x_{fwijpt} \\ & + \sum_{p \in P} \sum_{i \in I} \sum_{j \in J} \sum_{(f,w) \in O} \frac{TC_{fwijt}^{(1)} + TC_{fwijt}^{(2)} + TC_{fwijt}^{(3)} + TC_{fwijt}^{(4)}}{4} \\ & \times x_{fwijpt} + \sum_{p \in P} \sum_{j \in J} p_{jpt} \times \frac{CT_t^{(1)} + CT_t^{(2)} + CT_t^{(3)} + CT_t^{(4)}}{4} \\ & \left. + \sum_{p \in P} \sum_{j \in J} c_{jpt} \times \frac{CP_t^{(1)} + CP_t^{(2)} + CP_t^{(3)} + CP_t^{(4)}}{4} \right) \end{aligned}$$

$$PIC = \sum_{c \in C} \sum_{p \in P} \sum_{j \in J} \frac{CC_{cpj}^{(1)} + CC_{cpj}^{(2)} + CC_{cpj}^{(3)} + CC_{cpj}^{(4)}}{4} \times q_{jcp} \quad \text{Eq. 5-55}$$

$$DEP = \sum_{c \in C} \sum_{p \in P} \sum_{j \in J} \frac{DP_{cpt}^{(1)} + DP_{cpt}^{(2)} + DP_{cpt}^{(3)} + DP_{cpt}^{(4)}}{4} \times q_{jcp} \quad \text{Eq. 5-56}$$

Constraints

$$\sum_{p \in P} \sum_{w \in W} x_{fwijpt} \leq SS_{fijt} \quad \forall t \in T, f \in F, i \in I, j \in J \quad \text{Eq. 5-57}$$

$$\sum_{p \in P} \sum_{i \in I} \sum_{(f,w) \in O} PY_p \times x_{fwijpt} = y_{jpt} \quad \forall t \in T, j \in J, p \in P \quad \text{Eq. 5-58}$$

$$\sum_{i \in I} \sum_{(f,w) \in O} x_{fwijpt} \leq \sum_{c \in C} KK_{cp} \times q_{jcp} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-59}$$

$$\sum_{c \in C} q_{jcp} \leq 1 \quad \forall j \in J, p \in P \quad \text{Eq. 5-60}$$

$$0.7 \times \sum_{c \in C} KK_{cp} \times q_{jcp} \leq \sum_{i \in I} \sum_{(f,w) \in O} x_{fwijpt} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-61}$$

$$\sum_{j \in J} y_{jpt} \leq \alpha DM_{pt}^{(1)} + (1 - \alpha) DM_{pt}^{(2)} \quad \forall t \in T, p \in P \quad \text{Eq. 5-62}$$

$$\begin{aligned} \sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} - M \times a_{jpt} \\ \leq \left[\beta EL_{pt}^{(1)} + (1 - \beta) EL_{pt}^{(2)} \right] \times y_{jpt} \quad \forall j \in J, p \in P, t \in T \end{aligned} \quad \text{Eq. 5-63}$$

$$\begin{aligned} \sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} + M \times (1 - a_{jpt}) \\ \geq \left[(1 - \beta) EL_{pt}^{(3)} + \beta EL_{pt}^{(4)} \right] \times y_{jpt} \quad \forall j \in J, p \in P, t \in T \end{aligned} \quad \text{Eq. 5-64}$$

$$e_{jpt} \geq \sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} - EL_{pt}^{(3)} \times y_{jpt} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-65}$$

$$e_{jpt} \leq \sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} - EL_{pt}^{(2)} \times y_{jpt} + M \times (1 - a_{jpt}) \quad \text{Eq. 5-66}$$

$$\forall j \in J, p \in P, t \in T$$

$$e_{jpt} \leq M \times (a_{jpt}) \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-67}$$

$$g_{jpt} \geq EL_{pt}^{(2)} \times y_{jpt} - \sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-68}$$

$$g_{jpt} \leq EL_{pt}^{(3)} \times y_{jpt} - \sum_{(f,w) \in O} \sum_{i \in I} \sum_{c \in C} x_{fwijpt} \times PO_{wp} + M \times (a_{jpt}) \quad \text{Eq. 5-69}$$

$$\forall j \in J, p \in P, t \in T$$

$$g_{jpt} \leq M \times (1 - a_{jpt}) \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-70}$$

$$b_{jpt} = g_{jpt} - u_{jpt} - s_{jpt} \quad \forall j \in J, p \in P, t \in \{1\} \quad \text{Eq. 5-71}$$

$$b_{jpt} = b_{jpt-1} + g_{jpt} - u_{jpt} - s_{jpt} \quad \forall j \in J, p \in P, t \in \{2, \dots, T\} \quad \text{Eq. 5-72}$$

$$e_{jpt} = u_{jpt} + c_{jpt} + p_{jpt} \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-73}$$

$$u_{jpt} + c_{jpt} \leq CL_t \times (e_{jpt}) \quad \forall j \in J, p \in P, t \in T \quad \text{Eq. 5-74}$$

$$e_{jpt}, g_{jpt}, c_{jpt}, u_{jpt}, s_{jpt}, b_{jpt}, p_{jpt}, y_{jpt}, x_{fwijpt} \geq 0 \quad \text{Eq. 5-75}$$

$$\forall f \in F, w \in W, i \in I, j \in J, p \in P, t \in T$$

$$a_{jpt}, q_{jcp} \in \{0,1\} \quad \forall c \in C, i \in I, j \in J, p \in P \quad \text{Eq. 5-76}$$

$$y_{jpt}, x_{fwijpt} \geq 0 \quad \forall f \in F, w \in W, i \in I, j \in J, p \in P, t \in T \quad \text{Eq. 5-77}$$

5.5 Non-deterministic bi-objective model

The non-deterministic bi-objective model is solved using the same method explained in Section 4.5.

5.6 Results of the non-deterministic single objective model

Table 5-2 presents the facilities suggested for establishment by the deterministic and non-deterministic models under the all-policy scenario. The deterministic model results indicate that 16 facilities would be established to produce AC, CNF, pellets, and biochar.

Under the non-deterministic model with a confidence level of 0.5, 10 facilities are suggested for establishment. Based on these results, two biochar facilities, one pellet facility, and one CNF facility are excluded from the network, and one large AC facility is replaced with a medium-sized facility.

When the confidence level is increased to 1, representing a more conservative assumption in which uncertain parameters within constraints of the model take their worst-case values, only six facilities are suggested for establishment, producing CNF and pellets.

Table 5-2. Bioproduction facility establishments under the scenario where all policies are implemented deterministic and non-deterministic models

Location	Bioproduct	Capacity	Deterministic solution	Non-deterministic solution ($\alpha = \beta = 0.5$)	Non-deterministic solution ($\alpha = \beta = 1$)
Hanceville	AC (Activated Carbon)	Large (3,756 odt/year)	✓	✓	-
	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	✓	✓
	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓
	Biochar (wet torrefaction)	Small (80 odt/yr)	✓	-	-
	Biochar (dry torrefaction)	Small (50 odt/yr)	✓	-	-
Anahim Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓
Williams Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	-	-
Horsefly	AC (Activated Carbon)	Large (3,756 odt/year)	✓	-	-
	AC (Activated Carbon)	Medium (2,504 odt/year)	-	✓	-
	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	-	-
	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓
	Biochar (wet torrefaction)	Small (80 odt/yr)	✓	-	-
	Biochar (dry torrefaction)	Small (50 odt/yr)	✓	-	-

Figure 5-4 compares the financial performance and total GHG emissions of the deterministic and non-deterministic models under the all-policy scenario. The deterministic solution yields the highest economic performance, with an NPV of \$44 million, while total emissions reach 218 thousand tonnes of CO₂-eq.

When uncertainty is incorporated at a confidence level of 0.5, NPV decline to \$28 million, and total emissions decrease to 176 thousand tonnes of CO₂-eq. Increasing the confidence level to 1, representing a more conservative assumption, further reduces the NPV to \$25 million, while emissions drop significantly to one thousand tonnes of CO₂-eq.

Overall, incorporating uncertainty leads to more conservative investment decisions, resulting in fewer facilities suggested to be established, lower financial returns, and substantially reduced emissions.

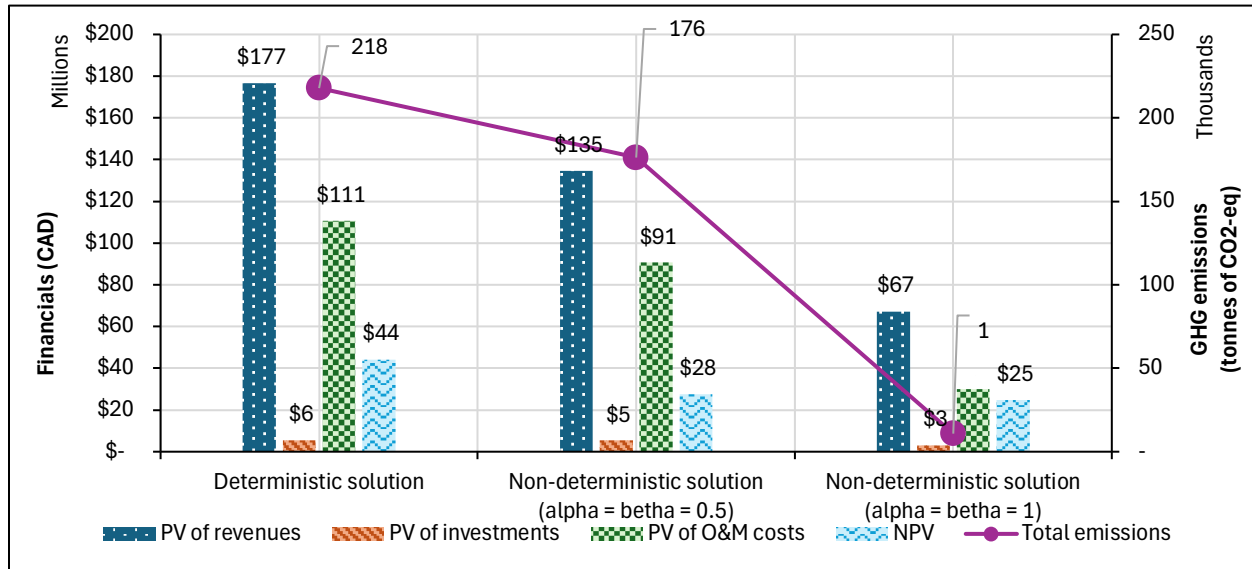


Figure 5-4. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions for the deterministic solution and two non-deterministic solutions (confidence level = 0.5 and 1) under the all-policy scenario.

5.7 Results of the non-deterministic bi-objective model

Figure 5-5 presents the Pareto front of the non-deterministic model with a confidence level of 0.5 for the scenario in which all policies are implemented.

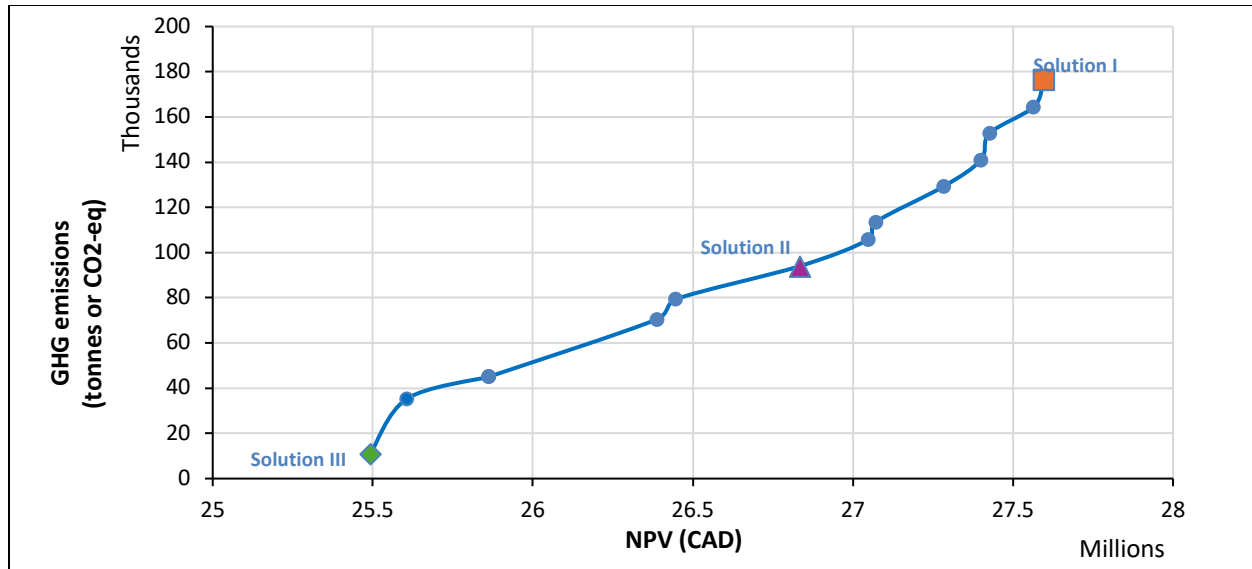


Figure 5-5. Pareto-optimal solutions of the non-deterministic bi-objective model (confidence level = 0.5) illustrating changes in NPV (net present value) as emissions vary under the scenario where all policies are implemented.

As shown in Table 5-3, Solution I, which is the same as the solution obtained from the associated non-deterministic single objective model where NPV was maximized without any emission minimization considerations, suggests establishing 10 facilities to produce AC, CNF, and pellets. When emission levels are reduced by approximately 47% in Solution II ($\epsilon = 93,991$), one AC is excluded from the supply chain network and NPV reduces by only 2.8%. Lowering emissions by 93% in Solution III ($\epsilon = 11,749$) results in the elimination of two AC from the network and a 7.6% reduction in the NPV.

Table 5-3. Bioproduction facility establishments under the scenario where all policies are implemented for three Pareto-optimal solutions (non-deterministic bi-objective model).

Location	Bioproduct	Capacity	Non-deterministic Solution I ($\alpha = \beta = 0.5$) ($\epsilon = 176,234$)	Non-deterministic Solution I ($\alpha = \beta = 0.5$) ($\epsilon = 93,991$)	Non-deterministic Solution I ($\alpha = \beta = 0.5$) ($\epsilon = 11,749$)
Hanceville	AC (Activated Carbon)	Large (3,756 odt/year)	✓	✓	-
	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	✓	✓
	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓
Anahim Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓
Williams Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
Horsefly	AC (Activated Carbon)	Medium (2,504 odt/year)	✓	-	-
	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	✓	✓

In Figure 5-6, Solution I shows the highest emissions (176 thousand tonnes of CO₂-eq) and NPV (\$28 million). In solution II, where emissions are lower at 94 thousand tonnes of CO₂-eq, the NPV decreases to approximately \$27 million. In Solution III, emissions are at the lowest level of 11 thousand tonnes of CO₂-eq, and NPV decreases to approximately \$25 million.

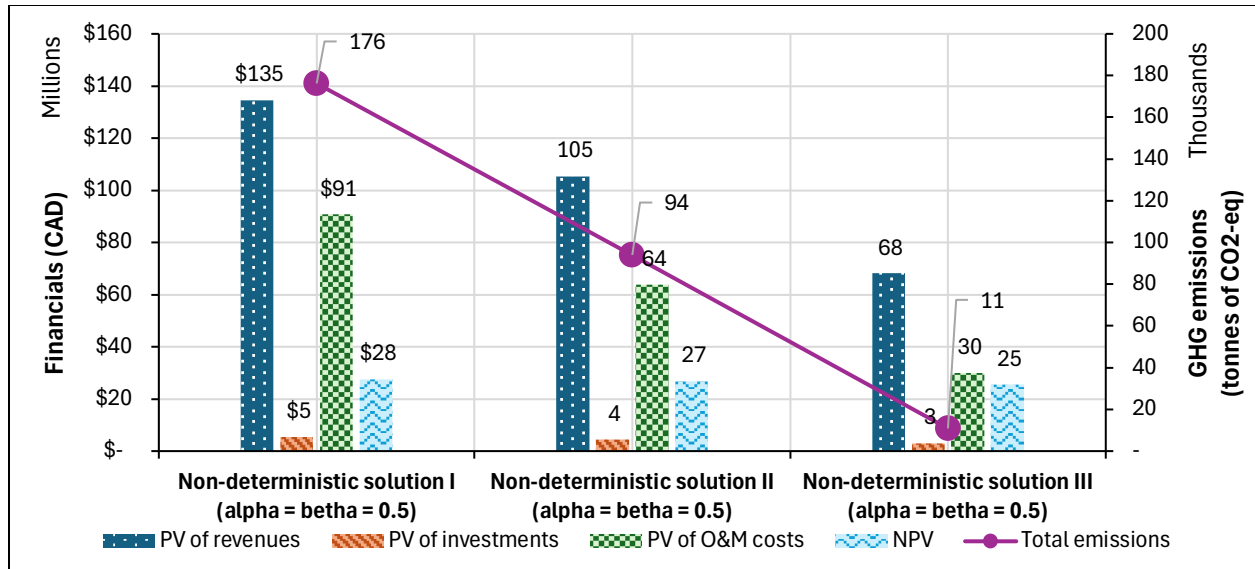


Figure 5-6. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the all-policy scenario for three Pareto-optimal solutions obtained from the bi-objective non-deterministic model (confidence level = 0.5).

Figure 5-7 presents the Pareto front of the non-deterministic model with a confidence level of one for the scenario in which all policies are implemented.

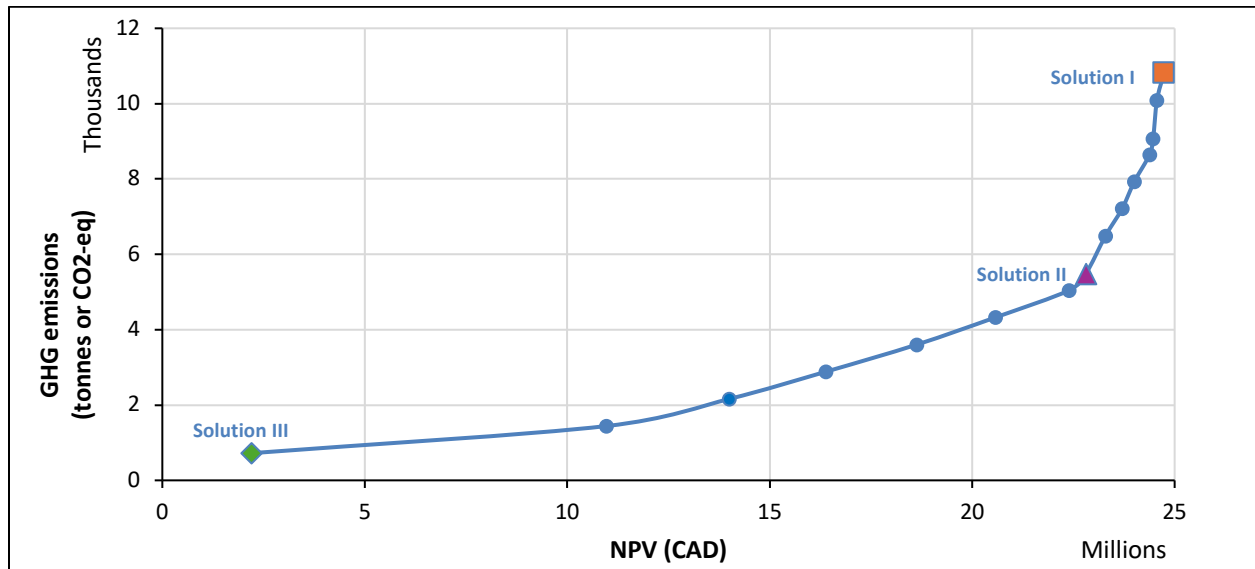


Figure 5-7. Pareto-optimal solutions of the non-deterministic bi-objective model (confidence level = 1) illustrating changes in NPV (net present value) as emissions vary under the scenario where all policies are implemented.

As shown in Table 5-4, Solution I, which is the same as the solution obtained from the associated non-deterministic single objective model where NPV was maximized without any emission minimization considerations, suggests establishing eight facilities to produce CNF and pellets. When emission levels are reduced by approximately 47% in Solution II ($\epsilon = 5,767$), three pellet production facilities are excluded from the supply chain network and NPV reduces by only 7.8%. Lowering emissions by 93% in Solution III ($\epsilon = 721$) results in establishment of only one pellet production facility and a 91.1% reduction in the NPV.

Table 5-4. Bioproduction facility establishments under the scenario where all policies are implemented for three Pareto-optimal solutions (non-deterministic bi-objective model).

Location	Bioproduct	Capacity	Non-deterministic Solution I ($\alpha = \beta = 1$) ($\epsilon = 10,814$)	Non-deterministic Solution I ($\alpha = \beta = 1$) ($\epsilon = 5,767$)	Non-deterministic Solution I ($\alpha = \beta = 1$) ($\epsilon = 721$)
Hanceville	CNF (Cellulose Nanofibrils)	Small (136 odt/year)	✓	✓	-
	High quality pellets	Small (3,912 odt/year)	✓	✓	-
	Low quality pellets	Small (2,778 odt/year)	✓	-	-
Anahim Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	-
	Low quality pellets	Small (2,778 odt/year)	✓	-	-
Williams Lake	High quality pellets	Small (3,912 odt/year)	✓	✓	-
Horsefly	High quality pellets	Small (3,912 odt/year)	✓	✓	✓
	Low quality pellets	Small (2,778 odt/year)	✓	-	-

Figure 5-8, Solution I shows the highest emissions (11 thousand tonnes of CO₂-eq) and NPV (\$25 million). In solution II, where emissions are lower at five thousand tonnes of CO₂-eq, the NPV decreases to approximately \$23 million. In Solution III, emissions are at the lowest level of one thousand tonnes of CO₂-eq, and NPV decreases to approximately \$2 million.

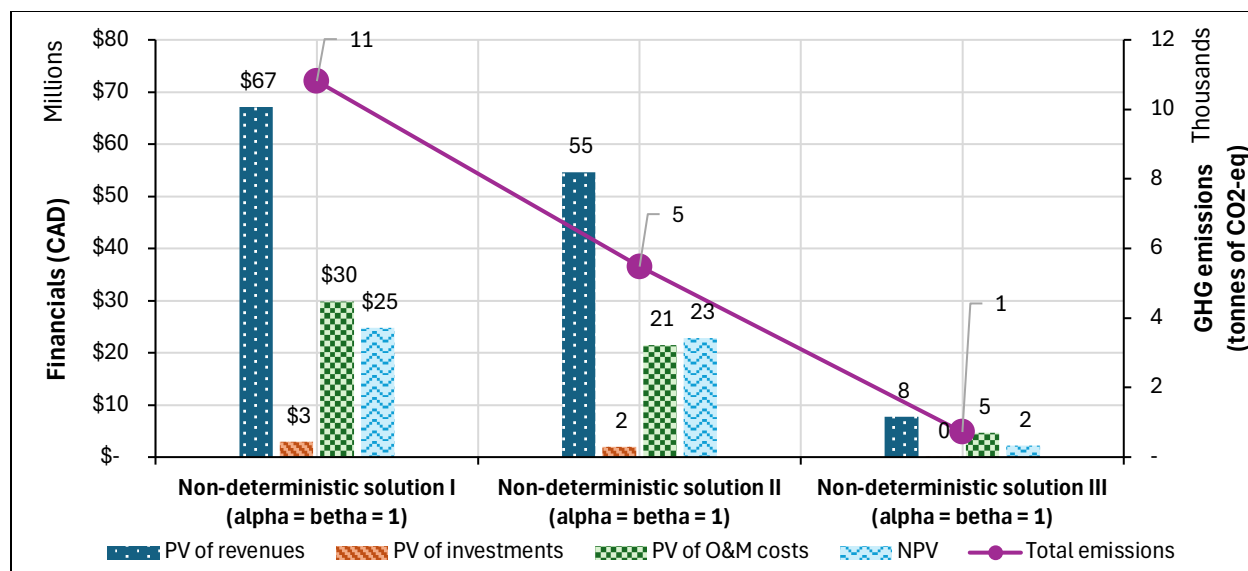


Figure 5-8. PV (present value) of revenues, O&M (operating & maintenance) costs, investments, NPV (net present value), and emissions under the all-policy scenario for three Pareto-optimal solutions obtained from the bi-objective non-deterministic model (confidence level = 1).

5.8 Comparison of pareto fronts across non-deterministic and deterministic models

Figure 5-9 compares the Pareto fronts of the deterministic model with those of the non-deterministic model under two confidence levels ($\alpha = \beta = 1$ and $\alpha = \beta = 0.5$). The deterministic model yields the highest NPV, ranging approximately from 40 to 44 million CAD; however, this is achieved at substantially higher GHG emissions (roughly 15 to over 218 thousand tonnes of CO₂-eq). In contrast, the non-deterministic model with $\alpha = \beta = 0.5$ produces moderate profit levels (around 26 to 29 million CAD) with emissions that increase sharply as profit rises, reaching nearly 180 thousand tonnes of CO₂-eq. The most conservative case ($\alpha = \beta = 1$) results in the lowest profit levels (approximately 5 to 24 million CAD) but maintains emissions at significantly lower levels, generally below 15 thousand tonnes of CO₂-eq.

Overall, the figure illustrates the trade-off between GHG emissions and NPV, and shows that higher confidence levels lead to more conservative solutions that reduce both profitability and emissions, while the deterministic model achieves greater profitability at the cost of substantially higher emissions.

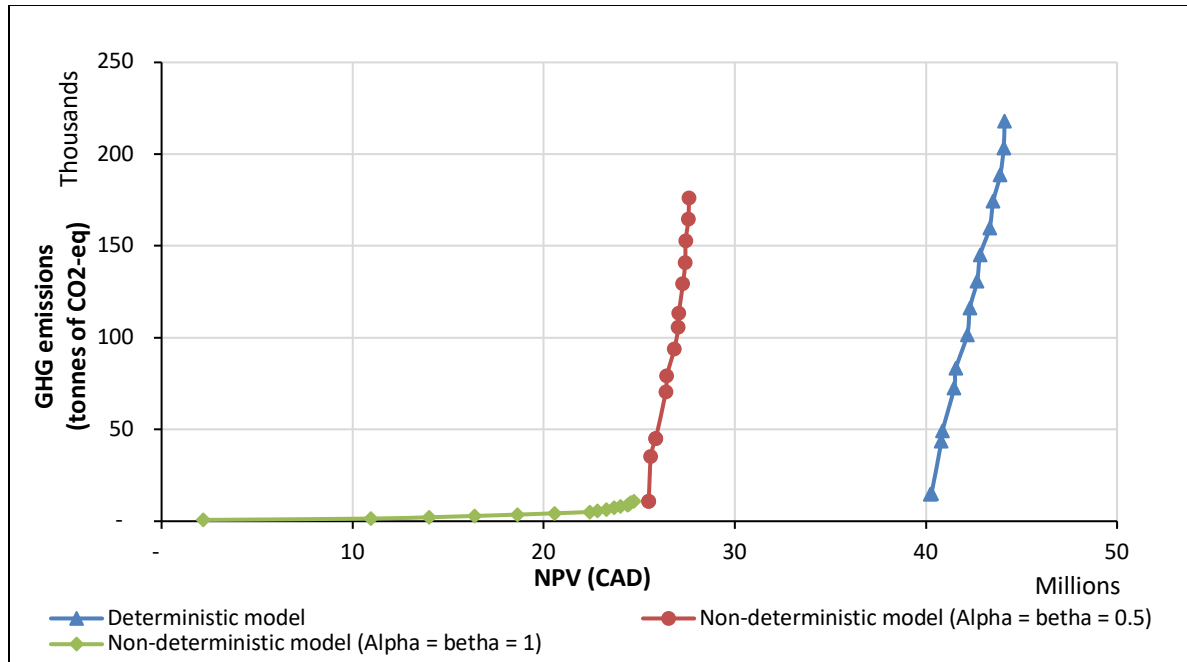


Figure 5-9. Comparison of Pareto fronts obtained from the deterministic model and the non-deterministic model under two confidence levels ($\alpha = \beta = 1$ and $\alpha = \beta = 0.5$)

5.9 Conclusion

In the non-deterministic model, uncertainty in policy-related parameters (feedstock subsidy levels, the percentage of initial investments that could be written off as depreciation, the percentage of capital investment cost coverage, carbon prices, and emission limits), as well as uncertainty in the maximum demand and variable operating and maintenance costs (identified through sensitivity analysis), were taken into account. Using possibilistic chance constraint programming, both single- and bi-objective models under all policies were solved.

The results of the non-deterministic models demonstrated that incorporating uncertainty substantially altered both the structure (i.e., number of facilities to be established) and performance (i.e., NPV and emissions) of the proposed supply chain network. Compared to the deterministic model, which recommended a larger and more investment-intensive network with the highest NPV and higher GHG emissions, the non-deterministic model yielded more conservative configurations with fewer facilities and reduced production capacity. At a 0.5 confidence level, the non-deterministic single-objective model resulted in 10 facilities with an NPV of \$28 million, compared to 16 facilities with an NPV of \$44 million in the deterministic case without uncertainty.

As the confidence level increased (reflecting greater conservatism toward uncertain parameters and ensuring that the obtained solutions remain feasible even under worst-case parameter values), the model resulted in smaller networks, lower profitability, and substantially reduced emissions, with the number of facilities decreasing from 10 to eight and NPV declining from \$28 million to \$25 million.

The bi-objective non-deterministic model also showed reductions in both NPV and emissions. The average NPV and emissions of the Pareto solutions in the deterministic model were \$42 million and 114 thousand tonnes of CO₂-eq, respectively. These values decreased to \$27 million and 92 thousand tonnes of CO₂-eq at a confidence level of 0.5, and further to \$20 million and 5 thousand tonnes of CO₂-eq at a confidence level of 1. This corresponds into 36% and 52% decrease in NPV at confidence levels of 0.5 and 1, respectively.

The results from the non-deterministic models indicate that accounting for uncertainty in policy-related and market parameters significantly affects decisions regarding the utilization of slash and biomass supply chain designs.

Chapter 6: Conclusions, Strengths, Limitations, and Future Research Direction

6.1 Conclusions

The forest-based biomass has significant potential for producing value-added products. This not only supports the development of the bioeconomy and reduces dependence on fossil-based products, but also mitigates issues related to residue management, such as piling and burning of residues. However, converting residues into bioproducts involves multiple stages, including collection, transportation, preprocessing, and final conversion, each associated with relatively high costs.

This highlights the need for a supply chain perspective, as these interconnected stages influence one another. To produce bioproducts at the lowest possible cost or highest profit, optimizing the entire biomass-to-bioproduct supply chain is essential. While such optimization can improve efficiency and profitability, bioproducts may still face challenges in achieving economic competitiveness. Therefore, their successful utilization depends heavily on supportive government policies and well-designed supply chains.

Although existing studies have developed optimization models for forest-based biomass supply chains, many did not explicitly incorporate governmental policies and programs, limiting their applicability to real-world scenarios. In addition, uncertainties within both supply chain parameters and policy frameworks should be considered when making decisions regarding supply chain design and planning.

The overall objective of this study was to optimize the design and planning of a forest biomass-to-bioproduct supply chain that maximizes profit and minimizes emissions, while accounting for governmental policies and the uncertainties associated with them.

Chapter 2 presented a review of the literature on optimization models for forest-based biomass supply chain planning that explicitly incorporated one or more forms of governmental programs or policies. The review revealed that the integration of governmental policies in such models remains relatively underexplored, with only a limited number of studies compared to the broader body of work on biomass supply chains.

The findings also indicated that carbon pricing policies were the most commonly addressed, while other policy categories, including tax-related, market-based, and financial incentive mechanisms, have received comparatively less attention. Furthermore, the majority of studies relied on deterministic models, often overlooking the presence of uncertainties within the supply chain and policy frameworks. Only a small number of studies considered both policy and uncertainty simultaneously (e.g., Abusaq et al., 2022; Walther et al., 2012), and notably, none accounted for uncertainties associated with policy-related parameters.

The aim of this research was to address these gaps and provide deeper insights into the role of governmental policies and programs in the design and optimization of forest-based biomass supply chains.

Chapter 3 presented the techno-economic assessment of utilizing forest-based biomass for production of selected bioproducts, with detailed analysis provided for cellulose nanocrystals and cellulose nanofibrils, while results for other products (biochar, pellets, and activated carbon) are included in 0 and 0. The primary purpose of this assessment was to determine the required equipment pieces and pathways within the biomass-to-bioproduct supply chain and to identify infeasible bioproducts and exclude them from the subsequent optimization model.

The analysis evaluated economic feasibility by calculating the net present value (NPV) of the supply chain across different production scales (small, medium, large) and locations within the Williams Lake Timber Supply Area in British Columbia. It also examined the impact of key governmental policies, including feedstock subsidies, capital investment incentives, enhanced first-year depreciation, and carbon pricing, on economic performance. The results indicated that policies generally had limited impact on the NPV of the individual facilities and that bio-oil production was economically infeasible across all production scales, locations, and supply chain pathways. Consequently, this product was excluded from further analysis in the optimization phase.

Chapter 4 presented deterministic single- and bi-objective models to design and plan for a forest-based biomass-to-bioproduct supply chain, considering NPV maximization and GHG emissions minimization of the supply chain. The mathematical models under without policy, each policy separately and all policy scenarios were developed and the results of them were compared. The

main decisions made through the model included: the size and type of the bioproduction technology to be established at a potential location in the beginning of the 20-year planning horizon, the annual amount of biomass of different types (small-diameter logs or other types of residues) to be transported from each cut block to each potential bioproduction location (i.e., biohub) to produce a specific product via bundled, ground, or small-diameter logs pathways. Decisions on the selected pathway would inform us on where and how biomass is suggested to be preprocessed. The decisions also include the amount of annual amounts of bioproducts produced at each location. The model was applied to a case study in Williams Lake Timber Supply Area using real data related to this location on supply, cost, demand, etc. obtained from literature review, FPInnovations, and contacting vendors.

The single-objective model without policies, with feedstock subsidies, and enhanced first-year allowance for depreciation, recommended establishing 10 facilities producing AC, CNF, and pellets across Hanceville, Williams Lake, Anahim Lake, and Horsefly. The scenario without policies resulted in approximately \$28.8 million NPV over the 20-year planning horizon. The feedstock subsidies and enhanced first-year allowance for depreciation provided modest improvements in NPV to \$33.7 million and \$ 29.1, while capital investment incentives significantly expanded the network to 16 facilities and increased NPV to \$41.5 million. In contrast, the output-based pricing system (carbon pricing) reduced both the number of facilities and NPV due to emission-related costs, while also achieving the lowest emissions. When all policies were applied simultaneously, the model recommended 16 facilities with the highest NPV of \$44 million, demonstrating the strong impact of combined policy support on economic performance.

To solve the bi-objective models, the AUGMECON method was employed considering NPV maximization as the main objective function, while moving the GHG emissions to the constraints. The results of the bi-objective models showed that, as expected, higher NPVs were generally associated with higher emissions. However, the generated Pareto fronts indicated that substantial emission reductions could often be achieved with relatively small losses in profit, particularly under the no-policy, enhanced first-year depreciation, and feedstock subsidy scenarios. For instance, a 47% reduction in emissions resulted in only a 1–2% decrease in the supply chain's NPV under these scenarios.

In the all-policy scenario, emission reductions had a moderate impact, with a 47% decrease in emissions corresponding to a 4% reduction in NPV. The capital investment policy showed a more pronounced effect, with NPV decreasing by about 6% for a 47% reduction in emissions.

The output-based pricing policy exhibited the highest sensitivity, as emissions are directly linked to costs through carbon pricing. Under this policy, a 47% reduction in emissions resulted in approximately a 7% decrease in NPV, while a 93% reduction leads to a substantial 95% decrease in NPV.

Chapter 5 presented non-deterministic models introducing uncertainty in parameters related to governmental policies, market-related (maximum demands for bioproducts), and operational related (variable operating and maintenance cost). Since these uncertainties in the models stemmed from imprecise information and lack of knowledge rather than historical variability, possibility distributions were considered for the uncertain parameters, and possibilistic chance constraint programming approach was taken to address the uncertainties.

The results showed that incorporating uncertainty significantly changed both the proposed network configuration and its performance in terms of NPV and emissions. In contrast to the deterministic model, which suggested a larger network with more facilities, higher profitability and greater GHG emissions, the non-deterministic approach produced more conservative solutions with fewer facilities and lower production capacity. The non-deterministic single-objective model suggested 10 facilities to be established compared with 16 facilities in the equivalent deterministic model, and a decline of 37% in the NPV of supply chain. As the confidence level increased, indicating greater caution toward uncertain parameters and ensuring feasibility under worst-case conditions, the resulting networks became smaller with reduced profitability. This resulted in eight facilities suggested to be established and a 43% decrease in the NPV compared to those from the non-deterministic model.

The bi-objective non-deterministic model also resulted in lower NPV and emissions. Compared to the deterministic case (average NPV of \$42 million and emissions of 114 thousand tonnes of CO₂-eq), values decreased to \$27 million and 92 thousand tonnes at a confidence level of 0.5, and to \$20 million and 5 thousand tonnes at a confidence level of 1, corresponding to 36% and 52% reductions in NPV, respectively.

These findings highlighted that explicitly accounting for uncertainty in policy, market, and operational parameters has a substantial impact on decisions related to slash utilization.

6.2 Strengths

From a modelling perspective, the primary strength and contribution of this research lies in the development of a novel optimization framework for the strategic design of forest-based biomass supply chains that convert logging residues (slash) into high-value bioproducts under different governmental policy settings. Additionally, accounting for uncertainties in these policies and other highly sensitive parameters enhances the practicality and relevance of the study.

The model is based on a real case in Williams Lake Timber Supply Area in BC, Canada, and explicitly considers different biomass formats, a wide range of bioproducts, and multiple supply chain pathways that define how biomass is handled (e.g., chipped at cut blocks or supply sources and then transported, or bundled at cut blocks and chipped at biohubs). This provides a detailed representation of supply chain pathways and decisions, including multiple biomass types, processing options (e.g., bundled, ground, and small-diameter logs), facility locations, production scales, and bioproducts. The problem is formulated based on a real case study in British Columbia, ensuring strong practical relevance and alignment with current challenges in forest management and bioeconomy development.

A key strength of this work is the progressive development of the modelling framework across multiple stages, which enables systematic comparison and evaluation of the impacts of policies and uncertainties on supply chain design. The model is systematically extended from a techno-economic assessment to single-objective deterministic optimization without policies and then under policy scenarios, followed by bi-objective deterministic optimization models with and without policies, and further to non-deterministic single- and bi-objective formulations. Each stage builds on the previous one, allowing for a structured evaluation of how incorporating additional real-world complexities, such as uncertainty, policy considerations, and emissions, affects supply chain decisions. This step-by-step approach enables meaningful comparison of results and provides clear insights into the implications of different modelling assumptions.

From both practical and modelling perspectives, an important contribution of this research is the consideration of multiple policy mechanisms, including the development of a model for the BC

Output-Based Pricing System and the incorporation of uncertainties associated with their parameters. Simultaneously considering multiple policies and accounting for uncertainty better captures real-world conditions and enables the generation of solutions that remain feasible under different scenarios. This aspect, which has not been adequately addressed in previous studies, enhances the reliability of the results and highlights the impact of policies and uncertainty on network configuration, profitability, and emissions.

The research is further strengthened by the integration of bi-objective optimization, where both profit and emissions of the supply chain are considered simultaneously. The resulting Pareto fronts provide decision-makers with a set of optimal alternatives rather than a single solution, enabling more informed and flexible decision-making.

Finally, the research contributes to broader sustainability goals by demonstrating the potential to utilize logging residues as a valuable resource, reducing emissions from slash-pile burning, while creating economic value and job opportunities in regions such as the Williams Lake TSA, which are heavily dependent on the forestry sector.

6.3 Implications

This study provides practical insights for government, industry, and investors interested in advancing forest-based bioproduct development in British Columbia. From a government perspective, the results suggest that stronger or more targeted policy instruments may be required to support the development of forest-based bioproduct supply chains. While feedstock subsidies, tax incentives, and carbon pricing mechanisms can improve economic performance and reduce GHG emissions, their effects may be limited when market demand, capital costs, and technology-specific economics are the main constraints. In contrast, direct capital incentives and targeted support for commercially promising pathways can play a stronger role in enabling investment, especially for facilities with high upfront capital requirements. The findings also suggest that policy design should consider regional differences in biomass availability, transportation costs, processing capacity, and product markets, rather than assuming that all biomass pathways respond similarly to the same policy.

For industry, the study demonstrates that forest biomass utilization is not only a question of feedstock availability, but also of selecting the right combination of feedstock type, location,

technology, product, and facility scale. The results show that some pathways are more economically and environmentally attractive than others. This can help forest companies, bioenergy producers, and bioproduct developers identify which biomass resources are most suitable for value-added applications and where facilities may be most strategically located. The study also shows that uncertainty in market demand and policy conditions can substantially change optimal investment decisions, emphasizing the need for flexible and risk-aware planning.

From an investment perspective, the results provide a framework for evaluating forest-based bioproduct projects under both policy and market uncertainty. The findings suggest that investment decisions should not be based solely on technical feasibility or biomass availability, but should also account for long-term policy changes and market demand limitations. By identifying pathways and locations that remain viable under uncertain conditions, this study can support more informed investment decisions and reduce the risk of overbuilding capacity or investing in pathways with limited market potential.

However, if the suggested supply chain designs are to be implemented, several practical barriers should be considered. These include the technology readiness of some bioproduct pathways, uncertainties related to land management, tenure, and engagement with First Nations, and the assumptions used in estimating capital, operating, transportation, and preprocessing costs. In practice, additional costs may also arise from permitting, site preparation, infrastructure development, utility connections, workforce availability, financing, and project delays. Therefore, while the proposed supply chain designs provide useful strategic guidance, further project-specific technical, economic, regulatory, and community engagement assessments would be required before implementation.

6.4 Limitations and future directions

While this research provides a comprehensive framework for designing forest-based biomass supply chains under uncertainty and policy considerations, there are some limitations that highlight opportunities for future studies.

One of the key contributions of this work is the incorporation of multiple forms of relevant governmental policies. While the selected policies capture those most relevant to the case study, the analysis focuses on a defined set of policy instruments. Future research can expand the

framework to include additional policy types such as regulatory mandates, broader market-based instruments, and policies applicable to different regions rather than focusing on a single case study. This would enhance the understanding of how evolving policy landscapes influence supply chain design. Moreover, this study did not explicitly model residual fibre utilization policies as a separate policy scenario. Their effects were assumed to be already reflected in the recoverable biomass supply data used in the model. As a result, the study does not separately assess how changes in utilization requirements, waste benchmark, or recovery targets could affect biomass availability and its price. Future research could also incorporate these policies by adjusting biomass availability, price, minimum recovery requirements, or introducing penalties for unused recoverable fibre.

Additionally, the ongoing land negotiations and reconciliation processes with First Nations in British Columbia (Government of BC, 2024b) were not explicitly modelled in this study. These processes may affect future biomass availability by changing forest access, harvesting permissions, tenure arrangements, and land-use priorities, while also creating opportunities for Indigenous-led biomass utilization. Therefore, actual feedstock availability may differ from the estimates used in this study, which can be taken into account in future studies.

Second, the evaluation of biomass supply chains is primarily based on maximizing the net present value (NPV) of net benefits and minimizing greenhouse gas (GHG) emissions. Although the results demonstrate the positive impact of governmental policies on economic performance, the financial returns of bioproduction facilities over a 20-year planning horizon remain relatively limited, which may reduce the attractiveness of such investments. Moreover, these metrics do not capture other important dimensions of sustainability. Future studies can extend this analysis by incorporating additional criteria such as job creation and regional economic development, particularly for Indigenous and rural communities, to provide a more comprehensive assessment of biomass utilization strategies.

Third, this research incorporates uncertainty in parameters related to policy, market, and operational aspects. While this improves decision making, structural uncertainties and limitations arising from simplifying assumptions and modeling choices are not explicitly addressed. Such structural uncertainties and limitations could include the representation of subsidies and incentives,

the exclusion of interactions with other regions or markets, assumptions regarding cost–scale relationships used to estimate costs, or the implementation of the output-based pricing system. Future work can explore approaches that account for such uncertainties to further enhance the robustness of the results.

Furthermore, this study does not explicitly consider supply chain disruptions such as infrastructure failures, labor shortages, or wildfires in the network design. Incorporating such risks and resilience considerations in future models would improve the robustness of supply chain configurations.

Finally, emissions are limited to those generated from biomass collection, transportation, and conversion processes. End-of-life emissions associated with product use or disposal are not considered. Integrating a full life cycle assessment into the optimization framework would enable a more comprehensive evaluation of environmental impacts.

Bibliography

- Abusaq, Z., Habib, M. S., Shehzad, A., Kanan, M., & Assaf, R. (2022). A Flexible Robust Possibilistic Programming Approach toward Wood Pellets Supply Chain Network Design. *Mathematics*, 10(19), 3657. <https://doi.org/10.3390/math10193657>
- Activated Carbon Market Size, Trend & Industry Share | 2034*. (2025). Expert Market Research. <https://www.expertmarketresearch.com/reports/activated-carbon-market>
- Activated Carbon Price per Ton June 2022*. (2022, August 15). INDEXBOX. <https://www.indexbox.io/blog/activated-carbon-price-per-ton-june-2022/>
- Acuna, M., Sessions, J., Zamora, R., Boston, K., Brown, M., & Ghaffariyan, M. R. (2019). Methods to Manage and Optimize Forest Biomass Supply Chains: A Review. *Current Forestry Reports*, 5(3), 124–141. <https://doi.org/10.1007/s40725-019-00093-4>
- AdvEn. (2021, March 25). AdvEn Secures Federal Government Grant For ASAC. *AdvEn Inc*. <http://adveninc.com/news/adven-secures-federal-government-grant-for-asac/>
- Agate, S., Joyce, M., Lucia, L., & Pal, L. (2018). Cellulose and nanocellulose-based flexible-hybrid printed electronics and conductive composites—A review. *Carbohydrate Polymers*, 198, 249–260. <https://doi.org/10.1016/j.carbpol.2018.06.045>
- Ahlström, J. M., Zetterholm, J., Pettersson, K., Harvey, S., & Wetterlund, E. (2020). Economic potential for substitution of fossil fuels with liquefied biomethane in Swedish iron and steel industry – Synergy and competition with other sectors. *Energy Conversion and Management*, 209, 112641. <https://doi.org/10.1016/j.enconman.2020.112641>
- Ahmadvand, S. (2023). *Supply chain optimization of forest-based biomass for gasification considering uncertainties*. The University of British Columbia.
- Ahmadvand, S., Khadivi, M., Arora, R., & Sowlati, T. (2021). Bi-objective optimization of forest-based biomass supply chains for minimization of costs and deviations from safety stock. *Energy Conversion and Management: X*, 11, 100101. <https://doi.org/10.1016/j.ecmx.2021.100101>
- Ahmadvand, S., & Sowlati, T. (2023). The attractiveness of syngas production from forest-based biomass for pulp mills considering carbon pricing and government regulations. *Renewable Energy Focus*, 45, 287–306. <https://doi.org/10.1016/j.ref.2023.04.007>
- Airex. (2025). *The largest biochar plant in North America*. <https://airex-energy.com/carbonity-plant/>
- Akbari, M., Oyedun, A. O., Gemechu, E., & Kumar, A. (2021). Comparative life cycle energy and greenhouse gas footprints of dry and wet torrefaction processes of various biomass

- feedstocks. *Journal of Environmental Chemical Engineering*, 9(4), 105415.
<https://doi.org/10.1016/j.jece.2021.105415>
- Akbari, M., Oyedun, A. O., & Kumar, A. (2020). Techno-economic assessment of wet and dry torrefaction of biomass feedstock. *Energy*, 207, 118287.
<https://doi.org/10.1016/j.energy.2020.118287>
- Akgul, O., Mac Dowell, N., Papageorgiou, L. G., & Shah, N. (2014). A mixed integer nonlinear programming (MINLP) supply chain optimisation framework for carbon negative electricity generation using biomass to energy with CCS (BECCS) in the UK. *International Journal of Greenhouse Gas Control*, 28, 189–202.
<https://doi.org/10.1016/j.ijggc.2014.06.017>
- Akhtari, S., Malladi, K. T., Sowlati, T., & Mirza, F. (2020). Incorporating risk in multi-criteria decision making: The case study of biofuel production from construction and demolition wood waste. *Resources, Conservation and Recycling*, 167, 105233.
<https://doi.org/10.1016/j.resconrec.2020.105233>
- Akhtari, S., Malladi, K. T., Sowlati, T., & Mirza, F. (2021). Incorporating risk in multi-criteria decision making: The case study of biofuel production from construction and demolition wood waste. *Resources, Conservation and Recycling*, 167, 105233.
<https://doi.org/10.1016/j.resconrec.2020.105233>
- Akhtari, S., & Sowlati, T. (2020). Hybrid optimization-simulation for integrated planning of bioenergy and biofuel supply chains. *Applied Energy*, 259, 114124.
<https://doi.org/10.1016/j.apenergy.2019.114124>
- Akhtari, S., Sowlati, T., & Day, K. (2014). The effects of variations in supply accessibility and amount on the economics of using regional forest biomass for generating district heat. *Energy*, 67, 631–640. <https://doi.org/10.1016/j.energy.2014.01.092>
- Akter, H. A., Huang, Y.-K., & Dwivedi, P. (2025). Developing a supply chain model for sustainable aviation fuel using logging residues in Georgia, United States. *Forest Policy and Economics*, 170, 103401. <https://doi.org/10.1016/j.forpol.2024.103401>
- Annual exchange rates*. (2024). Bank of Canada.
<https://www.bankofcanada.ca/rates/exchange/annual-average-exchange-rates/>
- Antonangelo, J. A., Sun, X., & Zhang, H. (2021). The roles of co-composted biochar (COMBI) in improving soil quality, crop productivity, and toxic metal amelioration. *Journal of Environmental Management*, 277, 111443.
<https://doi.org/10.1016/j.jenvman.2020.111443>
- Araki, D. S. (2002). *Chip recovery, quality, and productivity at a northern Alberta pulp mill*. 3(51).

- Arfelis, S., Aguado, R. J., Civancik, D., Fullana-i-Palmer, P., Pèlach, M. À., Tarrés, Q., & Delgado-Aguilar, M. (2023). Sustainability of cellulose micro-/nanofibers: A comparative life cycle assessment of pathway technologies. *Science of The Total Environment*, 874, 162482. <https://doi.org/10.1016/j.scitotenv.2023.162482>
- Arvidsson, R., Nguyen, D., & Svanström, M. (2015). Life Cycle Assessment of Cellulose Nanofibrils Production by Mechanical Treatment and Two Different Pretreatment Processes. *Environmental Science & Technology*, 49(11), 6881–6890. <https://doi.org/10.1021/acs.est.5b00888>
- Ba, B. H., Prins, C., & Prodhon, C. (2016). Models for optimization and performance evaluation of biomass supply chains: An Operations Research perspective. *Renewable Energy*, 87, 977–989. <https://doi.org/10.1016/j.renene.2015.07.045>
- BC building code. (2018). BC Publications. [https://free.bcpublications.ca/civix/document/id/public/bcbc2018/bcbc_2018dbs103r5#:~:text=2\)%20The%20emissions%20factors%20associated,CO2e/kWh%20for%20natural%20gas.](https://free.bcpublications.ca/civix/document/id/public/bcbc2018/bcbc_2018dbs103r5#:~:text=2)%20The%20emissions%20factors%20associated,CO2e/kWh%20for%20natural%20gas.)
- BC building code. (2018). *BC Publications*. https://www.bcpublications.ca/BCPublications/855_Division B - Section 10.3. Greenhouse Gas Emissions accessed on 14 August 2024
- BC Hydro. (2024). *Sustainable energy future Leading the clean energy industry*. <https://choose.bchydro.com/why-choose-bc/clean-energy>
- Ben Daya, B., & Nourelfath, M. (2019). Sustainability assessment of integrated forest biorefinery implemented in Canadian pulp and paper mills. *International Journal of Production Economics*, 214, 248–265. <https://doi.org/10.1016/j.ijpe.2018.06.014>
- Bergman, R., Sahoo, K., Englund, K., & Mousavi-Avval, S. H. (2022). Lifecycle Assessment and Techno-Economic Analysis of Biochar Pellet Production from Forest Residues and Field Application. *Energies*, 15(4), 1559. <https://doi.org/10.3390/en15041559>
- Best Business Lines of Credit in Canada for 2024*. (2024). WOWA. <https://wowa.ca/business-line-of-credit>
- Blackburn, K. (2019). *Using FPInterface to estimate available forest-origin biomass in British Columbia: Arrow, Boundary, and Kootenay Lake TSA*. <https://library.fpinnovations.ca/link/fpipub52869>
- Blair, M. J. (2020). *Building resilience in forest-dependent communities through sustainable forest bioeconomy development*.
- Blair, M. J., & Mabee, W. E. (2021). Techno-economic and market analysis of two emerging forest biorefining technologies. *Biofuels, Bioproducts and Biorefining*, 15(5), 1301–1317. <https://doi.org/10.1002/bbb.2218>

- Boukherroub, T., LeBel, L., & Lemieux, S. (2017). An integrated wood pellet supply chain development: Selecting among feedstock sources and a range of operating scales. *Applied Energy*, 198, 385–400. <https://doi.org/10.1016/j.apenergy.2016.12.013>
- Brammer, J. G., & Bridgwater, A. V. (1999). Drying technologies for an integrated gasification bio-energy plant. *Renewable and Sustainable Energy Reviews*, 3(4), 243–289. [https://doi.org/10.1016/S1364-0321\(99\)00008-8](https://doi.org/10.1016/S1364-0321(99)00008-8)
- Brammer, J. G., Lauer, M., & Bridgwater, A. V. (2006). Opportunities for biomass-derived “bio-oil” in European heat and power markets. *Energy Policy*, 34(17), 2871–2880. <https://doi.org/10.1016/j.enpol.2005.05.005>
- Brinley, K. (2021). *Bioenergy Advancement: Programs and Policies* [University of Saskatchewan]. https://renewableenergy.usask.ca/cases-resources/bioenergy-advancement_programs-and-policies_kelby-brinley.pdf
- British Columbia Ministry of Forests. (2024). *Williams Lake TSA Timber Supply Review Data Package*. British Columbia Ministry of Forests. 2025-10-29
- British Columbia’s Carbon Tax*. (2024). Government of British Columbia. <https://www2.gov.bc.ca/gov/content/environment/climate-change/clean-economy/carbon-tax>
- British Pound to Canadian Dollar Spot Exchange Rates for 2023*. (2024). Exchange Rates. <https://www.exchangerates.org.uk/GBP-CAD-spot-exchange-rates-history-2023.html>
- Buitrago-Tello, R., Venditti, R. A., Jameel, H., Yao, Y., & Echeverria, D. (2022). Carbon Footprint of Bleached Softwood Fluff Pulp: Detailed Process Simulation and Environmental Life Cycle Assessment to Understand Carbon Emissions. *ACS Sustainable Chemistry & Engineering*, 10(28), 9029–9040. <https://doi.org/10.1021/acssuschemeng.2c00840>
- Cambero, C., & Sowlati, T. (2016a). Incorporating social benefits in multi-objective optimization of forest-based bioenergy and biofuel supply chains. *Applied Energy*, 178, 721–735. <https://doi.org/10.1016/j.apenergy.2016.06.079>
- Cambero, C., & Sowlati, T. (2016b). Incorporating social benefits in multi-objective optimization of forest-based bioenergy and biofuel supply chains. *Applied Energy*, 178, 721–735. <https://doi.org/10.1016/j.apenergy.2016.06.079>
- Cambero, C., Sowlati, T., & Pavel, M. (2016). Economic and life cycle environmental optimization of forest-based biorefinery supply chains for bioenergy and biofuel production. *Chemical Engineering Research and Design, Biorefinery Value Chain Creation*, 107, 218–235. <https://doi.org/10.1016/j.cherd.2015.10.040>

- Canada—Wood Pellets—Market Analysis, Forecast, Size, Trends and Insights. (2024). INDEXBOX. <https://www.indexbox.io/store/canada-wood-pellets-market-report-analysis-and-forecast-to-2020-/>
- Canadian Council of Forest Ministers. (2017). *A forest bioeconomy framework for Canada*. Canadian Council of Forest Ministers.
- Canadian Forest Industries. (2024, December 2). *Tolko announces temporary layoffs at two B.C. mills*. <https://www.woodbusiness.ca/tolko-announces-temporary-layoffs-at-two-b-c-mills/#:~:text=Industry%20News%20News%20Mills%20Sawmilling,layoffs%20at%20two%20B.C.%20mills&text=Photo:%20Annex%20Business%20Media.,rest%20of%20the%20story%20here>.
- Cifuentes García, R., Galán, G., & Martín, M. (2024). Multiscale analysis for the valorization of biomass via pellets production towards energy security. *Journal of Cleaner Production*, 461, 142663. <https://doi.org/10.1016/j.jclepro.2024.142663>
- Cifuentes García, R., Galán, G., & Martín, M. (2025). Strategic analysis towards household heating sustainable transition. *Renewable Energy*, 250, 123311. <https://doi.org/10.1016/j.renene.2025.123311>
- Classes of depreciable property*. (2023, November 27). Government of Canada. <https://www.canada.ca/en/revenue-agency/services/tax/businesses/topics/sole-proprietorships-partnerships/report-business-income-expenses/claiming-capital-cost-allowance/classes-depreciable-property.html#class1>
- CleanBC - Roadmap to 2030*. (2021). Government of British Columbia. https://www2.gov.bc.ca/assets/gov/environment/climate-change/action/cleanbc/cleanbc_roadmap_2030.pdf
- Conway, D., Richards, K., Richards, S., Keenlyside, P., Mikolajczyk, S., Streck, C., Ross, J., Anthony Liu, A., & Tran, A. (2017). *Carbon Tax Guide: A Handbook for Policy Makers*. The World Bank. <http://documents.worldbank.org/curated/en/728421535605566659/Carbon-Tax-Guide-A-Handbook-for-Policy-Makers>
- Corporation tax rates*. (2024, January 3). Government of Canada. <https://www.canada.ca/en/revenue-agency/services/tax/businesses/topics/corporations/corporation-tax-rates.html>
- Daneshmandi, M., Sahebi, H., & Ashayeri, J. (2022). The incorporated environmental policies and regulations into bioenergy supply chain management: A literature review. *Science of The Total Environment*, 820, 153202. <https://doi.org/10.1016/j.scitotenv.2022.153202>
- Data Bridge Market Research. (2025). *Canada Biochar Market to 2032*. <https://www.databridgemarketresearch.com/nucleus/canada-biochar-market>

- Dietz, T., Rubio Jovel, K., Deciancio, M., Boldt, C., & Börner, J. (2023). Towards effective national and international governance for a sustainable bioeconomy: A global expert perspective. *EFB Bioeconomy Journal*, 3, 100058. <https://doi.org/10.1016/j.bioeco.2023.100058>
- Dubois, D., & Prade, H. (2012). Possibility Theory. In R. A. Meyers (Ed.), *Computational Complexity* (pp. 2240–2252). Springer New York. https://doi.org/10.1007/978-1-4614-1800-9_139
- Dufresne, A. (2019). Nanocellulose Processing Properties and Potential Applications. *Current Forestry Reports*, 2(5), 76–89. <https://doi.org/10.1007/s40725-019-00088-1>
- Dziejarski, B., Serafin, J., Andersson, K., & Krzyżyńska, R. (2023). CO2 Capture Materials: A Review of Current Trends and Future Challenges. *Materials Today Sustainability*, 100483.
- Economics and Trade Branch Ministry of Forests. (2022). *2022 Economic State of British Columbia's Forest Sector*. https://www2.gov.bc.ca/assets/gov/farming-natural-resources-and-industry/forestry/forest-industry-economics/economic-state/2022_economic_state_of_the_bc_forest_sector.pdf
- Electricity supplied from grid*. (2023). Climatiq. <https://www.climatiq.io/data/emission-factor/fb0323b8-d6d9-4acc-ab2b-d4a42589d297>
- Energy Innovation Program – Clean Fuels and Industrial Fuel Switching*. (2022). Natural Resources Canada. <https://natural-resources.canada.ca/science-and-data/funding-partnerships/funding-opportunities/funding-grants-incentives/energy-innovation-program/energy-innovation-program-clean-fuels-and-industrial-fuel-switching/23956>
- Ensyn. (2026a). *Canada—Vyterra Renewables*. <https://www.ensyn.com/canada---vyterra.html>
- Ensyn. (2026b). *ONTARIO FACILITY*. <https://www.ensyn.com/production.html>
- Ernsting, A., & van der Mark, M. (2019). *Risky Biomass Business: The reputational and financial risks of investing in forest biomass energy*. <https://environmentalpaper.org/wp-content/uploads/2019/04/Risky-Biomass-Business.pdf>
- Eversberg, D., Holz, J., & Pungas, L. (2023). The bioeconomy and its untenable growth promises: Reality checks from research. *Sustainability Science*, 18(2), 569–582. <https://doi.org/10.1007/s11625-022-01237-5>
- Fernando, J. (2026). *Compound Annual Growth Rate (CAGR) Formula and Calculation*. Investopedia. <https://www.investopedia.com/terms/c/cagr.asp>
- Ferreira, V., Fabregat-Aibar, L., Pié, L., & Terceño, A. (2022). Research trends and hotspots in bioeconomy impact analysis: A study of economic, social and environmental impacts.

- Environmental Impact Assessment Review*, 96, 106842.
<https://doi.org/10.1016/j.eiar.2022.106842>
- Financial Post. (2023). *Emergent Waste Solutions Inc. Sells 40,000 Litres of Biochar*.
<https://financialpost.com/globe-newswire/emergent-waste-solutions-inc-sells-40000-litres-of-biochar>
- Forest Carbon Initiative. (2020). *FPI Woody Debris Management Workshop—Avoiding Emissions*. https://www2.gov.bc.ca/assets/gov/farming-natural-resources-and-industry/forestry/timber-tenures/fibre-recovery/forest_carbon_initiative.pdf
- Forest Products Association of Canada. (2010). *Transforming Canada's forest products industry: Summary of findings from the Future Bio-pathways Project*.
<https://www.bioenergy.org.nz/documents/resource/Report-Biopathways-ENG3-1.pdf>
- Forest Products Association of Canada. (2011). *The new face of the Canadian forest industry: The emerging bio-revolution*. <http://www.fpac.ca/wp-content/uploads/BIOPATHWAYS-II-web.pdf>
- Friesen, C. (2012). *FPInterface Slash Supply Data for Williams Lake TSA*.
- Friesen, C. (2018). *Using FPInterface to Estimate Available Forest-Origin Biomass in British Columbia: Williams Lake TSA*. <https://www2.gov.bc.ca/assets/gov/farming-natural-resources-and-industry/forestry/timber-tenures/fibre-recovery/tr2018n8.pdf>
- Fu, D. Z., Yang, T. J., Pan, Y. J., & Tong, Y. M. (2023). An inexact multiple-recourse hybrid-fuel management model with considering carbon reduction requirement for a biofuel-penetrated heating system. *Energy Reports*, 9, 4224–4242.
<https://doi.org/10.1016/j.egyr.2023.03.081>
- Gayathiri, M., Pulingam, T., Lee, K. T., & Sudesh, K. (2022). Activated carbon from biomass waste precursors: Factors affecting production and adsorption mechanism. *Chemosphere*, 294, 133764. <https://doi.org/10.1016/j.chemosphere.2022.133764>
- Getting Started with the B.C. Output-Based Pricing System*. (2024). Government of British Columbia. https://www2.gov.bc.ca/assets/gov/environment/climate-change/ind/obps/guidance/bc_obps_guidance.pdf
- Godfrey, T., Bagheri, M., Bi, W., & Sandland, J. (2023). *Business case comparison of eight different bioproducts in BC*:
- Gómez H., C., Serpa, A., Velásquez-Cock, J., Gañán, P., Castro, C., Vélez, L., & Zuluaga, R. (2016). Vegetable nanocellulose in food science: A review. *Food Hydrocolloids*, 57, 178–186. <https://doi.org/10.1016/j.foodhyd.2016.01.023>
- Government of BC. (2020a). *Province confirms tax measure implementation dates, deferral deadlines for businesses*. <https://news.gov.bc.ca/releases/2020FIN0049-001647>

- Government of BC. (2020b, May 14). *Residual Fibre Utilization*.
<https://www2.gov.bc.ca/gov/content/industry/forestry/forest-tenures/forest-tenure-administration/residual-fibre-recovery>
- Government of BC. (2023). *2023 B.C. Best Practices Methodology for Quantifying Greenhouse Gas Emissions*. https://www2.gov.bc.ca/assets/gov/environment/climate-change/cng/methodology/2023_pso_methodology_for_quantifying_greenhouse_gas_emissions.pdf
- Government of BC. (2024a). *Carbon Offset Pricing 2014-forward*.
https://www2.gov.bc.ca/assets/gov/environment/climate-change/offsets/pricing/carbon_offset_portfolio_pricing.pdf
- Government of BC. (2024b). *First Nations Negotiations*.
<https://www2.gov.bc.ca/gov/content/environment/natural-resource-stewardship/consulting-with-first-nations/first-nations-negotiations>
- Government of BC. (2024c). *Getting Started with the B.C. Output-Based Pricing System*. Government of British Columbia.
https://www2.gov.bc.ca/assets/gov/environment/climate-change/ind/obps/guidance/bc_obps_guidance.pdf
- Government of Canada. (2018, January 31). *Carbon pricing: Regulatory framework for the output-based pricing system*.
<https://www.canada.ca/en/services/environment/weather/climatechange/climate-action/pricing-carbon-pollution/output-based-pricing-system.html>
- Grand View Research. (2022). *Canada Nanocellulose Market Size & Outlook*.
<https://www.grandviewresearch.com/horizon/outlook/nanocellulose-market/canada>
- Gu, H., & Bergman, R. (2016). LIFE-CYCLE ASSESSMENT OF A DISTRIBUTED-SCALE THERMOCHEMICAL BIOENERGY CONVERSION SYSTEM. *WOOD AND FIBER SCIENCE*, 48.
- Gu, H., Bergman, R., Anderson, N., & Alanya-Rosenbaum, S. (2018). LIFE-CYCLE ASSESSMENT OF ACTIVATED CARBON FROM WOODY BIOMASS. *Wood and Fiber Science*, 50(3), 229–243. <https://doi.org/10.22382/wfs-2018-024>
- Gutierrez-Franco, E., Polo, A., Clavijo-Buritica, N., & Rabelo, L. (2021). Multi-Objective Optimization to Support the Design of a Sustainable Supply Chain for the Generation of Biofuels from Forest Waste. *Sustainability*, 13(14), 7774.
<https://doi.org/10.3390/su13147774>
- Heidari, A., Khaki, E., Younesi, H., & Lu, H. R. (2019). Evaluation of fast and slow pyrolysis methods for bio-oil and activated carbon production from eucalyptus wastes using a life cycle assessment approach. *Journal of Cleaner Production*, 241, 118394.
<https://doi.org/10.1016/j.jclepro.2019.118394>

- Helal, M. A., Anderson, N., Wei, Y., & Thompson, M. (2023). A Review of Biomass-to-Bioenergy Supply Chain Research Using Bibliometric Analysis and Visualization. *Energies*, 16(3), 1187. <https://doi.org/10.3390/en16031187>
- Holland, C., & Shapira, P. (2024). Building the bioeconomy: A targeted assessment approach to identifying biobased technologies, challenges and opportunities. *Engineering Biology*, 8(1), 1–15. <https://doi.org/10.1049/enb2.12030>
- Homagain, K., Shahi, C., Luckai, N., & Sharma, M. (2015). Life cycle environmental impact assessment of biochar-based bioenergy production and utilization in Northwestern Ontario, Canada. *Journal of Forestry Research*, 26(4), 799–809. <https://doi.org/10.1007/s11676-015-0132-y>
- Hombach, L. E., Cambero, C., Sowlati, T., & Walther, G. (2016). Optimal design of supply chains for second generation biofuels incorporating European biofuel regulations. *Journal of Cleaner Production*, 133, 565–575. <https://doi.org/10.1016/j.jclepro.2016.05.107>
- Hummieda, A., Bouabid, A., Moawad, K., & Mayyas, A. (2023). The UAE’s energy system and GHG emissions: Pathways to achieving national goals by 2050. *Clean Energy*, 7(5), 962–980. <https://doi.org/10.1093/ce/zkad040>
- IEA. (2022). *Development of Techno-economic Model for Assessment of Bio-hubs in Canada* [IEA Bioenergy: Task 43]. <https://www.ieabioenergy.com/wp-content/uploads/2022/12/Biohub-IEA-Bioenergy-Task-43-Final-Report.pdf>
- Inflation Calculator*. (2024). Bank of Canada. <https://www.bankofcanada.ca/rates/related/inflation-calculator/>
- Inuiguchi, M., Greco, S., Slowinski, R., & Tanino, T. (2003). *Possibility and necessity measure specification using modifiers for decision making under fuzziness*.
- Inuiguchi, M., & Ramík, J. (2000). Possibilistic linear programming: A brief review of fuzzy mathematical programming and a comparison with stochastic programming in portfolio selection problem. *Fuzzy Sets and Systems*, 111(1), 3–28. [https://doi.org/10.1016/S0165-0114\(98\)00449-7](https://doi.org/10.1016/S0165-0114(98)00449-7)
- Investments in Forest Industry Transformation (IFIT)*. (2024, April 9). Natural Resources Canada. <https://natural-resources.canada.ca/the-office-the-chief-scientist/funding-partnerships/opportunities/forest-sector/investments-forest-industry-transformation/13139#CapInv>
- Jeong, S., Lee, H., Joo, Y., Kim, N., & Hwangbo, S. (2025). Sustainable ammonia production from unused biomass: Green hydrogen generation and supply chain optimization in South Korea. *International Journal of Hydrogen Energy*, 147, 149924. <https://doi.org/10.1016/j.ijhydene.2025.06.114>

- Kane, S., Miller, S. A., Kurtis, K. E., Youngblood, J. P., Landis, E. N., & Weiss, W. J. (2023). Harmonized Life-Cycle Inventories of Nanocellulose and Its Application in Composites. *Environmental Science & Technology*, 57(48), 19137–19147. <https://doi.org/10.1021/acs.est.3c04814>
- Khadivi, M. (2022). *Economic analysis and supply chain optimization of biomass gasification at a kraft pulp mill*. University of British Columbia.
- Kim, J.-H., Lee, D., Lee, Y.-H., Chen, W., & Lee, S.-Y. (2019). Nanocellulose for Energy Storage Systems: Beyond the Limits of Synthetic Materials. *Advanced Materials*, 31(20), 1804826. <https://doi.org/10.1002/adma.201804826>
- Lamb-Yorski, M. (2024, April 20). *Only 3-4% of B.C. residual fibre reports checked in the field*. <https://www.wltribune.com/local-news/only-3-4-of-bc-residual-fibre-reports-checked-in-the-field-7347655>
- Lan, K., Wang, H. S.-H., Lee, T., De Assis, C. A., Venditti, R. A., Zhu, Y., & Yao, Y. (2024). A modeling framework to identify environmentally greener and lower-cost pathways of nanomaterials. *Green Chemistry*, 26(6), 3466–3478. <https://doi.org/10.1039/D3GC04036D>
- LCFS Requirements. (2023). Government of British Columbia. <https://www2.gov.bc.ca/gov/content/industry/electricity-alternative-energy/transportation-energies/renewable-low-carbon-fuels/requirements>
- Legan, M., Gotvajn, A. Ž., & Zupan, K. (2022). Potential of biochar use in building materials. *Journal of Environmental Management*, 309, 114704. <https://doi.org/10.1016/j.jenvman.2022.114704>
- Liao, M., Kelley, S., & Yao, Y. (2020). Generating Energy and Greenhouse Gas Inventory Data of Activated Carbon Production Using Machine Learning and Kinetic Based Process Simulation. *ACS Sustainable Chemistry & Engineering*, 8(2), 1252–1261. <https://doi.org/10.1021/acssuschemeng.9b06522>
- Lim, C. H., Ngan, S. L., Ng, W. P. Q., How, B. S., & Lam, H. L. (2022). Biomass supply chain management and challenges. In *Value-Chain of Biofuels* (pp. 429–444). Elsevier. <https://doi.org/10.1016/B978-0-12-824388-6.00016-6>
- Lin, J., Li, Y., Qian, Y., & Liu, G. (2024). Effectiveness of government subsidies for biomass-based industries: Incorporating the feedstock acquisition process. *Energy Policy*, 192, 114251. <https://doi.org/10.1016/j.enpol.2024.114251>
- Lindroos, O., Nilsson, B., & Sowlati, T. (2011). Costs, CO₂ Emissions, and Energy Balances of Applying Nordic Slash Recovery Methods in British Columbia. *Western Journal of Applied Forestry*, 26(1), 30–36. <https://doi.org/10.1093/wjaf/26.1.30>

- Liu, W.-Y., Lin, C.-C., & Yeh, T.-L. (2017). Supply chain optimization of forest biomass electricity and bioethanol coproduction. *Energy*, 139, 630–645. <https://doi.org/10.1016/j.energy.2017.08.018>
- Maintenance of Rotary Drum Dryer*. (2024). Abc Machinery. <http://www.rotary-air-dryer.com/Maintenance-of-Rotary-Drum-Dryer.html>
- Malladi, K. T., & Sowlati, T. (2020a). Bi-objective optimization of biomass supply chains considering carbon pricing policies. *Applied Energy*, 264, 114719. <https://doi.org/10.1016/j.apenergy.2020.114719>
- Malladi, K. T., & Sowlati, T. (2020b). Impact of carbon pricing policies on the cost and emission of the biomass supply chain: Optimization models and a case study. *Applied Energy*, 267, 115069. <https://doi.org/10.1016/j.apenergy.2020.115069>
- Markets and Markets. (2024). *Nanocellulose Market worth \$3.4 billion by 2032*. <https://www.marketsandmarkets.com/PressReleases/nanocellulose.asp>
- Masum, F. H., Wang, W., Colson, G., & Dwivedi, P. (2022). Replacing coal in Georgia’s power plants with woody biomass to increase carbon benefit: A mixed integer linear programming model. *Journal of Environmental Management*, 316, 115060. <https://doi.org/10.1016/j.jenvman.2022.115060>
- Mavrotas, G. (2009). Effective implementation of the ϵ -constraint method in Multi-Objective Mathematical Programming problems. *Applied Mathematics and Computation*, 213(2), 455–465. <https://doi.org/10.1016/j.amc.2009.03.037>
- Memişoğlu, G., & Üster, H. (2016). Integrated Bioenergy Supply Chain Network Planning Problem. *Transportation Science*, 50(1), 35–56. <https://doi.org/10.1287/trsc.2015.0598>
- Ministry of Environment and Climate Change Strategy. (2021). *2020 B.C. BEST PRACTICES METHODOLOGY FOR QUANTIFYING GREENHOUSE GAS EMISSIONS*. <https://www2.gov.bc.ca/assets/gov/environment/climate-change/cng/methodology/2020-pso-methodology.pdf>
- Mottaghi, M., Bairamzadeh, S., & Pishvae, M. S. (2022). A taxonomic review and analysis on biomass supply chain design and planning: New trends, methodologies and applications. *Industrial Crops and Products*, 180, 114747. <https://doi.org/10.1016/j.indcrop.2022.114747>
- Mousazadeh, M., Torabi, S. A., & Zahiri, B. (2015). A robust possibilistic programming approach for pharmaceutical supply chain network design. *Computers & Chemical Engineering*, 82, 115–128. <https://doi.org/10.1016/j.compchemeng.2015.06.008>
- Nance, E. (2023). *SLASH-PILE BURNING IN BRITISH COLUMBIA: MANAGEMENT CHALLENGES, EMISSIONS UNCERTAINTIES, AND ALTERNATIVE PRACTICES*

- [The University of British Columbia].
<https://open.library.ubc.ca/soa/cIRcle/collections/ubctheses/24/items/1.0435767>
- Natural Resources Canada. (2022). *State of Canada's Forests Annual Report 2022*.
https://www.nrcan.gc.ca/sites/nrcan/files/forest/sof2022/SoF_Annual2022_EN_access.pdf
- Nelson, K., Retsina, T., Iakovlev, M., Van Heiningen, A., Deng, Y., Shatkin, J. A., & Mulyadi, A. (2016). American Process: Production of Low Cost Nanocellulose for Renewable, Advanced Materials Applications. In L. D. Madsen & E. B. Svedberg (Eds.), *Materials Research for Manufacturing* (Vol. 224, pp. 267–302). Springer International Publishing.
https://doi.org/10.1007/978-3-319-23419-9_9
- Ouhimmou, M., Rönqvist, M., & Lapointe, L.-A. (2021). Assessment of sustainable integration of new products into value chain through a generic decision support model: An application to the forest value chain. *Omega*, 99, 102173.
<https://doi.org/10.1016/j.omega.2019.102173>
- Palak, G., Ekşioğlu, S. D., & Geunes, J. (2014). Analyzing the impacts of carbon regulatory mechanisms on supplier and mode selection decisions: An application to a biofuel supply chain. *International Journal of Production Economics*, 154, 198–216.
<https://doi.org/10.1016/j.ijpe.2014.04.019>
- Park, C. S. (2007). *Contemporary engineering economics* (4th ed). Prentice Hall.
- Pascoli, D. U., Aui, A., Frank, J., Therasme, O., Dixon, K., Gustafson, R., Kelly, B., Volk, T. A., & Wright, M. M. (2022). The US bioeconomy at the intersection of technology, policy, and education. *Biofuels, Bioproducts and Biorefining*, 16(1), 9–26.
<https://doi.org/10.1002/bbb.2302>
- Peak Solutions Consulting Inc. (2018). *City of Williams Lake Economic Development Baseline Report*. <https://www.williamslake.ca/DocumentCenter/View/2395/FINAL-City-of-Williams-Lake-Economic-Development-Baseline-Report-Oct-30-2018>
- Penloglou, G., Basna, A., Pavlou, A., & Kiparissides, C. (2023). Techno-Economic Considerations on Nanocellulose's Future Progress: A Short Review. *Processes*, 11(8), 2312. <https://doi.org/10.3390/pr11082312>
- Perry, J. H., Green, D. W., & Southard, M. Z. (Eds.). (2019). *Perry's chemical engineers' handbook* (Ninth edition). McGraw-Hill Education.
- Peters, J. F., Iribarren, D., & Dufour, J. (2015). Biomass Pyrolysis for Biochar or Energy Applications? A Life Cycle Assessment. *Environmental Science & Technology*, 49(8), 5195–5202. <https://doi.org/10.1021/es5060786>

- Pishvaei, M. S., Razmi, J., & Torabi, S. A. (2012a). Robust possibilistic programming for socially responsible supply chain network design: A new approach. *Fuzzy Sets and Systems*, 206, 1–20. <https://doi.org/10.1016/j.fss.2012.04.010>
- Pishvaei, M. S., Razmi, J., & Torabi, S. A. (2012b). Robust possibilistic programming for socially responsible supply chain network design: A new approach. *Fuzzy Sets and Systems*, 206, 1–20. <https://doi.org/10.1016/j.fss.2012.04.010>
- Popp, J., Kovács, S., Oláh, J., Divéki, Z., & Balázs, E. (2021). Bioeconomy: Biomass and biomass-based energy supply and demand. *New Biotechnology*, 60, 76–84. <https://doi.org/10.1016/j.nbt.2020.10.004>
- Prakoso, I. A. (2019). Evaluasi produksi reclaim feeder di temporary stockpile 21 untuk memenuhi target produksi perbulan pada coal handling facility mtbu PT.Bukit Asam Tbk. *SKRIPSI-2018*. http://repository.trisakti.ac.id/usaktiana/index.php/home/detail/detail_koleksi/0/SKR/judul/0000000000000000095989/
- Rajendran, N., Runge, T., Bergman, R. D., Nepal, P., Alikhani, N., Li, L., O'Neill, S. R., & Wang, J. (2023). Techno-economic analysis and life cycle assessment of manufacturing a cellulose nanocrystal-based hybrid membrane. *Sustainable Production and Consumption*, 40, 503–515. <https://doi.org/10.1016/j.spc.2023.07.014>
- Rajendran, N., Runge, T., Bergman, R. D., Nepal, P., & Houtman, C. (2023). Techno-economic analysis and life cycle assessment of cellulose nanocrystals production from wood pulp. *Bioresource Technology*, 377, 128955. <https://doi.org/10.1016/j.biortech.2023.128955>
- Raymond, L. (2019). Policy perspective: Building political support for carbon pricing—Lessons from cap-and-trade policies. *Energy Policy*, 134, 110986. <https://doi.org/10.1016/j.enpol.2019.110986>
- Research and Markets. (2025a). *Activated Carbon – A Global Market Overview*. <https://www.researchandmarkets.com/reports/5211803/activated-carbon-a-global-market-overview#src-pos-3>
- Research and Markets. (2025b). *Biochar Market 2025-2033*. <https://www.researchandmarkets.com/reports/5946293/biochar-market#tag-pos-2>
- Saghaei, M., Dehghanimadvar, M., Soleimani, H., & Ahmadi, M. H. (2020). Optimization and analysis of a bioelectricity generation supply chain under routine and disruptive uncertainty and carbon mitigation policies. *Energy Science & Engineering*, 8(8), 2976–2999. <https://doi.org/10.1002/ese3.716>
- Saghaei, M., Ghaderi, H., & Soleimani, H. (2020). Design and optimization of biomass electricity supply chain with uncertainty in material quality, availability and market demand. *Energy*, 197, 117165. <https://doi.org/10.1016/j.energy.2020.117165>

- Sarkar, B., Singh, S. K., & Chauhan, A. (2025). An advanced robust possibilistic chance-constrained programming model for the animal fat-based biodiesel supply chain network. *Journal of Industrial Information Integration*, 47, 100884. <https://doi.org/10.1016/j.jii.2025.100884>
- Schmidt, J., Leduc, S., Dotzauer, E., & Schmid, E. (2011). Cost-effective policy instruments for greenhouse gas emission reduction and fossil fuel substitution through bioenergy production in Austria. *Energy Policy*, 39(6), 3261–3280. <https://doi.org/10.1016/j.enpol.2011.03.018>
- Seabra, A. B., Bernardes, J. S., Fávaro, W. J., Paula, A. J., & Durán, N. (2018). Cellulose nanocrystals as carriers in medicine and their toxicities: A review. *Carbohydrate Polymers*, 181, 514–527. <https://doi.org/10.1016/j.carbpol.2017.12.014>
- Shadbahr, J., Ebadian, M., Gonzales-Calienes, G., Kannangara, M., Ahmadi, L., & Bensebaa, F. (2022). Impact of waste management and conversion technologies on cost and carbon footprint—Case studies in rural and urban cities. *Renewable and Sustainable Energy Reviews*, 168, 112872. <https://doi.org/10.1016/j.rser.2022.112872>
- Shaheen, J., Fseha, Y. H., & Sizerici, B. (2022). Performance, life cycle assessment, and economic comparison between date palm waste biochar and activated carbon derived from woody biomass. *Heliyon*, 8(12), e12388. <https://doi.org/10.1016/j.heliyon.2022.e12388>
- Sikkema, R., Junginger, M., Pichler, W., Hayes, S., & Faaij, A. P. C. (2010). The international logistics of wood pellets for heating and power production in Europe: Costs, energy-input and greenhouse gas balances of pellet consumption in Italy, Sweden and the Netherlands. *Biofuels, Bioproducts and Biorefining*, 4(2), 132–153. <https://doi.org/10.1002/bbb.208>
- Song, J., Yang, W., Higano, Y., & Wang, X. (2015). Modeling the development and utilization of bioenergy and exploring the environmental economic benefits. *Energy Conversion and Management*, 103, 836–846. <https://doi.org/10.1016/j.enconman.2015.07.028>
- Sowlati, T. (2016). Modeling of forest and wood residues supply chains for bioenergy and biofuel production. In *Biomass Supply Chains for Bioenergy and Biorefining* (pp. 167–190). Elsevier. <https://doi.org/10.1016/B978-1-78242-366-9.00008-3>
- Statista. (2023). *Average monthly electricity costs for end-users in Canada as of September 2023, by province and territory*. <https://www.statista.com/statistics/516279/electricity-costs-for-end-users-canada-by-province/#:~:text=Industry%20electricity%20prices%20within%20Canadian,per%20kilo watt%2Dhour%20in%202022>
- Statistics Canada. (2023). *Win (for) diesel: Moving the economy cheaper in 2023*. <https://www.statcan.gc.ca/01/en/plus/4042-win-diesel-moving-economy-cheaper-2023>

- Tan, Q., Wang, T., Zhang, Y., Miao, X., & Zhu, J. (2017). Nonlinear multi-objective optimization model for a biomass direct-fired power generation supply chain using a case study in China. *Energy*, 139, 1066–1079. <https://doi.org/10.1016/j.energy.2017.08.050>
- Taylor, A., Raynolds, M., & Hornung, R. (2003). *Government Policies for Promoting and Managing the Production and Consumption of Bioenergy*. Pembina Institute. https://www.pembina institute.org/reports/bioenergy_policies_promo.pdf
- Technical guide to class 43.1 and 43.2* (2019 edition). (2020). Natural Resources Canada = Ressources naturelles Canada. [https://www.nrcan.gc.ca/sites/nrcan/files/energy/pdf/Class_431-432_Technical_Guide\(En\)_-Dec-16-ACC.pdf?_gl=1*b5njlk*_ga*MTkwNzQxNjE2NC4xNjgxNzYyNzU3*_ga_C2N57Y7DX5*MTcxNDY3Mjc1NS41Ni4xLjE3MTQ2NzMyMjguMC4wLjA](https://www.nrcan.gc.ca/sites/nrcan/files/energy/pdf/Class_431-432_Technical_Guide(En)_-Dec-16-ACC.pdf?_gl=1*b5njlk*_ga*MTkwNzQxNjE2NC4xNjgxNzYyNzU3*_ga_C2N57Y7DX5*MTcxNDY3Mjc1NS41Ni4xLjE3MTQ2NzMyMjguMC4wLjA)
- Theozzo, B., & Teles dos Santos, M. (2021). A MILP framework for optimal biorefinery design that accounts for forest biomass dynamics. *Computers & Chemical Engineering*, 146, 107201. <https://doi.org/10.1016/j.compchemeng.2020.107201>
- Thermodynamics of Steam*. (n.d.). Retrieved <https://rananaseemshahid.wordpress.com/wp-content/uploads/2015/09/chapter-19.pdf>
- Timber Pricing Branch, BC Ministry of Forests. (2026). *Waste Manual*. https://www2.gov.bc.ca/assets/gov/farming-natural-resources-and-industry/forestry/timber-pricing/residue-and-waste/2026_provincial_waste_manual_master.pdf
- Torabi, S. A., Namdar, J., Hatefi, S. M., & Jolai, F. (2016). An enhanced possibilistic programming approach for reliable closed-loop supply chain network design. *International Journal of Production Research*, 54(5), 1358–1387. <https://doi.org/10.1080/00207543.2015.1070215>
- Vadenbo, C., Tonini, D., Burg, V., Astrup, T. F., Thees, O., & Hellweg, S. (2018). Environmental optimization of biomass use for energy under alternative future energy scenarios for Switzerland. *Biomass and Bioenergy*, 119, 462–472. <https://doi.org/10.1016/j.biombioe.2018.10.001>
- Valipour, M., Mafakheri, F., Gagnon, B., Prinz, R., Bergström, D., Brown, M., & Wang, C. (2024). Integrating bio-hubs in biomass supply chains: Insights from a systematic literature review. *Journal of Cleaner Production*, 467, 142930. <https://doi.org/10.1016/j.jclepro.2024.142930>
- van Schalkwyk, D. L., Mandegari, M., Farzad, S., & Görgens, J. F. (2020). Techno-economic and environmental analysis of bio-oil production from forest residues via non-catalytic and catalytic pyrolysis processes. *Energy Conversion and Management*, 213, 112815. <https://doi.org/10.1016/j.enconman.2020.112815>

- Walther, G., Schatka, A., & Spengler, T. S. (2012). Design of regional production networks for second generation synthetic bio-fuel – A case study in Northern Germany. *European Journal of Operational Research*, 218(1), 280–292. <https://doi.org/10.1016/j.ejor.2011.09.050>
- Web of Science. (2024). Clarivate. <https://clarivate.com/webofsciencegroup/solutions/%20web-of-science/>
- Wetterlund, E., Leduc, S., Dotzauer, E., & Kindermann, G. (2013). Optimal use of forest residues in Europe under different policies—Second generation biofuels versus combined heat and power. *Biomass Conversion and Biorefinery*, 3(1), 3–16. <https://doi.org/10.1007/s13399-012-0054-2>
- Wolfslehner, B., Linser, S., Pülzl, H., Bastrup-Birk, A., Camia, A., & Marchetti, M. (2016). *Forest bioeconomy—A new scope for sustainability indicators* (From Science to Policy) [From Science to Policy]. European Forest Institute. <https://doi.org/10.36333/fs04>
- Wood Pellet Association of Canada. (2021). *Canadian Biomass Pellet Map* [Map]. <https://www.canadianbiomassmagazine.ca/wp-content/uploads/2021/04/CBM-PELLET-MAP-APR21-JLR-LR.pdf>
- Wood Pellet Association of Canada. (2024). *2024 Canadian pellet facilities map*. <https://pellet.org/wp-content/uploads/2023/10/2024-canadian-pellet-facilities-map.pdf>
- Yazan, D. M., van Duren, I., Mes, M., Kersten, S., Clancy, J., & Zijm, H. (2016). Design of sustainable second-generation biomass supply chains. *Biomass and Bioenergy*, 94, 173–186. <https://doi.org/10.1016/j.biombioe.2016.08.004>
- Yun, H., Clift, R., & Bi, X. (2020a). Environmental and economic assessment of torrefied wood pellets from British Columbia. *Energy Conversion and Management*, 208, 112513.
- Yun, H., Clift, R., & Bi, X. (2020b). Process simulation, techno-economic evaluation and market analysis of supply chains for torrefied wood pellets from British Columbia: Impacts of plant configuration and distance to market. *Renewable and Sustainable Energy Reviews*, 127, 109745. <https://doi.org/10.1016/j.rser.2020.109745>
- Zargar, S., Jiang, J., Jiang, F., & Tu, Q. (2022). Isolation of lignin-containing cellulose nanocrystals: Life-cycle environmental impacts and opportunities for improvement. *Biofuels, Bioproducts and Biorefining*, 16(1), 68–80. <https://doi.org/10.1002/bbb.2261>
- Zetterholm, J., Ahlström, J., & Bryngemark, E. (2020). Large-scale introduction of forest-based biorefineries: Actor perspectives and the impacts of a dynamic biomass market. *Biomass and Bioenergy*, 142, 105782. <https://doi.org/10.1016/j.biombioe.2020.105782>
- Zetterholm, J., Bryngemark, E., Ahlström, J., Söderholm, P., Harvey, S., & Wetterlund, E. (2020). Economic Evaluation of Large-Scale Biorefinery Deployment: A Framework

Integrating Dynamic Biomass Market and Techno-Economic Models. *Sustainability*, 12(17), 7126. <https://doi.org/10.3390/su12177126>

Appendices

Appendix A (Input Data)

A.1 Input data for biomass transportation through different pathways

The input data required to calculate the delivered cost of biomass via bundled slash pathway and small-diameter logs pathway can be found in Table A-1 and Table A-2.

Table A-1. Input data for calculating the biomass delivered cost via the bundled slash pathway.

Item	Formula	Value	Reference
Input parameters			
Maximum payload of bundles in truck (odt)	-	14	(Lindroos et al., 2011)
Trucking cost (2008 CAD/hour)	-	135	
Grapple loader productivity for loading bundles to truck (odt/hour)	-	44	
Grapple loader productivity for unloading bundles to truck (odt/hour)	-	58	
Grapple loader cost (2008 CAD/hour)	-	104	
Bundling cost (2008 CAD/hour)	-	200	
Bundler productivity (Bundles/hour)	-	17	
Bundle dry mass (odt)	-	0.43	(Friesen, 2012)
Average travel speed in Williams Lake TSA (km/hour)	-	78	
Inflation factor from 2008 to 2023 CAD	-	1.3	(Inflation Calculator, 2024)
Intermediate calculations			
Loading time onto truck (hour)	Maximum payload of bundles in truck / Grapple loader productivity for loading bundles to truck	0.33	Calculated
Unloading time from truck (hour)	Maximum payload of bundles in truck / Grapple loader productivity for unloading bundles to truck	0.24	Calculated
Derived cost parameters			
Bundling cost (2023 CAD/odt)	Inflation from 2008 to 2023 * [Bundling cost / (Bundler productivity*Bundle dry mass)]	38	Calculated
Loading cost of bundles using grapple loader (2023 CAD/odt)	Inflation from 2008 to 2023 * [Grapple loader cost/Grapple loader productivity for loading bundles to trucks]	3	Calculated
Truck cost while loading and unloading bundles (2023 CAD/odt)	Inflation from 2008 to 2023 * [(Loading time onto truck + Unloading time from truck) * Trucking cost/maximum payload of bundles]	8	Calculated
Truck transport cost for bundled slash (2023 CAD/hour-odt)	Inflation from 2008 to 2023 * [Trucking cost / maximum payload of bundles in truck]	13	Calculated

Table A-2. Input data for calculating the biomass delivered cost via the small-diameter slash pathway.

Item	Formula or description	Value	Reference
Input parameters			
Maximum payload of small logs (or bundles) (tonne)		42	(Lindroos et al., 2011)
Trucking cost (2008 CAD/hour)	-	135	
Moisture content		50%	(Personal communications, PFInnovations, 2023)
Intermediate calculations			
Maximum payload of small logs (or bundles) (odt)		21	Calculated
Derived cost parameters			
Loading cost of logs using grapple loader (2023 CAD/odt)		3	Calculated (Same as the corresponding cost for bundles)
Truck cost while loading and unloading logs (2023 CAD/odt)		8	Calculated (Same as the corresponding cost for bundles)
Truck transport cost for logs (2023 CAD/hour-odt)	Inflation from 2008 to 2023 * [Trucking cost / maximum payload of small logs in truck]	9	Calculated

A.2 Input data for preprocessing and handling biomass at the biohubs

Cost of preprocessing and handling equipment pieces can be found in Table A-3 to Table A-11.

Table A-3. Input data for calculating unit cost (\$/odt) of handling biomass with front-end loader.

Item	Value
Annual capacity ^a	90,418
Capital cost ^a	\$748,865
Delivery cost (10% of capital cost) ^a	\$74,887
Salvage value (10% of capital cost) ^a	\$74,887
Installation cost (2.6 of capital cost if any) ^a	\$0
Service life (years) ^a	5
Interest rate ^b	10%
Annualized capital cost	\$205,037
Annual insurance cost (2.5% of purchase cost) ^a	\$18,722
Hourly operating and maintenance cost ^a	139.52
Annual operating and maintenance cost ^c	\$390,654
Total annual cost	\$614,413
Unit cost (\$/odt) ^d	\$7
Variable operating and maintenance cost (\$/odt) ^e	\$4

a)	Data obtained from (Khadivi, 2022) and (Sales Manager at TerraSource, personal communication, December 1, 2020) and converted to 2023 rates from 2020 using inflation rate of 15.21% (<i>Inflation Calculator</i> , 2024)
b)	(Blair & Mabee, 2021)
c)	Considering 350 working days and an 8-hour shift a day
d)	Used in optimization models and calculated as follows: (Annual insurance cost (fixed O&M costs) + Annualized capital cost + Annual O&M cost)/Annual capacity
e)	Used in techno-economic analysis models and calculated as follows: Annual O&M cost/ Annual capacity

Table A-4. Input data for calculating unit cost (\$/odt) of handling biomass with reclaim feeder.

Item	Value
Annual capacity ^{a, b}	24,480
Capital cost ^a	\$478,519
Delivery cost (10% of capital cost) ^a	\$47,852
Salvage value (10% of capital cost) ^a	\$47,852
Installation cost (2.6 of capital cost if any) ^a	\$0
Service life (years) ^a	20
Interest rate ^c	10%
Annual capital cost	\$60,992
Annual insurance cost (2.5% of purchase cost) ^a	\$11,963
Power ^a	75 kW
Productive machine hour ^a	6300
BC industrial power rate in 2023 ^d	0.114 kWh
Annual power cost ^e	\$53,865
Annual maintenance (25% of capital cost)	\$119,630
Annual operating and maintenance cost	\$173,495
Total annual cost	\$234,487
Unit cost (\$/odt) ^f	\$10
Variable operating and maintenance cost (\$/odt) ^g	\$7
a)	Data obtained from (Khadivi, 2022) and (Sales Manager at TerraSource, personal communication, December 1, 2020) and converted to 2023 rates from 2020 using inflation rate of 15.21% (<i>Inflation Calculator</i> , 2024)
b)	Converted to 8-hour shift from 24-hour
c)	(Blair & Mabee, 2021)
d)	(Statista, 2023)
e)	Power × Productive machine hour × BC industrial power rate
f)	Used in optimization models and calculated as follows: (Annual insurance cost (fixed O&M costs) + Annualized capital cost + Annual O&M cost)/Annual capacity
g)	Used in techno-economic analysis models and calculated as follows: Annual O&M cost/ Annual capacity

Table A-5. Input data for calculating unit cost (\$/odt) of handling biomass with scalping disk screener.

Item	Value
Annual capacity ^{a, b}	23,328
Capital cost ^a	\$86,268

Delivery cost (10% of capital cost) ^a	\$8,627
Salvage value (10% of capital cost) ^a	\$8,627
Installation cost (2.6 of capital cost if any) ^a	\$224,297
Service life (years) ^a	20
Interest rate ^c	10%
Annual capital cost	\$37,342
Annual insurance cost (2.5% of purchase cost) ^a	\$2,157
Power ^a	4 kW
Productive machine hour ^a	6300
BC industrial power rate in 2023 ^d	0.114 kWh
Annual power cost ^e	\$2,678
Annual maintenance (25% of capital cost) ^a	\$21,567
Annual operating and maintenance cost	\$24,245
Total annual cost	\$63,744
Unit cost (\$/odt) ^f	\$3
Variable operating and maintenance cost (\$/odt) ^g	\$1
a) Data obtained from (Khadivi, 2022) and (Sales Manager at TerraSource, personal communication, December 1, 2020) and converted to 2023 rates from 2020 using inflation rate of 15.21% (<i>Inflation Calculator</i> , 2024) b) Converted to 8-hour shift from 24-hour c) (Blair & Mabee, 2021) d) (Statista, 2023) e) Power × Productive machine hour × BC industrial power rate f) Used in optimization models and calculated as follows: (Annual insurance cost (fixed O&M costs) + Annualized capital cost + Annual O&M cost)/Annual capacity g) Used in techno-economic analysis models and calculated as follows: Annual O&M cost/ Annual capacity	

Table A-6. Input data for calculating unit cost (\$/odt) of preprocessing biomass with drop feed hogger.

Item	Value
Annual capacity ^{a, b}	31,355
Capital cost ^a	\$246,521
Delivery cost (10% of capital cost) ^a	\$24,652
Salvage value (10% of capital cost) ^a	\$24,652
Installation cost (2.6 of capital cost if any) ^a	\$640,954
Service life (years) ^a	20
Interest rate ^c	10%
Annual capital cost	\$106,708
Annual insurance cost (2.5% of purchase cost) ^a	\$6,163
Power ^a	248 kW
Productive machine hour ^a	6300
BC industrial power rate in 2023 ^d	0.114 kWh
Annual power cost ^e	\$178,050
Annual maintenance (25% of capital cost) ^a	\$61,630

Annual oil and lubricant cost ^a	\$28,452
Annual operating and maintenance cost	\$268,133
Total annual cost	\$408,085
Unit cost (\$/odt) ^f	\$12
Variable operating and maintenance cost (\$/odt) ^g	\$9
a) Data obtained from (Khadivi, 2022) and (Sales Manager at TerraSource, personal communication, December 1, 2020) and converted to 2023 rates from 2020 using inflation rate of 15.21% (<i>Inflation Calculator</i> , 2024) b) Converted to 8-hour shift from 24-hour c) (Blair & Mabee, 2021) d) (Statista, 2023) e) Power × Productive machine hour × BC industrial power rate f) Used in optimization models and calculated as follows: (Annual insurance cost (fixed O&M costs) + Annualized capital cost + Annual O&M cost)/Annual capacity g) Used in techno-economic analysis models and calculated as follows: Annual O&M cost/ Annual capacity	

Table A-7. Input data for calculating unit cost (\$/odt) of handling biomass with butt-n-top loader.

Item	Value
Annual capacity	445,520
Capital cost	\$704,610
Delivery cost (10% of capital cost)	\$0
Salvage value (25% of capital cost)	\$176,153
Installation cost (2.6 of capital cost if any)	\$0
Service life (years)	5
Interest rate	10%
Annualized capital cost	\$157,021
Annual insurance cost (2.5% of purchase cost)	\$0
Annual operating and maintenance cost	\$1,152,273
Total annual cost	\$1,309,294
Unit cost (\$/odt) ^a	\$3
Variable operating and maintenance cost (\$/odt) ^b	\$3
a) Used in optimization models and calculated as follows: (Annual insurance cost (fixed O&M costs) + Annualized capital cost + Annual O&M cost)/Annual capacity b) Used in techno-economic analysis models and calculated as follows: Annual O&M cost/ Annual capacity	

The original values for the butt-n-top loader can be found in Table A-8.

Table A-8. Input data for calculating unit cost (\$/odt) of handling biomass with butt-n-top loader.

Item	Formula	Value	Reference
Capital cost (2002 CAD)		450,000	(Araki, 2002)
Average productivity (odt/hour)	-	62	
Expected life (year)	-	3-5	
Expected life (hour)	-	21600	

Scheduled machine hours per year	Expected life (hour)/ Expected life (year)	7200	
Salvage value	25%* Capital cost	112,500	
Average investment (2002 CAD)	-	281,250	
Insurance rate	-	3%	
Insurance (2002 CAD/hour)	Insurance rate * (Average investment/Scheduled machine hours per year)	1.2	
Annual capacity	Average productivity* Scheduled machine hours per year	445,520	
Fuel consumption (L/hour)	-	40	
BC diesel price rate (2023 CAD/L)	-	1.79	(Statistics Canada, 2023)
Annual repair and maintenance (2002 CAD)	30% * Capital cost	135,000	(Araki, 2002)
Lube and oil (2002 CAD/hour)	-	15% of fuel	
Wages (2002 CAD/hour)	-	22	
Wages benefits	-	35%	
Wages and benefits	(1+ Wages benefits %) * Wages	29.7	
Inflation from 2002 to 2023	-	57%	(Inflation Calculator, 2024)
Total operating and maintenance costs (2023 CAD/Scheduled machine hour)	(1+inflation) [Insurance +Annual repair and maintenance /Scheduled machine hours per year + Wages and benefits] + Fuel consumption*BC diesel price rate + (1+Lub and oil%)	160	Calculated
Total operating and maintenance costs (2023 CAD/odt)	Total operating and maintenance costs (2023 CAD/Scheduled machine hour)/Average productivity	2.6	Calculated

Table A-9. Input data for calculating unit cost (\$/odt) of preprocessing biomass with debarker and chipper.

Items	Value
Annual capacity	445,520
Capital cost	\$10,960,600
Delivery cost (10% of capital cost if any)	\$0
Salvage value (25% of capital cost)	\$2,740,150
Installation cost (2.6 of capital cost if any)	\$0
Service life (years)	7
Interest rate	10%
Annualized capital cost	\$1,962,541
Annual insurance cost (2.5% of purchase cost)	\$0
Annual operating and maintenance cost	\$7,582,026
Total annual cost	\$9,544,566
Unit cost (\$/odt) ^a	\$21

Variable operating and maintenance cost (\$/odt)	\$17
a) Used in optimization models and calculated as follows: (Annual insurance cost (fixed O&M costs) + Annualized capital cost + Annual O&M cost)/Annual capacity	
b) Used in techno-economic analysis models and calculated as follows: Annual O&M cost/ Annual capacity	

The original values for the debarker and chipper can be found in Table A-10.

Table A-10. Input data for calculating unit cost (\$/odt) of preprocessing biomass with debarker and chipper.

Item	Formula	Value	Reference
Capital cost (2002 CAD)		7,000,000	(Araki, 2002)
Average productivity (odt/hour)	-	62	
Expected life (year)	-	7	
Expected life (hour)	-	50400	
Scheduled machine hours per year	Expected life (hour)/ Expected life (year)	7200	
Salvage value	25%* Capital cost	1,750,000	
Average investment (2002 CAD)	-	4,375,000	
Insurance rate	-	3%	
Insurance (2002 CAD/hour)	Insurance rate * (Average investment/Scheduled machine hours per year)	18	
Annual capacity	Average productivity* Scheduled machine hours per year	445,520	
Power consumption (kW/hour)	-	4000	(Statista, 2023)
BC industrial power rate (2023 CAD/kW)	-	0.114	
Annual repair and maintenance (2002 CAD)	20% * Capital cost	1,400,000	(Araki, 2002)
Chipper and deparker knives (2002 CAD/year)	-	145,000	
Wages (2002 CAD/hour)	-	110	
Wages benefits	-	35%	
Wages and benefits	(1+ Wages benefits %) * Wages	148.5	
Inflation from 2002 to 2023	-	57%	(Inflation Calculator, 2024)
Total operating and maintenance costs (2023 CAD/Scheduled machine hour)	(1+inflation) [Insurance +((Annual repair and maintenance + Chipper and debarker knives)/Scheduled machine hours per year) + Wages and benefits]	1,053	Calculated
Total operating and maintenance costs (2023 CAD/odt)	Total operating and maintenance costs (2023 CAD/Scheduled machine hour)/Average productivity	17.02	Calculated

For AC production, the woodchips need to be dried before entering the AC production unit (Gu & Bergman, 2016). Therefore, in addition to the equipment pieces mentioned for small-diameter logs pathway, a rotary cascade dryer is also considered to be acquired for the biohub. The data for this equipment is shown in Table A-11. Inflation rate of 69% from 1999 to 2023 (Inflation Calculator, 2024) and exchange rate of 1.7% from British Pound to CAD (British Pound to Canadian Dollar Spot Exchange Rates for 2023, 2024) is used to convert the cost data into 2023 CAD rates .

Table A-11. Input data for calculating unit cost (\$/odt) of preprocessing biomass with rotary cascade dryer.

Items	Value
Annual capacity ^a	25,142
Capital cost ^a	\$794,268
Delivery cost (10% of capital cost if any) ^b	\$79,427
Salvage value (10% of capital cost) ^b	\$79,427
Installation cost (2.6 of capital cost if any) ^b	\$2,065,097
Service life (years) ^c	4
Interest rate ^d	10%
Annualized capital cost	\$909,989
Annual operating and maintenance cost	\$27,799
Total annual cost	\$937,788
Unit cost (\$/odt) ^e	\$37
Variable operating and maintenance cost (\$/odt) ^f	\$1.1
a) (Brammer & Bridgwater, 1999) b) (Khadivi, 2022) c) (<i>Maintenance of Rotary Drum Dryer</i> , 2024) d) Used in optimization models and calculated as follows: (Annual insurance cost (fixed O&M costs) + Annualized capital cost + Annual O&M cost)/Annual capacity e) Used in techno-economic analysis models and calculated as follows: Annual O&M cost/ Annual capacity	

A.3 Input data for bioproduction technologies

These original data were adjusted using Eq. 3-1, Eq. 3-2, and appropriate inflation and exchange (Annual Exchange Rates, 2024; Inflation Calculator, 2024).

Table A-12. Original input data for bioproduction technologies

Product	Input data type	Value	Unit	Reference
CNC & CNF (Cellulose Nanocrystals)	Capacity (input biomass)	150,000	odt/year	(Blair, 2020)
	AVAP (American value-added pulping) equipment cost	\$191.9	(million USD in 2019)	
	Engineering and management	\$42.4		

and Nanofibrils)	Contingency	\$41		
	Land and site preparation	\$8.5		
	Variable operating costs	\$31.9		
	Fixed operating costs	\$11.5		
	Working capital	\$21.8		
AC (Activated Carbon)	Annual capacity (input biomass)	640	odt/year	(Shaheen et al., 2022)
	Equipment cost	\$90,000	(USD in 2020)	
	Total capital investment (direct plant cost + indirect plant costs + equipment cost)	\$481,300	(USD in 2020)	
	Annual fixed O&M costs	\$4,813	(USD in 2020)	
	Annual variable O&M and overhead costs	\$967	(USD in 2020)	
Biochar (Dry torrefaction)	Annual capacity (input biomass)	88,000	odt/year	(Akbari et al., 2020)
	Equipment cost (total capital investment)	\$631,463	(USD in 2016)	
	Annual variable O&M costs	\$965,591	(USD in 2016)	
Biochar (Wet torrefaction)	Annual capacity (input biomass)	88,000	odt/year	(Akbari et al., 2020)
	Equipment cost (total capital investment)	\$1,804,185	(USD in 2016)	
	Annual variable O&M costs	\$1,913,763	(USD in 2016)	
Bio-oil	Capacity	118,300	odt/year	(van Schalkwyk et al., 2020)
	Total capital investment	\$98.9	(million USD in 2020)	
	Annual fixed O&M costs	\$6.0	(million USD in 2020)	
	Annual variable O&M costs	\$3.3	(million USD in 2020)	
	Working capital	\$0.7	(million USD in 2020)	
Pellets	Capacity	111,111	odt/year	(Yun et al., 2020b)
	Total capital investment	0.3	(million CAD in 2020)	
	Working capital	0.5	(million CAD in 2020)	
	Annual O&M costs	2.3	(million CAD in 2020)	

A.4 Supply data

The supply data over the 20-year planning horizon can be found in the Table A-13 below. This is the adjusted supply data as explained in Section 4.6.1.

Table A-13. Original input data for bioproduction technologies

Biohub location	Small-diameter logs (odt)	Residues (odt)	Total (odt)
Anahim Lake	559,189	1,880,608	2,439,797
Hanceville	956,399	3,405,682	4,362,081
Horsefly	618,325	1,320,674	1,939,000
Williams Lake	577,543	1,338,602	1,916,146
Total	2,711,457	7,945,566	10,657,023

Appendix B (Emissions Calculations)

The emission calculations are used in the techno-economic and optimization models developed under the output-based pricing system, as well as in the bi-objective optimization models in which supply chain GHG emissions are considered as an objective.

B.1 Roadside, preprocessing, and handling emissions

Depending on the pathway, different activities and equipment are involved, each associated with different levels of emissions.

Ground slash pathway

Table B-1. Greenhouse gas (GHG) emissions (tonne of CO₂-eq/odt) for preprocessing slash at road side.

Activity (Equipment)	Fuel type	Fuel consumption	Unit	Productivity (odt/PMH ¹)	Fuel consumption (L/ odt) or (kWh/ odt)	Emission factor (g CO ₂ -eq /L) or (g CO ₂ -eq /kWh)	Emission factor reference	GHGs emitted (t CO ₂ - eq /odt)
Grinding (Mobile horizontal grinder) ^a	Diesel	135	L/PMH ²	24.70	5.47	3,007	GHGs emitted from diesel (g CO ₂ -eq /L) ^c	0.016
Loading (Grapple loader) ^b	Diesel	26	L/PMH	43.5	0.60	3,007.00	GHGs emitted from diesel (g CO ₂ -eq /L) ^c	0.002
GHGs emitted (t CO₂-eq/odt)								0.0182
a) (Blackburn, 2019) b) (Lindroos et al., 2011) c) Akhtari et al., 2020)								

¹ PMH: productive machine hour

Table B-2. Greenhouse gas (GHG) emissions (tonne of CO₂-eq/odt) for handling and preprocessing of ground slash at bioproduction facilities (i.e., biohubs)

Activity (Equipment)	Fuel type	Fuel consumption	Unit	Productivity (odt/PMH)	Fuel consumption (L/ odt) or (kWh/ odt)	Emission factor (g CO ₂ -eq /L) or (g CO ₂ -eq /kWh)	Emission factor reference	GHGs emitted (t CO ₂ -eq/odt)
Loading and unloading (Front-end-loader middle size) ^a	Diesel	30.10	L/PMH	32.29	0.93	3,007.00	GHGs emitted from diesel (g CO ₂ -eq /L) ^b	0.003
Reclaiming (Reclaim feeder) ^c	Electricity	75.00	kWh/PMH	11.66	6.43	11.50	GHG Intensities of BC-Hydro total electricity generation (g CO ₂ -eq/kWh) ^d	0.00007
Screening (Screener) ^e	Electricity	3.73	kWh/PMH	11.11	0.34	11.50	GHG Intensities of BC-Hydro total electricity generation (g CO ₂ -eq/kWh) ^d	0.000004
Total GHG emitted (t CO₂-eq/odt)								0.003
a) Tobias Ziegenbein, Project Manager at Merce Celgar, personal communication, September 25, 2020 b) (Akhtari et al., 2020) c) (Prakoso, 2019) d) (BC Hydro, 2024) e) Sales Head at Acrowood, personal communication, December 2, 2020								

Bundled slash pathway

Table B-3. Greenhouse gas (GHG) emissions (tonne of CO₂-eq/odt) for activities at road side for bundled slash pathway.

Activity (Equipment)	Fuel type	Fuel consumption	Unit	Productivity (odt/PMH)	Fuel consumption (L/odt) or (kWh/ odt)	Emission factor (g CO ₂ -eq /L) or (g CO ₂ -eq /kWh)	Emission factor reference	GHGs emitted (t CO ₂ -eqs/odt)
Loading (Grapple loader) ^a	Diesel	26.00	L/PMH	43.50	0.60	3,007.00	GHGs emitted from diesel (g CO ₂ -eq /L) ^b	0.0018
Bundling (Bundler) ^a	Diesel	30.00	L/PMH	7.31	4.10	3,007.00	GHGs emitted from diesel (g CO ₂ -eq /L) ^b	0.0123
Total GHG emitted (t CO₂-eq/odt)								0.0141

a) (Lindroos et al., 2011)
b) (Akhtari et al., 2020)

Table B-4. Greenhouse gas (GHG) emissions (tonne of CO₂-eq/odt) for handling and preprocessing of bundled slash at bioproduction facilities (i.e., biohubs).

Activity (Equipment)	Fuel type	Fuel consumption	Unit	Productivity (odt/PMH)	Fuel consumption (L/odt) or (kWh/odt)	Emission factor (g CO ₂ -eq /L) or (g CO ₂ -eq /kWh)	Emission factor reference	GHGs emitted (t CO ₂ -eq/odt)
Feeding bundles to grinder (Grapple loader butt-n-top) ^a	Diesel	40.00	L/PMH	62.00	0.65	3,007	GHGs emitted from diesel (g CO ₂ -eq /L) ^f	0.0019
Grinding (Stationary grinder) ^b	Electricity	255.50	kWh/PMH	91.00	2.81	11.50	GHG Intensities of electricity generation (g CO ₂ -eq/kWh) ^g	0.000032
Loading and unloading (Front-end-loader) ^c	Diesel	30.10	L/PMH	32.29	0.93	3,007	GHGs emitted from diesel (g CO ₂ -eq /L) ^f	2,803
Reclaiming (Reclaim feeder) ^d	Electricity	75.00	kWh/PMH	11.66	6.43	11.50	GHG Intensities of electricity generation (g CO ₂ -eq/kWh) ^g	0.000074
Screening (Screener) ^e	Electricity	3.73	kWh/PMH	11.11	0.34	11.50	GHG Intensities of electricity generation (g CO ₂ -eq/kWh) ^g	0.0028
Total GHG emitted (t CO₂-eq/odt)								0.0049
a) (Araki, 2002) b) (Lindroos et al., 2011) c) Tobias Ziegenbein, Project Manager at Merce Celgar, personal communication, September 25, 2020 d) (Prakoso, 2019) e) Sales Head at Acrowood, personal communication, December 2, 2020 f) (Akhtari et al., 2020) g) (BC Hydro, 2024)								

Small-diameter logs pathway

Table B-5. Greenhouse gas (GHG) emissions (tonne of CO₂-eq/odt) for loading small diameter logs to trucks at road side

Activity (Equipment)	Fuel type	Fuel consumption	Unit	Productivity (ODT/PMH)	Fuel consumption (L/ODT) or (kWh/ODT)	Emission factor (g CO ₂ -eq /L) or (g CO ₂ -eq /kWh)	Emission factor reference	GHGs emitted (t CO ₂ -eq/odt)
Loading (Grapple loader) ^a	Diesel	26.00	L/PMH	43.50	0.60	3,007	GHGs emitted from diesel (g CO ₂ -eq /L) ^b	0.0018
Total GHG emitted (t CO₂-eq/odt)								0.0018

- a) (Lindroos et al., 2011)
b) (Akhtari et al., 2020)

Table B-6. Greenhouse gas (GHG) emissions (tonne of CO₂-eq/odt) for handling and preprocessing of small-diameter logs at bioproduction facilities (i.e., biohubs).

Activity (Equipment)	Fuel type	Fuel consumption	Unit	Productivity (odt/PMH)	Fuel consumption (L/odt) or (kWh/odt)	Emission factor (g CO ₂ -eq /L) or (g CO ₂ -eq /kWh)	Emission factor reference	GHGs emitted (t CO ₂ -eq/odt)
Unloading from trucks and loading to debarker (Grapple loader) ^a	Diesel	40.00	L/PMH	62.00	0.65	3,007.00	GHGs emitted from diesel (g CO ₂ -eq /L) ^d	0.0019
Debarking and chipping (Debarker and chipper) ^a	Electricity	4,000.00	kWh/PMH	62.00	64.52	11.50	GHG Intensities of electricity generation (g CO ₂ -eq/kWh) ^e	0.0007
Reclaiming (Reclaim feeder) ^b	Electricity	75.00	kWh/PMH	11.66	6.43	11.50	GHG Intensities of electricity generation (g CO ₂ -eq/kWh) ^e	0.00007
Screening (Screener) ^c	Electricity	3.73	kWh/PMH	11.11	0.34	11.50	GHG Intensities of electricity generation (g CO ₂ -eq/kWh) ^e	0.000004
Total GHG emitted (t CO₂-eq/odt)								0.00276
a) (Araki, 2002) b) (Prakoso, 2019) c) Sales Head at Acrowood, personal communication, December 2, 2020 d) (Akhtari et al., 2020) e) (BC Hydro, 2024)								

B.2 Transportation emissions

The transportation-related emissions are the same among all the pathways and are divided into two components: 1) emissions from the actual transportation, and 2) emissions generated while the truck is waiting to be loaded and unloaded. These emissions are calculated based on data in Table B-7.

Table B-7. Transportation data

Type of truck	Supply chain pathway	Capacity (tonne)	Fuel consumption (L of diesel/km)	Emission factor (g CO ₂ -eq/L) ^c
Tri-axle truck (chip van) ^a	Ground slash	43.25	0.68	3,007
Seven-axle short-log truck ^b	Bundled slash, small-diameter logs	42	0.511	3,007
a) (Cambero et al., 2016) b) (Lindroos et al., 2011) c) (Akhtari et al., 2020)				

Eq. B- 1

$$\begin{aligned}
& \text{GHG emission of transportation} \left(t \text{ CO}_2 \text{ eq.} \frac{\text{emissions}}{\text{odt}} \right) (\text{roundtrip}) \\
&= \text{fuel consumption} \left(\frac{\text{Liter of diesel}}{\text{km}} \right) \times 2 \text{ Distance between cutblocks and biohubs (km)} \\
&\times \frac{1}{\text{Capacity of trucks(odt)}} \times \text{emission factor of diesel} \left(\frac{t \text{ CO}_2 \text{ eq. emissions}}{\text{Liter of diesel}} \right)
\end{aligned}$$

Eq. B- 2

$$\begin{aligned}
& \text{GHG emission of trucks when loading and unloading} \left(t \text{ CO}_2 \text{ eq.} \frac{\text{emissions}}{\text{odt}} \right) \\
&= \text{fuel consumption} \left(\frac{\text{Liter of diesel}}{\text{km}} \right) \\
&\times \text{average speed in williams Lake TSA} \left(\frac{\text{km}}{\text{hour}} \right) \\
&\times \text{Loading and unloading time (hour)} \times \frac{1}{\text{Capacity of trucks (odt)}} \\
&\times \text{emission factor of diesel} \left(\frac{t \text{ CO}_2 \text{ eq. emissions}}{\text{Liter of diesel}} \right)
\end{aligned}$$

Eq. B- 3

$$\begin{aligned}
& \text{Annual transportation emissions} (t \text{ CO}_2 \text{ eq. emissions}) \\
&= \text{Transported biomass (odt)} \\
&\times (\text{GHG emission of transportation} \\
&+ \text{GHG emission of trucks when loading and unloading})
\end{aligned}$$

The loading and unloading time for small-diameter logs and bundled slash pathway were considered 0.57 hours as calculated in Table A-1 and for ground slash it is assumed to be one hour. The average speed in Williams Lake TSA is estimated at 78 km/hour as given in Table A-1.

B.3 Bioproduction facilities emissions

CNC and CNF

From Blair (2020) the following energy inputs for the conversion process were obtained:

- Electricity: 500 kWh per tonne of CNC/CNF for the electricity consumption of the disk refiner.
- Stripper steam demand: 4.5 kg of steam per kg of ethanol used in the process.

Considering the CNC yield of 28%, the electricity demand per odt of input biomass can be calculated as 140 kWh, and for CNF, considering yield of 39%, the electricity demand per odt of input biomass can be calculated as 195 kWh.

For steam demand, based on the ratios provided for the required water, ethanol, and SO₂ to dry biomass, the steam demand per odt of input biomass can be calculated as 4.5 tonnes. Assuming that natural gas is utilized to produce the steam, 11,285 MJ of natural gas per odt of biomass is required for the conversion. The assumptions and calculation steps of the natural gas requirement can be found in Table B-8.

Table B-8. Required information and assumptions to calculate natural gas demand for CNC (cellulose nanocrystal) production using AVAP (American value-added pulping)

Calculation of natural gas required to produce the steam	
Required energy to produce 1 kg of steam (assuming that we're converting water at 25°C to steam at 100°C at standard atmospheric pressure) (MJ per tonne kg of steam) [1]	2,257
MJ of natural gas required to generate one tonne of steam assuming 90% efficiency	2,507.8
Natural gas required (MJ per tonne of biomass)	11,285
a) (Thermodynamics of Steam, n.d.)	

The emissions from chemicals for bleaching pulp in the CNC production is added based on the study done by Buitrago-Tello et al. (2022), in which the GWP for these bleaching chemicals were reported 238.98 g CO₂-eq per kg of softwood fluff pulp. Similarly, GWP of waste and wastewater emissions of bleaching softwood fluff pulp is reported at 60.22 g CO₂-eq per kg of softwood fluff pulp in (Buitrago-Tello et al., 2022).

Based on the information about the AVAP process in (Nelson et al., 2016), one ton of bleached pulp yields one ton of CNC/CNF. Therefore, we can estimate the GWP of bleaching chemicals and waste and wastewater emissions for CNC/CNF production at 238.98 and 60.22 g CO₂-eq per kg of CNC/F, respectively. Considering the yield of 0.28 (tonne of CNC/odt) for and 0.39 (tonne of CNF/odt), the emissions per odt of input biomass for CNC and CNF productions can be estimated as shown in Table B-9.

Table B-9. GHG emissions (tonne of CO₂-eq/odt) from CNC (cellulose nanocrystal) production using AVAP (American value-added pulping).

Activity (Equipment)	Source of emissions	Fuel consumption/ odt	Unit	Fuel consumption /odt	Emission factor (g CO ₂ -eq /L) or (g CO ₂ -eq /kWh)	Emission factor reference	GHGs emitted (t CO ₂ -eq /odt)
AVAP (CNC) ^a	Electricity ^a	-	kWh	140	11.50	GHG intensities of electricity generation (g CO ₂ -eq/kWh) ^b	0.00161
	Natural gas ^a	-	MJ	11,285	180	The emissions factors of natural gas (g CO ₂ -eq/kWh) ^c	0.56425
	Chemicals for bleaching ^d	-	-	-	-	-	0.06691
	Water/waste water ^d	-	-	-	-	-	0.01686
CNC production emissions (t CO₂-eq /odt)							0.64964
AVAP (CNF) ^a	Electricity ^a	-	kWh	195	11.50	GHG intensities of electricity generation (g CO ₂ -eq/kWh) ^b	0.00224
	Natural gas ^a	-	MJ	11,285	180	The emissions factors of natural gas (g CO ₂ -eq/kWh) ^c	0.56425
	Chemicals for bleaching ^d	-	-	-	-	-	0.09320
	Water/waste water ^d	-	-	-	-	-	0.02349
CNF production emissions (t CO₂-eq /odt)							0.68318
a) (Blair, 2020) b) (BC Hydro, 2024) c) (BC building code, 2018) d) (Buitrago-Tello et al., 2022; Nelson et al., 2016)							

Biochar

For biochar, two technologies are considered for conversion: wet torrefaction and dry torrefaction. In the reference paper (Akbari et al., 2021), the fuel consumption per green tonne of biomass is given. Based on the given moisture content and Table B-4 and Table B-5, the GHG emissions per odt of input biomass can be calculated as shown in Table B-10.

$$MC (\%) = \frac{m_{wet} - m_{dry}}{m_{wet}} \times 100 \quad \text{Eq. B- 4}$$

Where m_{wet} is the mass of the wet material and m_{dry} is the mass of the dry material.

$$(Fuel\ consumption) / (odt) = (Fuel\ consumption\ per\ green\ tonne)/0.55 \quad \text{Eq. B- 5}$$

Table B-10. Greenhouse gas (GHG) emissions (tonne of CO₂-eq/odt) for biochar conversion facility using dry and wet torrefaction.

Activity (Equipment)	Fuel type	Fuel consumption/green tonne	Unit	Fuel consumption/odt (Considering 45% MC wet basis)	Emission factor (g CO ₂ -eq /L) or (g CO ₂ -eq /kWh)	Emission factor reference	GHGs emitted (t CO ₂ -eq /odt)
Dry Torrefaction technology (Biochar) ^a	Electricity ^a	193.7	kWh	352	11.50	GHG intensities of electricity generation (g CO ₂ -eq/kWh) ^b	0.00405
	Natural gas ^a	472.7	MJ	859	180	The emissions factors of natural gas (g CO ₂ -eq/kWh) ^c	0.04297
Biochar (dry torrefaction) production emissions (t CO₂-eq /odt)							0.04702
Wet Torrefaction technology (Biochar) ^a	Electricity ^a	331.5	kWh	603	11.50	GHG intensities of electricity generation (g CO ₂ -eq/kWh) ^b	0.00693
	Natural gas ^a	428.7	MJ	779	180	The emissions factors of natural gas (g CO ₂ -eq/kWh) ^c	0.03897
Biochar (wet torrefaction) production emissions (t CO₂-eq /odt)							0.04590

a) (Akbari et al., 2020)

b) (BC Hydro, 2024)

c) (BC building code, 2018)

Activated carbon (AC)

For AC, based on the reference paper by Shaheen et al. (2022), natural gas and electricity are utilized for the conversion technology. The paper does not specify the exact amount of utilities consumed exclusively for the conversion process. However, it provides a Life Cycle Assessment (LCA) and reports the global warming impact as percentages for different stages of AC production, in terms of total CO₂-eq. emissions. According to Shaheen et al. (2022), 8.33 kg of CO₂-eq. is generated per kilogram of AC produced. Using the reported percentages and total CO₂-eq., we calculate the emission contributions for each conversion step. Since the original study was conducted in the UAE while this project is in British Columbia, Canada, the emissions related to natural gas and electricity were adjusted considering the regional emission factors. Finally, with a

yield of 45%, the values are reported based on the odt of input biomass. Table B-11 provides these calculations.

Table B-11. Greenhouse gas (GHG) emissions (tonne of CO₂-eq/odt) for activated carbon (AC) conversion facility

Activity (Equipment)	Fuel type	Global warming impact % ^a	CO ₂ eq amount (kg per 1 kg of AC)	Converting the CO ₂ eq amounts to BC ratios (BC emission factors ^{b,c} /UAE emission factors ^{d,e}) (kg per kg of AC)	GHGs emitted (t CO ₂ -eq /odt) considering 0.45 as yield ^a
Pyrolysis (i.e., carbonization)	Natural gas ^a	0.62%	0.051646	0.021	0.00971
Carbon activation	Natural gas ^a	80.54%	6.708982	2.776	1.26188
Drying and shaking	Electricity ^a	13.32%	1.109556	0.185	0.08406
Activated carbon (AC) production emissions (t CO₂-eq /odt)					1.35565
a) (Shaheen et al., 2022) b) (BC Hydro, 2024) c) (BC building code, 2018) d) (<i>Electricity Supplied from Grid</i> , 2023) e) (Hummieda et al., 2023)					

Pellets

According to Yun et al. (2020a), approximately 73 MJ of energy is required per GJ of pellets produced for the pelletizing process. Given that the energy content of wood pellets is 17 GJ per tonne (15), the energy required to produce one tonne of pellets is 1,241 MJ. Since 1 kWh is equal to 3.6 MJ (16), this corresponds to about 345 kWh of electricity per tonne of pellet produced. Given that 1.38 odt of biomass is required to produce one tonne of pellets, the required electricity would be approximately 250 kWh/odt. The electricity required for pellet production is presented in Table B-12.

Table B-12. Greenhouse gas (GHG) emissions (tonne of CO₂-eq/odt) for pellet conversion facility

Activity (Equipment)	Fuel type	Unit	Fuel consumption/odt	Emission factor (g CO ₂ -eq /L) or (g CO ₂ -eq /kWh)	GHGs emitted (t CO ₂ -eq /odt)
Pelletization technology ^a	Electricity ^a	kWh	249.8	11.50	0.00287
Total GHG emitted (t CO₂-eq /odt)					0.00287
Yun et al., (2020a)					

Appendix C (Techno-economic Analysis without Policies)

Based on the input data from Appendix A and the explanations in Sections 3.2.2 and 3.2.3, the adjusted data used in the economic analyses of small-, medium-, and large-scale CNC, CNF, Biochar, AC, Bio-oil and pellets productions can be found in Sections C.1 to C.5.

C.1 CNC and CNF

For CNC and CNF productions the appropriate cumulative inflation rate (Inflation Calculator, 2024) of 16% is used to convert 2019 cost figures to 2023, and the exchange rate of 1.33 is used to convert USD to CAD (Annual Exchange Rates, 2024).

Table C-1. Economic data for Cellulose Nanocrystal (CNC) production for ground slash pathway.

Production scales	Small	Medium	Large
1. CNC production scale (tonne/year)	3.5	175	350
2. Technology	AVAP	AVAP	AVAP
3. AVAP yield	28%	28%	28%
4. Feedstock demand (odt/year)	12.5	625	1250
5. Mixed sugar yield	37%	37%	37%
6. Lignosulphonate yield	13%	13%	13%
7. Lignin yield	13%	13%	13%
8. Mixed sugar quantity (tonne/year)	5	231	463
9. Lignosulphonate quantity (tonne/year)	1.625	81.25	162.5
10. Lignin quantity (tonne/year)	1.625	81.25	162.5
11. Mixed sugar sales (CAD/year)	\$2,420	\$121,020	\$242,040
12. Lignosulphonate sales (CAD/year)	\$750	\$37,518	\$75,036
13. Lignin sales (CAD/year)	\$450	\$22,511	\$45,022
14. Installed equipment cost (AVAP Technology) (using 0.70 exponent for scaling (Perry et al., 2019))	\$412,045	\$6,371,230	\$10,350,094
15. Plant investment cost (AVAP equipment + engineering & management + contingencies + preparation) (using 0.70 exponent for scaling (Perry et al., 2019))	\$609,371	\$9,422,382	\$15,306,705
16. Handling/preprocessing equipment capital cost (using 0.77 exponent for scaling (Khadivi, 2022))	\$826,255	\$874,655	\$910,555
17. Land and storage cost (annual) to accommodate the plant and storage of all residues from: Hanceville	\$292,815	\$292,815	\$292,815
Williams Lake	\$2,269,932	\$2,269,932	\$2,269,932
Anahim Lake	\$2,151,357	\$2,151,357	\$2,151,357
Horsefly	\$287,415	\$287,415	\$287,415

18. Total capital investment [15+16+17] at: Hanceville	\$1,728,441	\$10,589,851	\$16,510,074
Williams Lake	\$3,705,558	\$12,566,968	\$18,487,191
Anahim Lake	\$3,586,983	\$12,448,393	\$18,368,616
Horsefly	\$1,723,041	\$10,584,452	\$16,504,675
19. Working capital	\$2,796	\$139,811	\$279,622
20. Annual fixed and variable O&M for the bioproduction plant	\$28,814	\$586,860	\$1,030,177
21. Fixed O&M of handling/preprocessing equipment (insurance)	\$18,763	\$19,565	\$20,159
22. Variable O&M costs of handling/preprocessing equipment	\$160	\$7,999	\$15,999
23. Feedstock cost (CAD/year) for ground slash at the biohub gate: Hanceville	\$574	\$28,716	\$57,433
Williams Lake	\$870	\$46,518	\$94,760
Anahim Lake	\$604	\$30,214	\$60,429
Horsefly	\$823	\$42,947	\$88,192
24. Selling price of CNC per tonne (Godfrey et al., 2023)	\$50,000	\$50,000	\$50,000

Table C-2. Economic data for Cellulose Nanocrystal (CNC) production for bundled slash pathway.

Production scales	Small	Medium	Large
1. CNC production scale (tonne/year)	3.5	175	350
2. Technology	AVAP	AVAP	AVAP
3. AVAP yield	28%	28%	28%
4. Feedstock demand (odt/year)	12.5	625	1250
5. Mixed sugar yield	37%	37%	37%
6. Lignosulphonate yield	13%	13%	13%
7. Lignin yield	13%	13%	13%
8. Mixed sugar quantity (tonne/year)	5	231	463
9. Lignosulphonate quantity (tonne/year)	1.625	81.25	162.5
10. Lignin quantity (tonne/year)	1.625	81.25	162.5
11. Mixed sugar sales (CAD/year)	\$2,420	\$121,020	\$242,040
12. Lignosulphonate sales (CAD/year)	\$750	\$37,518	\$75,036
13. Lignin sales (CAD/year)	\$450	\$22,511	\$45,022
14. Installed equipment cost (AVAP Technology) (using 0.70 exponent for scaling (Perry et al., 2019))	\$412,045	\$6,371,230	\$10,350,094
15. Plant investment cost (AVAP equipment + engineering & management + contingencies + preparation) (using 0.70 exponent for scaling (Perry et al., 2019))	\$609,371	\$9,422,382	\$15,306,705
16. Handling/preprocessing equipment capital cost (using 0.77 exponent for scaling (Khadivi, 2022))	\$1,533,065	\$1,624,008	\$1,691,465

17. Land and storage cost (annual) to accommodate the plant and storage of all residues from Hanceville	\$292,815	\$292,815	\$292,815
Williams Lake	\$2,269,932	\$2,269,932	\$2,269,932
Anahim Lake	\$2,151,357	\$2,151,357	\$2,151,357
Horsefly	\$287,415	\$287,415	\$287,415
18. Total capital investment [15+16+17] at: Hanceville	\$2,435,251	\$11,339,205	\$17,290,984
Williams Lake	\$4,412,368	\$13,316,322	\$19,268,101
Anahim Lake	\$4,293,793	\$13,197,747	\$19,149,526
Horsefly	\$2,429,852	\$11,333,806	\$17,285,585
19. Amortized capital cost	\$286,044	\$1,331,899	\$2,030,993
20. Working capital	\$2,796	\$139,811	\$279,622
21. Annual fixed and variable O&M for the bioproduction plant	\$28,814	\$586,860	\$1,030,177
22. Fixed O&M of handling/preprocessing equipment (insurance)	\$18,778	\$19,867	\$20,675
23. Variable O&M costs of handling/preprocessing equipment	\$310	\$15,501	\$31,001
24. Feedstock cost (CAD/year) for bundled slash at the biohub gate: Hanceville	\$668	\$33,390	\$66,780
Williams Lake	\$990	\$51,010	\$103,701
Anahim Lake	\$683	\$34,125	\$68,251
Horsefly	\$1,003	\$50,763	\$102,056
25. Selling price of CNC per tonne (Godfrey et al., 2023)	\$50,000	\$50,000	\$50,000

Table C-3. Economic data for Cellulose Nanofibrils (CNF) production for ground slash pathway.

Production scales	Small	Medium	Large
1. CNF production scale (tonne/year)	53	3500	7350
2. Technology	AVAP	AVAP	AVAP
3. AVAP yield	39%	39%	39%
4. Feedstock demand (odt/year)	136	8974	18846
5. Mixed sugar yield	24%	24%	24%
6. Lignosulphonate yield	13%	13%	13%
7. Lignin yield	7%	7%	7%
8. Mixed sugar quantity (tonne/year)	33	2154	4523
9. Lignosulphonate quantity (tonne/year)	18	1167	2450
10. Lignin quantity (tonne/year)	10	628	1319
11. Mixed sugar sales (CAD/year)	\$17,069	\$1,127,171	\$2,367,059
12. Lignosulphonate sales (CAD/year)	\$8,158	\$538,721	\$1,131,315
13. Lignin sales (CAD/year)	\$2,636	\$174,048	\$365,502

14. Installed equipment cost (AVAP Technology) (using 0.70 exponent for scaling (Perry et al., 2019))	\$2,189,551	\$41,134,828	\$69,145,383
15. Plant investment cost (AVAP equipment + engineering & management + contingencies + preparation) (using 0.70 exponent for scaling (Perry et al., 2019))	\$3,238,117	\$60,834,102	\$102,258,780
16. Handling/preprocessing equipment capital cost (using 0.77 exponent for scaling (Khadivi, 2022))	\$839,473	\$1,219,782	\$1,524,945
17. Land and storage cost (annual) to accommodate the plant and storage of all residues from Hanceville	\$292,815	\$292,815	\$292,815
Williams Lake	\$2,269,932	\$2,269,932	\$2,269,932
Anahim Lake	\$2,151,357	\$2,151,357	\$2,151,357
Horsefly	\$287,415	\$287,415	\$287,415
18. Total capital investment [15+16+17] at: Hanceville	\$4,370,405	\$62,346,699	\$104,076,539
Williams Lake	\$6,347,522	\$64,323,816	\$106,053,656
Anahim Lake	\$6,228,947	\$64,205,241	\$105,935,082
Horsefly	\$4,365,006	\$62,341,299	\$104,071,140
19. Working capital	\$30,400	\$2,007,543	\$4,215,840
20. Annual fixed and variable O&M for the bioproduction plant	\$175,857	\$5,405,733	\$10,317,774
21. Fixed O&M of handling/preprocessing equipment (insurance)	\$18,982	\$25,279	\$30,332
22. Variable O&M costs of handling/preprocessing equipment	\$1,739	\$114,865	\$241,216
23. Feedstock cost (CAD/year) for ground slash at the biohub gate: Hanceville	\$6,244	\$491,384	\$1,127,927
Williams Lake	\$9,598	\$714,855	\$1,532,707
Anahim Lake	\$6,570	\$436,984	\$1,030,165
Horsefly	\$8,952	\$672,231	\$1,437,262
24. Selling price of CNF per tonne (Godfrey et al., 2023)	\$50,000	\$50,000	\$50,000

Table C-4. Economic data for Cellulose Nanofibrils (CNF) production for bundled slash pathway.

Production scales	Small	Medium	Large
1. CNF production scale (tonne/year)	53	3500	7350
2. Technology	AVAP	AVAP	AVAP
3. AVAP yield	39%	39%	39%
4. Feedstock demand (odt/year)	136	8974	18846
5. Mixed sugar yield	24%	24%	24%

6. Lignosulphonate yield	13%	13%	13%
7. Lignin yield	7%	7%	7%
8. Mixed sugar quantity (tonne/year)	33	2154	4523
9. Lignosulphonate quantity (tonne/year)	18	1167	2450
10. Lignin quantity (tonne/year)	10	628	1319
11. Mixed sugar sales (CAD/year)	\$17,069	\$1,127,171	\$2,367,059
12. Lignosulphonate sales (CAD/year)	\$8,158	\$538,721	\$1,131,315
13. Lignin sales (CAD/year)	\$2,636	\$174,048	\$365,502
14. Installed equipment cost (AVAP Technology) (using 0.70 exponent for scaling (Perry et al., 2019))	\$2,189,551	\$41,134,828	\$69,145,383
15. Plant investment cost (AVAP equipment + engineering & management + contingencies + preparation) (using 0.70 exponent for scaling (Perry et al., 2019))	\$3,238,117	\$60,834,102	\$102,258,780
16. Handling/preprocessing equipment capital cost (using 0.77 exponent for scaling (Khadivi, 2022))	\$1,557,902	\$2,272,502	\$2,845,901
17. Land and storage cost (annual) to accommodate the plant and storage of all residues from: Hanceville	\$292,815	\$292,815	\$292,815
Williams Lake	\$2,269,932	\$2,269,932	\$2,269,932
Anahim Lake	\$2,151,357	\$2,151,357	\$2,151,357
Horsefly	\$287,415	\$287,415	\$287,415
18. Total capital investment [15+16+17] at: Hanceville	\$5,088,834	\$63,399,418	\$105,397,496
Williams Lake	\$7,065,951	\$65,376,535	\$107,374,613
Anahim Lake	\$6,947,376	\$65,257,961	\$107,256,038
Horsefly	\$5,083,435	\$63,394,019	\$105,392,097
19. Amortized capital cost	\$597,733	\$7,446,872	\$12,379,950
20. Working capital	\$30,400	\$2,007,543	\$4,215,840
21. Annual fixed and variable O&M for the bioproduction plant	\$175,857	\$5,405,733	\$10,317,774
22. Fixed O&M of handling/preprocessing equipment (insurance)	\$19,075	\$27,631	\$34,497
23. Variable O&M costs of handling/preprocessing equipment	\$3,370	\$222,572	\$467,402
24. Feedstock cost (CAD/year) for bundled slash at the biohub gate: Hanceville	\$7,260	\$515,171	\$1,126,536
Williams Lake	\$10,763	\$768,587	\$1,628,577
Anahim Lake	\$7,420	\$491,215	\$1,077,251
Horsefly	\$10,910	\$749,588	\$1,589,997
25. Selling price of CNF per tonne (Godfrey et al., 2023)	\$50,000	\$50,000	\$50,000

C.2 Biochar

For biochar productions the appropriate cumulative inflation rate (Inflation Calculator, 2024) of 23% is used to convert 2016 cost figures to 2023, and the exchange rate of 1.33 is used to convert USD to CAD (Annual Exchange Rates, 2024).

Table C-5. Economic data for biochar production using wet torrefaction for ground slash pathway

Production scales	Small	Medium	Large
1. Biochar production scale (tonne/year)	40	10,000	15,000
2. Technology	Wet torrefaction	Wet torrefaction	Wet torrefaction
3. Biochar yield	50%	50%	50%
4. Feedstock demand (odt/year)	80	20000	30000
5. Installed wet torrefaction equipment cost (using 0.70 exponent for scaling (Perry et al., 2019))	\$4,576	\$218,317	\$289,969
6. Plant investment cost (wet torrefaction equipment + installation + indirect costs + contingencies + location factor) (using 0.70 exponent for scaling (Perry et al., 2019))	\$21,831	\$1,041,417	\$1,383,211
7. Handling/preprocessing equipment (using 0.77 exponent for scaling (Khadivi, 2022))	\$834,206	\$1,557,774	\$1,826,749
8. Land and storage cost (annual) to accommodate the plant and storage of all residues at: Hanceville	\$292,815	\$292,815	\$292,815
Williams Lake	\$2,269,932	\$2,269,932	\$2,269,932
Anahim Lake	\$2,151,357	\$2,151,357	\$2,151,357
Horsefly	\$287,415	\$287,415	\$287,415
9. Total capital investment [6+7+8] at: Hanceville	\$1,148,851	\$2,892,006	\$3,502,774
Williams Lake	\$3,125,968	\$4,869,123	\$5,479,891
Anahim Lake	\$3,007,393	\$4,750,548	\$5,361,317
Horsefly	\$1,143,452	\$2,886,606	\$3,497,375
10. Working capital	\$567	\$141,653	\$212,479
11. Annual fixed and variable O&M for the Wet Torrefaction equipment	\$2,833	\$708,265	\$1,062,397
12. Fixed O&M of handling/preprocessing equipment (insurance)	\$18,895	\$30,876	\$35,330
13. Variable O&M costs of handling/preprocessing equipment	\$1,024	\$255,984	\$383,976
14. Feedstock cost (CAD/year) for ground slash at the biohub gate at: Hanceville	\$3,676	\$1,203,895	\$1,863,781
Williams Lake	\$5,615	\$1,629,057	\$2,468,346

Anahim Lake	\$3,867	\$1,102,734	\$1,754,139
Horsefly	\$5,266	\$1,528,306	\$2,329,656
15. Selling price of biochar per tonne (Godfrey et al., 2023)	\$800	\$800	\$800

Table C-6. Economic data for biochar production using wet torrefaction for bundled slash pathway

Production scales	Small	Medium	Large
1. Biochar production scale (tonne/year)	40	10,000	15,000
2. Technology	Wet torrefaction	Wet torrefaction	Wet torrefaction
3. Biochar yield	50%	50%	50%
4. Feedstock demand (odt/year)	80	20000	30000
5. Installed wet torrefaction equipment cost (using 0.70 exponent for scaling (Perry et al., 2019))	\$4,576	\$218,317	\$289,969
6. Plant investment cost (wet torrefaction equipment + installation + indirect costs + contingencies + location factor) (using 0.70 exponent for scaling (Perry et al., 2019))	\$21,831	\$1,041,417	\$1,383,211
7. Handling/preprocessing equipment (using 0.77 exponent for scaling (Khadivi, 2022))	\$1,548,005	\$2,907,587	\$3,412,990
8. Land and storage cost (annual) to accommodate the plant and storage of all residues at: Hanceville	\$292,815	\$292,815	\$292,815
Williams Lake	\$2,269,932	\$2,269,932	\$2,269,932
Anahim Lake	\$2,151,357	\$2,151,357	\$2,151,357
Horsefly	\$287,415	\$287,415	\$287,415
9. Total capital investment [6+7+8] at: Hanceville	\$1,862,650	\$4,241,819	\$5,089,015
Williams Lake	\$3,839,768	\$6,218,936	\$7,066,132
Anahim Lake	\$3,721,193	\$6,100,361	\$6,947,557
Horsefly	\$1,857,251	\$4,236,419	\$5,083,616
10. Amortized capital cost	\$218,786	\$498,242	\$597,754
11. Working capital	\$567	\$141,653	\$212,479
12. Annual fixed and variable O&M for the Wet Torrefaction equipment	\$2,833	\$708,265	\$1,062,397
13. Fixed O&M of handling/preprocessing equipment (insurance)	\$18,957	\$35,236	\$41,287
14. Variable O&M costs of handling/preprocessing equipment	\$1,984	\$496,018	\$744,027
15. Feedstock cost (CAD/year) for bundled slash at the biohub gate at: Hanceville	\$4,274	\$1,199,443	\$1,836,818
Williams Lake	\$6,334	\$1,729,555	\$2,608,261
Anahim Lake	\$4,368	\$1,146,275	\$1,766,761
Horsefly	\$6,422	\$1,688,828	\$2,548,633

16. Selling price of biochar per tonne (Godfrey et al., 2023)	\$800	\$800	\$800
--	-------	-------	-------

Table C-7. Economic data for biochar production using dry torrefaction for ground slash pathway

Production scales	Small	Medium	Large
1. Biochar production scale (tonne/year)	40	10,000	15,000
2. Technology	Dry torrefaction	Dry torrefaction	Dry torrefaction
3. Biochar yield	80%	80%	80%
4. Feedstock demand (odt/year)	50	12500	18750
5. Installed dry torrefaction equipment cost (using 0.70 exponent for scaling (Perry et al., 2019))	\$1,153	\$54,988	\$73,036
6. Plant investment cost (dry torrefaction equipment + installation + indirect costs + contingencies + location factor) (using 0.70 exponent for scaling (Perry et al., 2019))	\$5,499	\$262,306	\$348,395
7. Handling/preprocessing equipment (using 0.77 exponent for scaling (Khadivi, 2022))	\$831,031	\$1,334,888	\$1,522,189
8. Land and storage cost (annual) to accommodate the plant and storage of all residues at: Hanceville	\$292,815	\$292,815	\$292,815
Williams Lake	\$2,269,932	\$2,269,932	\$2,269,932
Anahim Lake	\$2,151,357	\$2,151,357	\$2,151,357
Horsefly	\$287,415	\$287,415	\$287,415
9. Total capital investment [6+7+8] at: Hanceville	\$1,129,345	\$1,890,009	\$2,163,398
Williams Lake	\$3,106,462	\$3,867,126	\$4,140,515
Anahim Lake	\$2,987,887	\$3,748,551	\$4,021,940
Horsefly	\$1,123,945	\$1,884,609	\$2,157,999
10. Working capital	\$179	\$44,669	\$67,004
11. Annual fixed and variable O&M for the Dry Torrefaction equipment	\$893	\$223,347	\$335,021
12. Fixed O&M of handling/preprocessing equipment (insurance)	\$18,842	\$27,185	\$30,287
13. Variable O&M costs of handling/preprocessing equipment	\$640	\$159,990	\$239,985
14. Feedstock cost (CAD/year) for ground slash at the biohub gate at: Hanceville	\$2,297	\$717,096	\$1,121,597
Williams Lake	\$3,490	\$1,003,970	\$1,524,678
Anahim Lake	\$2,417	\$641,826	\$1,024,140
Horsefly	\$3,291	\$943,578	\$1,429,675
15. Selling price of biochar per tonne (Godfrey et al., 2023)	\$500	\$500	\$500

Table C-8. Economic data for biochar production using dry torrefaction for bundled slash pathway

Production scales	Small	Medium	Large
1. Biochar production scale (tonne/year)	40	10,000	15,000
2. Technology	Dry torrefaction	Dry torrefaction	Dry torrefaction
3. Biochar yield	80%	80%	80%
4. Feedstock demand (odt/year)	50	12500	18750
5. Installed dry torrefaction equipment cost (using 0.70 exponent for scaling (Perry et al., 2019))	\$1,153	\$54,988	\$73,036
6. Plant investment cost (dry torrefaction equipment + installation + indirect costs + contingencies + location factor) (using 0.70 exponent for scaling (Perry et al., 2019))	\$5,499	\$262,306	\$348,395
7. Handling/preprocessing equipment (using 0.77 exponent for scaling (Khadivi, 2022))	\$1,542,040	\$2,488,786	\$2,840,722
8. Land and storage cost (annual) to accommodate the plant and storage of all residues at: Hanceville	\$292,815	\$292,815	\$292,815
Williams Lake	\$2,269,932	\$2,269,932	\$2,269,932
Anahim Lake	\$2,151,357	\$2,151,357	\$2,151,357
Horsefly	\$287,415	\$287,415	\$287,415
9. Total capital investment [6+7+8] at: Hanceville	\$1,840,354	\$3,043,906	\$3,481,932
Williams Lake	\$3,817,471	\$5,021,023	\$5,459,049
Anahim Lake	\$3,698,896	\$4,902,448	\$5,340,474
Horsefly	\$1,834,954	\$3,038,507	\$3,476,532
10. Working capital	\$179	\$44,669	\$67,004
11. Annual fixed and variable O&M for the Dry Torrefaction Equipment	\$893	\$223,347	\$335,021
12. Fixed O&M of handling/preprocessing equipment (insurance)	\$18,885	\$30,221	\$34,435
13. Variable O&M costs of handling/preprocessing equipment	\$1,240	\$310,011	\$465,017
14. Feedstock cost (CAD/year) for bundled slash at the biohub gate at: Hanceville	\$2,671	\$729,801	\$1,120,488
Williams Lake	\$3,959	\$1,074,986	\$1,620,162
Anahim Lake	\$2,730	\$699,478	\$1,071,499
Horsefly	\$4,014	\$1,048,026	\$1,581,769
15. Selling price of biochar per tonne (Godfrey et al., 2023)	\$500	\$500	\$500

C.3 AC

For AC productions the appropriate cumulative inflation rate (Inflation Calculator, 2024) of 15.21% is used to convert 2020 cost figures to 2023, and the exchange rate of 1.33 is used to convert USD to CAD (Annual Exchange Rates, 2024).

Table C-9. Economic data for production of Activated Carbon (AC) for small-diameter logs pathway

Production scales	Small	Medium	Large
1. AC production scale (tonne/year)	400	800	1200
2. Technology	Elevated Tucker RNG	Elevated Tucker RNG	Elevated Tucker RNG
3. AC yield	45%	45%	45%
4. Feedstock demand (odt/year) (considering the bark)	1,252	2,504	3,756
5. Installed equipment cost (AC Technology) (using 0.70 exponent for scaling (Perry et al., 2019))	\$388,341	\$630,862	\$837,911
6. Plant investment cost (equipment) (using 0.70 exponent for scaling (Perry et al., 2019))	\$388,341	\$630,862	\$837,911
7. Handling/preprocessing equipment capital cost (using 0.77 exponent for scaling (Khadivi, 2022))	\$1,202,206	\$1,553,146	\$1,864,083
8. Land and storage cost (annual) to accommodate the plant and storage of all residues at:			
Hanceville	\$65,078	\$65,078	\$65,078
Williams Lake	\$836,452	\$836,452	\$836,452
Anahim Lake	\$483,153	\$483,153	\$483,153
Horsefly	\$119,588	\$119,588	\$119,588
9. Total capital investment [6+7+8] at:			
Hanceville	\$2,850,178	\$4,189,641	\$5,344,521
Williams Lake	\$3,621,551	\$4,961,015	\$6,115,894
Anahim Lake	\$3,268,252	\$4,607,716	\$5,762,595
Horsefly	\$2,904,687	\$4,244,151	\$5,399,030
10. Working capital	\$220,099	\$440,199	\$660,298
11. Annual fixed and variable O&M for the bioproduction plant	\$1,225,099	\$2,450,197	\$3,675,296
12. Fixed O&M of handling/preprocessing equipment (insurance)	\$1,439	\$2,454	\$3,353
13. Variable O&M costs of handling/preprocessing equipment	\$36,543	\$73,087	\$109,630
14. Feedstock cost (CAD/year) for small-diameter logs at the biohub gate:			
Hanceville	\$47,352	\$96,140	\$146,805

Williams Lake	\$55,686	\$113,212	\$171,331
Anahim Lake	\$49,453	\$98,906	\$148,390
Horsefly	\$53,994	\$109,740	\$165,754
15. Selling price of AC per tonne (<i>Activated Carbon Price per Ton June 2022, 2022; Annual Exchange Rates, 2024; Inflation Calculator, 2024</i>)	\$4,147	\$4,147	\$4,147

C.4 Bio-oil

For bio-oil productions the appropriate cumulative inflation rate (Inflation Calculator, 2024) of 15.21% is used to convert 2020 cost figures to 2023, and the exchange rate of 1.33 is used to convert USD to CAD (Annual Exchange Rates, 2024).

Table C-10. Economic data for production of bio-oil for ground slash pathway

Production scales	Small	Medium	Large
1. Bio-oil production scale (tonne/year)	9,933	21,522	33,111
2. Technology	Pyrolysis reactor	Pyrolysis reactor	Pyrolysis reactor
3. Bio-oil yield	23%	23%	23%
4. Biochar yield (co-product)	28%	28%	28%
5. Biochar sale ^a (CAD/year)	\$6,083,202	\$13,180,580	\$20,278,020
6. Feedstock demand (odt/year)	43,451	94,147	144,843
7. Installed equipment cost (pyrolysis reactor) (using 0.70 exponent for scaling (Perry et al., 2019))	\$74,859,333	\$128,619,698	\$173,888,257
8. Plant investment cost (equipment) (using 0.70 exponent for scaling (Perry et al., 2019))	\$74,859,333	\$128,619,698	\$173,888,257
9. Handling/preprocessing equipment capital cost (using 0.77 exponent for scaling (Khadivi, 2022))	\$2,157,825	\$4,067,124	\$5,018,873
10. Land and storage cost (annual) to accommodate the plant and storage of all residues at: Hanceville	\$292,815	\$292,815	\$292,815
Williams Lake	\$2,269,932	\$2,269,932	\$2,269,932
Anahim Lake	\$2,151,357	\$2,151,357	\$2,151,357
Horsefly	\$287,415	\$287,415	\$287,415
11. Total capital investment [8+9+10] at: Hanceville	\$77,309,972	\$132,979,637	\$179,199,945
Williams Lake	\$79,287,089	\$134,956,754	\$181,177,062
Anahim Lake	\$79,168,514	\$134,838,179	\$181,058,487
Horsefly	\$77,304,573	\$132,974,237	\$179,194,545

12. Working capital	\$374,397	\$4,458,988	\$4,458,988
13. Annual fixed and variable O&M for the bioproduction plant	\$5,240,432	\$11,354,534	\$17,468,635
14. Fixed O&M of handling/preprocessing equipment (insurance)	\$40,812	\$77,509	\$93,269
15. Variable O&M costs of handling/preprocessing equipment	\$556,143	\$1,205,005	\$1,853,868
16. Feedstock cost (CAD/year) for ground slash at the biohub gate:			
Hanceville	\$2,774,125	\$6,507,586	\$10,518,816
Williams Lake	\$3,794,641	\$8,357,292	\$13,078,576
Anahim Lake	\$2,696,746	\$6,583,319	\$10,632,039
Horsefly	\$3,721,429	\$8,383,944	\$13,111,748
17. Selling price of bio-oil per tonne (<i>Inflation Calculator, 2024; van Schalkwyk et al., 2020</i>)	\$357	\$385	\$412
^a Biochar sale is calculated by multiplying the biochar production by its selling price (500 CAD). The amount of biochar production is calculated by multiplying biochar yield by amount of the input feedstock.			

Table C-11. Economic data for bio-oil production for bundled slash pathway

Production scales	Small	Medium	Large
1. Bio-oil production scale (tonne/year)	9,933	215,22	33,111
2. Technology	Pyrolysis reactor	Pyrolysis reactor	Pyrolysis reactor
3. Bio-oil yield	23%	23%	23%
4. Biochar yield (co-product)	28%	28%	28%
5. Biochar sale ^a (CAD/year)	\$6,083,202	\$13,180,580	\$20,278,020
6. Feedstock demand (odt/year)	43,451	94,147	144,843
7. Installed equipment cost (pyrolysis reactor) (using 0.70 exponent for scaling (Perry et al., 2019))	\$74,859,333	\$128,619,698	\$173,888,257
8. Plant investment cost (equipment) (using 0.70 exponent for scaling (Perry et al., 2019))	\$74,859,333	\$128,619,698	\$173,888,257
9. Handling/preprocessing equipment capital cost (using 0.77 exponent for scaling (Khadivi, 2022))	\$4,035,080	\$6,898,571	\$8,686,904
10. Land and storage cost (annual) to accommodate the plant and storage of all residues at:			
Hanceville	\$292,815	\$292,815	\$292,815
Williams Lake	\$2,269,932	\$2,269,932	\$2,269,932
Anahim Lake	\$2,151,357	\$2,151,357	\$2,151,357
Horsefly	\$287,415	\$287,415	\$287,415
11. Total capital investment [8+9+10] at:	\$79,187,227	\$135,811,084	\$182,867,976

Hanceville			
Williams Lake	\$81,164,344	\$137,788,201	\$184,845,093
Anahim Lake	\$79,168,514	\$134,838,179	\$181,058,487
Horsefly	\$79,181,828	\$135,805,685	\$182,862,576
12. Working capital	\$374,397	\$811,212	\$1,248,027
13. Annual fixed and variable O&M for the bioproduction plant	\$5,240,432	\$11,354,534	\$17,468,635
14. Fixed O&M of handling/preprocessing equipment (insurance)	\$48,735	\$91,879	\$113,292
15. Variable O&M costs of handling/preprocessing equipment	\$1,077,635	\$2,334,930	\$3,592,225
16. Feedstock cost (CAD/year) for bundled slash (at the biohub gate) at: Hanceville	\$2,701,380	\$6,075,575	\$9,762,690
Williams Lake	\$3,794,641	\$8,357,292	\$13,078,576
Anahim Lake	\$2,696,746	\$6,583,319	\$10,632,039
Horsefly	\$3,721,429	\$8,383,944	\$13,111,748
17. Selling price of bio-oil per tonne	\$357	\$385	\$412
^a Biochar sale is calculated by multiplying the biochar production by its selling price (500 CAD) (Godfrey et al., 2023). The amount of biochar production is calculated by multiplying biochar yield by amount of the input feedstock.			

C.5 Pellets

For pellets production, the cost elements of the reference study are adjusted by the cumulative inflation rate of 15.21% (Inflation Calculator, 2024) in order to convert 2020 cost figures to 2023.

Table C-12. Economic data for pellets production for ground slash pathway.

Production scales	Small	Medium	Large
1. Pellets production scale (tonne/year)	2,000	72,000	365,000
2. Technology	Pelletization	Pelletization	Pelletization
3. Pelletization yield	72%	72%	72%
4. Feedstock demand (odt/year)	2,778	100,000	506,944
5. Installed equipment cost (using 0.70 exponent for scaling (Perry et al., 2019))	\$29,616	\$363,864	\$1,133,473
6. Plant investment cost (equipment) (using 0.70 exponent for scaling (Perry et al., 2019))	\$29,616	\$363,864	\$1,133,473
7. Handling/preprocessing equipment capital cost (using 0.77 exponent for scaling (Khadivi, 2022))	\$984,284	\$4,182,144	\$13,788,284
8. Land and storage cost (annual) to accommodate the plant and storage of all residues at: Hanceville	\$292,815	\$292,815	\$292,815

Williams Lake	\$2,269,932	\$2,269,932	-
Anahim Lake	\$2,151,357	\$2,151,357	-
Horsefly	\$287,415	\$287,415	-
9. Total capital investment [6+7+8] at: Hanceville	\$1,306,715	\$4,838,822	\$15,214,572
Williams Lake	\$3,283,832	\$6,815,939	-
Anahim Lake	\$3,165,257	\$6,697,364	-
Horsefly	\$1,301,316	\$4,833,423	-
10. Working capital	\$13,307	\$479,043	\$2,428,483
11. Annual fixed and variable O&M for the bioproduction plant	\$66,534	\$2,395,216	\$12,142,414
12. Fixed O&M of handling/preprocessing equipment (insurance)	\$21,380	\$79,413	\$258,804
13. Variable O&M costs of handling/preprocessing equipment	\$35,553	\$1,279,919	\$6,488,480
14. Feedstock cost (CAD/year) for ground slash at the biohub gate at: Hanceville	\$134,701	\$6,953,487	\$44,243,805
Williams Lake	\$214,745	\$8,694,750	-
Anahim Lake	\$134,287	\$6,738,793	-
Horsefly	\$202,019	\$8,595,992	-
15. Selling price of pellets per tonne (<i>Canada - Wood Pellets - Market Analysis, Forecast, Size, Trends and Insights, 2024</i>)	\$239	\$239	\$239

Table C-13. Economic data for pellets production for bundled slash pathway

Production scales	Small	Medium	Large
1. Pellets production scale (tonne/year)	2,000	72,000	365,000
2. Technology	Pelletization	Pelletization	Pelletization
3. Pelletization yield	72%	72%	72%
4. Feedstock demand (odt/year)	2,778	100,000	506,944
5. Installed equipment cost (using 0.70 exponent for scaling (Perry et al., 2019))	\$29,616	\$363,864	\$1,133,473
6. Plant investment cost (equipment) (using 0.70 exponent for scaling (Perry et al., 2019))	\$29,616	\$363,864	\$1,133,473
7. Handling/preprocessing equipment capital cost (using 0.77 exponent for scaling (Khadivi, 2022))	\$1,830,002	\$7,114,693	\$22,972,906
8. Land and storage cost (annual) to accommodate the plant and storage of all residues at: Hanceville	\$292,815	\$292,815	\$292,815
Williams Lake	\$2,269,932	\$2,269,932	-

Anahim Lake	\$2,151,357	\$2,151,357	-
Horsefly	\$287,415	\$287,415	-
9. Total capital investment [6+7+8] at: Hanceville	\$2,152,433	\$7,771,372	\$24,399,194
Williams Lake	\$3,283,832	\$6,815,939	-
Anahim Lake	\$3,165,257	\$6,697,364	-
Horsefly	\$1,301,316	\$4,833,423	-
10. Working capital	\$13,307	\$479,043	\$2,428,483
11. Annual fixed and variable O&M for the bioproduction plant	\$66,534	\$2,395,216	\$12,142,414
12. Fixed O&M of handling/preprocessing equipment (insurance)	\$22,333	\$94,467	\$311,340
13. Variable O&M costs of handling/preprocessing equipment	\$68,891	\$2,480,090	\$12,572,680
14. Feedstock cost (CAD/year) for bundled slash at the biohub gate at: Hanceville	\$150,744	\$6,482,085	\$41,659,817
Williams Lake	\$214,745	\$8,694,750	-
Anahim Lake	\$134,287	\$6,738,793	-
Horsefly	\$202,019	\$8,595,992	-
15. Selling price of pellets per tonne (Canada - Wood Pellets - Market Analysis, Forecast, Size, Trends and Insights, 2024)	\$239	\$239	\$239

Table C-14. Economic data for Pellets production for small-diameter logs pathway

Production scales	Small	Medium	Large
1. Pellets production scale (tonne/year)	2,000	72,000	365,000
2. Technology	Pelletization	Pelletization	Pelletization
3. Pelletization yield	72%	72%	72%
4. Feedstock demand (odt/year)	3,912	140,845	714,006
5. Installed equipment cost (using 0.70 exponent for scaling (Perry et al., 2019))	\$37,640	\$462,443	-
6. Plant investment cost (equipment) (using 0.70 exponent for scaling (Perry et al., 2019))	\$37,640	\$462,443	-
7. Handling/preprocessing equipment capital cost (using 0.77 exponent for scaling (Khadivi, 2022))	\$1,199,597	\$8,519,936	-
8. Land and storage cost (annual) to accommodate the plant and storage of all residues at: Hanceville	\$65,078	\$65,078	-
Williams Lake	\$836,452	-	-

Anahim Lake	\$483,153	-	-
Horsefly	\$119,588	-	-
9. Total capital investment [6+7+8] at: Hanceville	\$1,302,316	\$9,047,457	-
Williams Lake	\$2,073,689	-	-
Anahim Lake	\$1,720,390	-	-
Horsefly	\$1,356,825	-	-
10. Working capital	\$18,742	\$674,709	-
11. Annual fixed and variable O&M for the bioproduction plant	\$93,710	\$3,373,544	-
12. Fixed O&M of handling/preprocessing equipment (insurance)	\$3,460	\$54,635	-
13. Variable O&M costs of handling/preprocessing equipment	\$109,872	\$3,955,404	-
14. Feedstock cost (CAD/year) for small-diameter logs at the biohub gate at: Hanceville	\$153,151	\$6,789,807	-
Williams Lake	\$178,613	-	-
Anahim Lake	\$154,579	-	-
Horsefly	\$172,765	-	-
15. Selling price of pellets per tonne (Canada - Wood Pellets - Market Analysis, Forecast, Size, Trends and Insights, 2024)	\$482	\$482	-

The NPV of all scenarios without policy considerations can be found in Table C-15.

Table C-15. NPV (net present value) of bioproduction scenarios without policy considerations.

Product	Pathway	Amount of input feedstock needed for various capacities	NPV (CAD)			
			Hanceville	Horsefly	Anahim Lake	Williams lake
CNC (Cellulose Nanocrystal)	Ground slash	Small (12.5 odt)	-\$1,398,279	-\$1,395,820	-\$2,932,348	-\$3,032,338
		Medium (625 odt)	\$42,923,894	\$42,839,289	\$41,593,463	\$41,407,850
		Large (1,250 odt)	\$91,001,668	\$90,814,338	\$89,661,926	\$89,364,275
	Bundled slash	Small (12.5 odt)	-\$2,768,362	-\$2,766,720	-\$4,305,176	-\$4,405,799
		Medium (625 odt)	\$41,774,212	\$41,670,078	\$40,448,522	\$40,259,298
		Large (1,250 odt)	\$89,748,749	\$89,533,351	\$88,418,489	\$88,113,883
CNF (Cellulose Nanofibril)	Ground slash	Small (53 odt)	\$11,467,676	\$11,454,686	\$10,144,530	\$10,041,420
		Medium (3,500 odt)	\$1,014,200,317	\$1,013,080,203	\$1,013,217,282	\$1,011,406,059
		Large (7,350 odt)	\$2,156,708,116	\$2,154,789,471	\$2,155,994,578	\$2,152,787,042
	Bundled slash	Small (53 odt)	\$10,404,226	\$10,385,383	\$9,082,112	\$8,977,048
		Medium (3,500 odt)	\$1,012,044,011	\$1,010,590,973	\$1,010,871,776	\$1,009,063,648
		Large (7,350 odt)	\$2,153,737,593	\$2,150,861,068	\$2,152,722,778	\$2,149,212,054
Biochar (dry torrefaction)	Ground slash	Small (50 odt)	-\$1,911,832	-\$1,915,790	-\$3,449,538	-\$3,556,668
		Medium (12,500 odt)	\$21,997,237	\$20,593,514	\$21,143,915	\$18,808,937
		Large (18,750 odt)	\$33,598,864	\$31,688,027	\$32,883,427	\$29,688,346

	Bundled slash	Small (50 odt)	-\$3,306,300	-\$3,313,214	-\$4,843,489	-\$4,951,940
		Medium (12,500 odt)	\$19,558,433	\$17,584,533	\$18,425,762	\$16,007,731
		Large (18,750 odt)	\$30,635,876	\$27,772,900	\$29,619,219	\$26,125,045
Biochar (wet torrefaction)	Ground slash	Small (80 odt)	-\$1,861,526	-\$1,870,538	-\$3,399,842	-\$3,512,687
		Medium (20,000 odt)	\$33,170,581	\$31,158,238	\$32,478,167	\$29,122,833
		Large (30,000 odt)	\$50,422,850	\$47,531,321	\$49,783,142	\$45,260,129
	Bundled slash	Small (80 odt)	-\$3,263,896	-\$3,277,636	-\$4,801,384	-\$4,916,080
		Medium (20,000 odt)	\$30,107,805	\$27,070,164	\$29,117,114	\$25,407,802
		Large (30,000 odt)	\$46,547,511	\$42,127,489	\$45,661,783	\$40,347,659
Bio-oil	Ground slash	Small (43,451 odt)	-\$69,210,719	-\$77,507,642	-\$70,710,917	-\$79,757,091
		Medium (94,147 odt)	-\$117,127,740	-\$135,987,680	-\$122,663,985	-\$137,358,669
		Large (144,843 odt)	-\$157,183,720	-\$184,584,036	-\$165,578,276	-\$185,887,239
	Bundled slash	Small (43,451 odt)	-\$75,949,379	-\$84,569,372	-\$77,448,377	-\$86,795,095
		Medium (94,147 odt)	-\$129,705,661	-\$149,238,389	-\$135,433,522	-\$150,597,097
		Large (144,843 odt)	-\$175,510,027	-\$203,899,353	-\$184,282,159	-\$205,202,556
AC (Activated Carbon)	Small-diameter logs	Small (400 odt)	-\$1,261,256	-\$1,355,796	-\$1,618,619	-\$1,954,228
		Medium (800 odt)	-\$429,107	-\$564,946	-\$771,707	-\$1,143,648
		Large (1,200 odt)	\$530,700	\$368,818	\$214,573	-\$191,652
Pellet	Ground slash	Small (2,778 odt)	-\$298,592	-\$800,279	-\$1,808,344	-\$2,535,050
		Medium (100,000odt)	\$35,566,255	\$25,362,083	\$35,579,438	\$23,339,070
		Large (506,944 odt)	\$134,878,038	-	-	-
	Bundled slash	Small (2,778 odt)	-\$2,155,991	-\$2,805,776	-\$3,699,795	-\$4,488,920
		Medium (100,000odt)	\$28,055,487	\$12,820,462	\$23,221,795	\$11,644,861
		Large (506,944 odt)	\$104,261,111	-	-	-
	Small-diameter logs	Small (3,912 odt)	\$2,135,797	\$1,975,152	\$1,829,742	\$1,429,234
		Medium (140,845 odt)	\$118,199,247	-	-	-
		Large (714,006 odt)	-	-	-	-

Appendix D (Techno-economic Analysis with Policies)

Since bio-oil was economically infeasible across different locations, capacities, and pathways, it was excluded from further analysis.

D.1 Feedstock subsidies

NPV of bioproduction scenarios under feedstock subsidies policy are shown in Table D-1 to Table D-6.

Table D-1. Required feedstock, feedstock delivered cost, subsidies, NPV (net present value) after subsidies, and the percentage of change in the NPV for CNC (cellulose nanocrystals) production scenarios considering carbon price of \$12/t CO₂-eq to calculate the subsidies.

Biohub location	Pathway	CNC production scenario	Required feedstock amount (odt)	Feedstock delivered cost (CAD)	Subsidies (CAD) considering carbon price of \$12/t CO ₂ -eq	NPV value of the scenario after subsidies	Percentage of change in NPV
Hanceville	Ground slash	Small-scale	12.5	\$574	\$338	-\$1,395,567	0.19%
		Medium-scale	625	\$28,716	\$16,875	\$43,028,770	0.24%
		Large-scale	1,250	\$57,433	\$33,750	\$91,211,421	0.23%
Anahim Lake		Small-scale	12.5	\$604	\$338	-\$2,929,636	0.09%
		Medium-scale	625	\$30,214	\$16,875	\$41,698,339	0.25%
		Large-scale	1,250	\$60,429	\$33,750	\$89,871,678	0.23%
Horsefly		Small-scale	12.5	\$823	\$338	-\$1,393,108	0.19%
		Medium-scale	625	\$42,947	\$16,875	\$42,944,166	0.24%
		Large-scale	1,250	\$88,192	\$33,750	\$91,024,091	0.23%
Williams Lake		Small-scale	12.5	\$870	\$338	-\$3,029,625	0.09%
		Medium-scale	625	\$46,518	\$16,875	\$41,512,726	0.25%
		Large-scale	1,250	\$94,760	\$33,750	\$89,574,028	0.23%
Hanceville	Bundled slash	Small-scale	12.5	\$668	\$338	-\$2,765,524	0.10%
		Medium-scale	625	\$33,390	\$16,875	\$41,879,089	0.25%
		Large-scale	1,250	\$66,780	\$33,750	\$89,958,502	0.23%
Anahim Lake		Small-scale	12.5	\$683	\$338	-\$4,302,338	0.07%
		Medium-scale	625	\$34,125	\$16,875	\$40,553,398	0.26%
		Large-scale	1,250	\$68,251	\$33,750	\$88,628,242	0.24%
Horsefly		Small-scale	12.5	\$1,003	\$338	-\$2,763,882	0.10%
		Medium-scale	625	\$50,763	\$16,875	\$41,774,954	0.25%
		Large-scale	1,250	\$102,056	\$33,750	\$89,743,104	0.23%
Williams Lake		Small-scale	12.5	\$990	\$338	-\$4,402,961	0.06%
		Medium-scale	625	\$51,010	\$16,875	\$40,364,174	0.26%
		Large-scale	1,250	\$103,701	\$33,750	\$88,323,636	0.24%

Table D-2. Required feedstock, feedstock delivered cost, subsidies, NPV (net present value) after subsidies, and the percentage of change in the NPV for CNF (cellulose nanofibrils) production scenarios considering carbon price of \$12/t CO₂-eq to calculate the subsidies.

Biohub location	Pathway	CNF production scenario	Required feedstock amount (odt)	Feedstock delivered cost (CAD)	Subsidies (CAD) considering carbon price of \$12/t CO ₂ -eq	NPV value of the scenario after subsidies	Percentage of change in NPV
Hanceville	Ground slash	Small-scale	136	\$6,244	\$3,669	\$11,490,480	0.20%
		Medium-scale	8,974	\$491,384	\$242,308	\$1,015,706,235	0.15%
		Large-scale	18,846	\$1,127,927	\$508,846	\$2,159,870,545	0.15%
Anahim Lake		Small-scale	136	\$6,570	\$3,669	\$10,167,334	0.22%
		Medium-scale	8,974	\$436,984	\$242,308	\$1,014,723,201	0.15%
		Large-scale	18,846	\$1,030,165	\$508,846	\$2,159,157,007	0.15%
Horsefly		Small-scale	136	\$8,952	\$3,669	\$11,477,490	0.20%
		Medium-scale	8,974	\$672,231	\$242,308	\$1,014,586,122	0.15%
		Large-scale	18,846	\$1,437,262	\$508,846	\$2,157,951,899	0.15%
Williams Lake		Small-scale	136	\$9,598	\$3,669	\$10,064,224	0.23%
		Medium-scale	8,974	\$714,855	\$242,308	\$1,012,911,977	0.15%
		Large-scale	18,846	\$1,532,707	\$508,846	\$2,155,949,470	0.15%
Hanceville	Bundled slash	Small-scale	136	\$7,260	\$3,669	\$10,427,030	0.22%
		Medium-scale	8,974	\$515,171	\$242,308	\$1,013,549,929	0.15%
		Large-scale	18,846	\$1,126,536	\$508,846	\$2,156,900,022	0.15%
Anahim Lake		Small-scale	136	\$7,420	\$3,669	\$9,104,916	0.25%
		Medium-scale	8,974	\$491,215	\$242,308	\$1,012,377,694	0.15%
		Large-scale	18,846	\$1,077,251	\$508,846	\$2,155,885,206	0.15%
Horsefly		Small-scale	136	\$10,910	\$3,669	\$10,408,187	0.22%
		Medium-scale	8,974	\$749,588	\$242,308	\$1,012,096,891	0.15%
		Large-scale	18,846	\$1,589,997	\$508,846	\$2,154,023,497	0.15%
Williams Lake		Small-scale	136	\$10,763	\$3,669	\$8,999,852	0.25%
		Medium-scale	8,974	\$768,587	\$242,308	\$1,010,569,566	0.15%
		Large-scale	18,846	\$1,628,577	\$508,846	\$2,152,374,483	0.15%

Table D-3. Required feedstock, feedstock delivered cost, subsidies, NPV (net present value) after subsidies, and the percentage of change in the NPV for biochar in dry torrefaction production scenarios considering carbon price of \$12/t CO₂-eq to calculate the subsidies.

Biohub location	Pathway	Biochar production scenario	Required feedstock amount (odt)	Feedstock delivered cost (CAD)	Subsidies (CAD) considering carbon price of \$12/t CO ₂ -eq	NPV value of the scenario after subsidies	Percentage of change in NPV
Hanceville	Ground slash	Small-scale	50	\$2,297	\$1,350	-\$1,900,393	0.60%
		Medium-scale	12,500	\$717,096	\$337,500	\$24,094,766	9.54%
		Large-scale	18,750	\$1,121,597	\$506,250	\$36,745,158	9.36%
Anahim Lake		Small-scale	50	\$2,417	\$1,350	-\$3,438,099	0.33%
		Medium-scale	12,500	\$641,826	\$337,500	\$23,241,444	9.92%
		Large-scale	18,750	\$1,024,140	\$506,250	\$36,029,721	9.57%

Horsefly		Small-scale	50	\$3,291	\$1,350	-\$1,904,351	0.60%	
		Medium-scale	12,500	\$943,578	\$337,500	\$22,691,044	10.19%	
		Large-scale	18,750	\$1,429,675	\$506,250	\$34,834,321	9.93%	
Williams Lake		Small-scale	50	\$3,490	\$1,350	-\$3,545,229	0.32%	
		Medium-scale	12,500	\$1,003,970	\$337,500	\$20,906,466	11.15%	
		Large-scale	18,750	\$1,524,678	\$506,250	\$32,834,640	10.60%	
Hanceville		Bundled slash	Small-scale	50	\$2,671	\$1,350	-\$3,294,861	0.35%
			Medium-scale	12,500	\$729,801	\$337,500	\$21,655,962	10.72%
			Large-scale	18,750	\$1,120,488	\$506,250	\$33,782,170	10.27%
Anahim Lake	Small-scale		50	\$2,730	\$1,350	-\$4,832,050	0.24%	
	Medium-scale		12,500	\$699,478	\$337,500	\$20,523,291	11.38%	
	Large-scale		18,750	\$1,071,499	\$506,250	\$32,765,513	10.62%	
Horsefly	Small-scale		50	\$4,014	\$1,350	-\$3,301,775	0.35%	
	Medium-scale		12,500	\$1,048,026	\$337,500	\$19,682,062	11.93%	
	Large-scale		18,750	\$1,581,769	\$506,250	\$30,919,194	11.33%	
Williams Lake	Small-scale	50	\$3,959	\$1,350	-\$4,940,501	0.23%		
	Medium-scale	12,500	\$1,074,986	\$337,500	\$18,105,260	13.10%		
	Large-scale	18,750	\$1,620,162	\$506,250	\$29,271,339	12.04%		

Table D-4. Required feedstock, feedstock delivered cost, subsidies, NPV (net present value) value after subsidies, and the percentage of change in the NPV for biochar in wet torrefaction production scenarios considering carbon price of \$12/t CO₂-eq to calculate the subsidies

Biohub location	Pathway	Biochar production scenario	Required feedstock amount (odt)	Feedstock delivered cost (CAD)	Subsidies (CAD) considering carbon price of \$12/t CO ₂ -eq	NPV value of the scenario after subsidies	Percentage of change in NPV
Hanceville	Ground slash	Small-scale	80	\$3,676	\$2,160	-\$1,843,224	0.98%
		Medium-scale	20,000	\$1,203,895	\$540,000	\$36,526,628	10.12%
		Large-scale	30,000	\$1,863,781	\$810,000	\$55,456,920	9.98%
Anahim Lake		Small-scale	80	\$3,867	\$2,160	-\$3,381,539	0.54%
		Medium-scale	20,000	\$1,102,734	\$540,000	\$35,834,214	10.33%
		Large-scale	30,000	\$1,754,139	\$810,000	\$54,817,213	10.11%
Horsefly		Small-scale	80	\$5,266	\$2,160	-\$1,852,235	0.98%
		Medium-scale	20,000	\$1,528,306	\$540,000	\$34,514,285	10.77%
		Large-scale	30,000	\$2,329,656	\$810,000	\$52,565,391	10.59%
Williams Lake		Small-scale	80	\$5,615	\$2,160	-\$3,494,384	0.52%
		Medium-scale	20,000	\$1,629,057	\$540,000	\$32,478,880	11.52%
		Large-scale	30,000	\$2,468,346	\$810,000	\$50,294,200	11.12%
Hanceville	Bundled slash	Small-scale	80	\$4,274	\$2,160	-\$3,245,594	0.56%
		Medium-scale	20,000	\$1,199,443	\$540,000	\$33,463,852	11.15%
		Large-scale	30,000	\$1,836,818	\$810,000	\$51,581,582	10.81%
Anahim Lake		Small-scale	80	\$4,368	\$2,160	-\$4,783,082	0.38%
		Medium-scale	20,000	\$1,146,275	\$540,000	\$32,473,161	11.53%
		Large-scale	30,000	\$1,766,761	\$810,000	\$50,695,853	11.02%
Horsefly		Small-scale	80	\$6,422	\$2,160	-\$3,259,334	0.56%
		Medium-scale	20,000	\$1,688,828	\$540,000	\$30,426,211	12.40%

Williams Lake		Large-scale	30,000	\$2,548,633	\$810,000	\$47,161,559	11.95%
		Small-scale	80	\$6,334	\$2,160	-\$4,897,778	0.37%
		Medium-scale	20,000	\$1,729,555	\$540,000	\$28,763,849	13.21%
		Large-scale	30,000	\$2,608,261	\$810,000	\$45,381,729	12.48%

Table D-5. Required feedstock, feedstock delivered cost, subsidies, NPV (net present value) after subsidies, and the percentage of change in the NPV for AC (activated carbon) production scenarios considering carbon price of \$12/t CO₂-eq to calculate the subsidies.

Biohub location	Pathway	AC production scenario	Required feedstock amount (odt)	Feedstock delivered cost (CAD)	Subsidies (CAD) considering carbon price of \$12/t CO ₂ -eq	NPV value of the scenario after subsidies	Percentage of change in NPV
Hanceville	Small-diameter logs	Small-scale	1,252	\$47,352	\$33,803	-\$1,014,720	19.55%
		Medium-scale	2,504	\$96,140	\$67,606	\$24,371	105.68%
		Large-scale	3,756	\$146,805	\$101,408	\$1,180,036	122.35%
Anahim Lake		Small-scale	1,252	\$49,453	\$33,803	-\$1,364,105	15.72%
		Medium-scale	2,504	\$98,906	\$67,606	-\$306,151	60.33%
		Large-scale	3,756	\$148,390	\$101,408	\$867,445	304.27%
Horsefly		Small-scale	1,252	\$53,994	\$33,803	-\$1,105,974	18.43%
		Medium-scale	2,504	\$109,740	\$67,606	-\$103,072	81.76%
		Large-scale	3,756	\$165,754	\$101,408	\$1,021,690	177.02%
Williams Lake		Small-scale	1,252	\$55,686	\$33,803	-\$1,699,670	13.03%
		Medium-scale	2,504	\$113,212	\$67,606	-\$678,092	40.71%
		Large-scale	3,756	\$171,331	\$101,408	\$461,220	340.65%

Table D-6. Required feedstock, feedstock delivered cost, subsidies, NPV (net present value) after subsidies, and the percentage of change in the NPV for Pellet production scenarios considering carbon price of \$12/t CO₂-eq to calculate the subsidies.

Biohub location	Pathway	Pellet production scenario	Required feedstock amount (odt)	Feedstock delivered cost (CAD)	Subsidies (CAD) considering carbon price of \$12/t CO ₂ -eq	NPV value of the scenario after subsidies	Percentage of change in NPV
Hanceville	Ground slash	Small-scale	2,778	\$134,701	\$75,006	\$212,512	171.17%
		Medium-scale	100,000	\$6,953,487	\$2,700,000	\$52,346,489	47.18%
		Large-scale	506,944	\$44,243,805	\$13,687,488	\$219,944,503	63.07%
Anahim Lake		Small-scale	2,778	\$134,287	\$75,006	-\$1,237,692	31.56%
		Medium-scale	100,000	\$6,738,793	\$2,700,000	\$52,359,672	47.16%
		Large-scale	506,944	N/A	N/A	N/A	N/A
Horsefly		Small-scale	2,778	\$202,019	\$75,006	-\$240,408	69.96%
		Medium-scale	100,000	\$8,595,992	\$2,700,000	\$42,142,317	66.16%
		Large-scale	506,944	N/A	N/A	N/A	N/A
Williams Lake		Small-scale	2,778	\$214,745	\$75,006	-\$1,947,604	23.17%
		Medium-scale	100,000	\$8,694,750	\$2,700,000	\$40,119,304	71.90%
		Large-scale	506,944	N/A	N/A	N/A	N/A
Hanceville		Small-scale	2,778	\$150,744	\$75,006	-\$1,543,776	28.40%

	Bundled slash	Medium-scale	100,000	\$6,482,085	\$2,700,000	\$44,835,721	59.81%
		Large-scale	506,944	\$41,659,817	\$13,687,488	\$189,327,575	81.59%
Anahim Lake		Small-scale	2,778	\$151,668	\$75,006	-\$3,085,034	16.62%
		Medium-scale	100,000	\$7,047,270	\$2,700,000	\$40,002,029	72.26%
Horsefly		Large-scale	506,944	N/A	\$13,687,488	N/A	N/A
		Small-scale	2,778	\$228,341	\$75,006	-\$2,173,104	22.55%
		Medium-scale	100,000	\$8,934,072	\$2,700,000	\$29,600,696	130.89%
Williams Lake		Large-scale	506,944	N/A	N/A	N/A	N/A
		Small-scale	2,778	\$233,528	\$75,006	-\$3,855,516	14.11%
		Medium-scale	100,000	\$8,896,478	\$2,700,000	\$28,425,095	144.10%
		Large-scale	506,944	N/A	N/A	N/A	N/A
Hanceville	Small-diameter logs	Small-scale	3,912	\$153,151	\$105,624	\$2,792,301	30.74%
		Medium-scale	140,845	\$6,789,807	\$3,802,815	\$141,833,379	20.00%
Large-scale		714,006	N/A	N/A	N/A	N/A	
Anahim Lake		Small-scale	3,912	\$154,579	\$105,624	\$2,486,246	35.88%
		Medium-scale	140,845	N/A	N/A	N/A	N/A
Horsefly		Large-scale	714,006	N/A	N/A	N/A	N/A
		Small-scale	3,912	\$172,765	\$105,624	\$2,631,655	33.24%
		Medium-scale	140,845	N/A	N/A	N/A	N/A
Williams Lake		Large-scale	714,006	N/A	N/A	N/A	N/A
		Small-scale	3,912	\$178,613	\$105,624	\$2,085,738	45.93%
		Medium-scale	140,845	N/A	N/A	N/A	N/A
			Large-scale	714,006	N/A	N/A	N/A

D.2 Direct incentives for capital investments

The NPVs of bioproduction scenarios under the capital investment policy are shown in Table D-7 to Table D-12.

Table D-7. Required feedstock, capital cost, covered portion of the capital cost, NPV (net present value) after incentives, and the percentage of change in the NPV values for CNC (cellulose nanocrystal) production scenarios.

Biohub location	Pathway	CNC production scenario	Required feedstock amount (odt)	Capital cost	Covered portion of the capital cost with incentives	NPV after the direct incentives	Percentage of change in NPV
Hanceville	Ground slash	Small-scale	12.5	\$1,728,441	\$864,221	-\$535,767	61.68%
		Medium-scale	625	\$10,589,851	\$5,294,926	\$47,604,669	10.90%
		Large-scale	1,250	\$16,510,074	\$8,255,037	\$98,299,215	8.02%
Anahim Lake		Small-scale	12.5	\$3,586,983	\$1,793,492	-\$1,141,619	61.07%
		Medium-scale	625	\$12,448,393	\$6,224,197	\$47,095,724	13.23%
		Large-scale	1,250	\$18,368,616	\$9,184,308	\$97,780,959	9.06%
Horsefly		Small-scale	12.5	\$1,723,041	\$861,521	-\$535,984	61.60%
		Medium-scale	625	\$10,584,452	\$5,292,226	\$47,517,677	10.92%
		Large-scale	1,250	\$16,504,675	\$8,252,338	\$98,109,499	8.03%
Williams Lake		Small-scale	12.5	\$3,705,558	\$1,852,779	-\$1,182,412	61.01%
		Medium-scale	625	\$12,566,968	\$6,283,484	\$46,962,522	13.41%

		Large-scale	1,250	\$18,487,191	\$9,243,596	\$97,535,719	9.14%	
Hanceville	Bundled slash	Small-scale	12.5	\$2,435,251	\$1,217,626	-\$1,550,736	43.98%	
		Medium-scale	625	\$11,339,205	\$5,669,603	\$46,786,205	12.00%	
		Large-scale	1,250	\$17,290,984	\$8,645,492	\$97,391,463	8.52%	
		Anahim Lake		Small-scale	12.5	\$4,293,793	\$2,146,897	-\$2,158,279
Medium-scale				625	\$13,197,747	\$6,598,874	\$46,282,001	14.42%
Large-scale				1,250	\$19,149,526	\$9,574,763	\$96,882,689	9.57%
Horsefly		Small-scale	12.5	\$2,429,852	\$1,214,926	-\$1,551,794	43.91%	
		Medium-scale	625	\$11,333,806	\$5,666,903	\$46,679,685	12.02%	
		Large-scale	1,250	\$17,285,585	\$8,642,793	\$97,173,679	8.53%	
Williams Lake		Small-scale	12.5	\$4,412,368	\$2,206,184	-\$2,199,615	50.07%	
		Medium-scale	625	\$13,316,322	\$6,658,161	\$46,145,188	14.62%	
		Large-scale	1,250	\$19,268,101	\$9,634,051	\$96,630,494	9.67%	

Table D-8. Required feedstock, capital cost, covered portion of the capital cost, NPV (net present value) after incentives, and the percentage of change in the NPV values for CNF (cellulose nanofibrils) production scenarios.

Biohub location	Pathway	CNF production scenario	Required feedstock amount (odt)	Capital cost	Covered portion of the capital cost with incentives	NPV after the direct incentives	Percentage of change in NPV
Hanceville	Ground slash	Small-scale	136	\$4,370,405	\$2,185,203	\$13,399,420	16.85%
		Medium-scale	8,974	\$62,346,699	\$10,000,000	\$1,023,040,431	0.87%
		Large-scale	18,846	\$104,076,539	\$10,000,000	\$2,165,548,231	0.41%
Anahim Lake		Small-scale	136	\$6,228,947	\$3,114,474	\$12,897,761	27.14%
		Medium-scale	8,974	\$64,205,241	\$10,000,000	\$1,022,057,396	0.87%
		Large-scale	18,846	\$105,935,082	\$10,000,000	\$2,164,834,693	0.41%
Horsefly		Small-scale	136	\$4,365,006	\$2,182,503	\$13,384,043	16.84%
		Medium-scale	8,974	\$62,341,299	\$10,000,000	\$1,021,920,318	0.87%
		Large-scale	18,846	\$104,071,140	\$10,000,000	\$2,163,629,585	0.41%
Williams Lake		Small-scale	136	\$6,347,522	\$3,173,761	\$12,847,061	27.94%
		Medium-scale	8,974	\$64,323,816	\$10,000,000	\$1,020,246,173	0.87%
		Large-scale	18,846	\$106,053,656	\$10,000,000	\$2,161,627,156	0.41%
Hanceville	Bundled slash	Small-scale	136	\$5,088,834	\$2,544,417	\$12,653,520	21.62%
		Medium-scale	8,974	\$63,399,418	\$10,000,000	\$1,020,884,125	0.87%
		Large-scale	18,846	\$105,397,496	\$10,000,000	\$2,162,577,707	0.41%
Anahim Lake		Small-scale	136	\$6,947,376	\$3,473,688	\$12,152,892	33.81%
		Medium-scale	8,974	\$65,257,961	\$10,000,000	\$1,019,711,890	0.87%
		Large-scale	18,846	\$107,256,038	\$10,000,000	\$2,161,562,892	0.41%
Horsefly		Small-scale	136	\$5,083,435	\$2,541,718	\$12,632,290	21.64%
		Medium-scale	8,974	\$63,394,019	\$10,000,000	\$1,019,431,087	0.87%
		Large-scale	18,846	\$105,392,097	\$10,000,000	\$2,159,701,182	0.41%
Williams Lake		Small-scale	136	\$7,065,951	\$3,532,976	\$12,100,239	34.79%
		Medium-scale	8,974	\$65,376,535	\$10,000,000	\$1,017,903,762	0.88%
		Large-scale	18,846	\$107,374,613	\$10,000,000	\$2,158,052,169	0.41%

Table D-9. Required feedstock, capital cost, covered portion of the capital cost, NPV (net present value) after incentives, and the percentage of change in the NPV values for Biochar production in dry torrefaction scenarios.

Biohub location	Pathway	Biochar production scenario	Required feedstock amount (odt)	Capital cost	Covered portion of the capital cost with incentives	NPV after the direct incentives	Percentage of change in NPV
Hanceville	Ground slash	Small-scale	50	\$1,129,345	\$564,672	-\$1,347,160	29.54%
		Medium-scale	12,500	\$1,890,009	\$945,004	\$22,832,631	3.80%
		Large-scale	18,750	\$2,163,398	\$1,081,699	\$34,555,099	2.85%
Anahim Lake		Small-scale	50	\$2,987,887	\$1,493,943	-\$1,955,595	43.31%
		Medium-scale	12,500	\$3,748,551	\$1,874,275	\$22,800,796	7.84%
		Large-scale	18,750	\$4,021,940	\$2,010,970	\$34,661,147	5.41%
Horsefly		Small-scale	50	\$1,123,945	\$561,973	-\$1,353,818	29.33%
		Medium-scale	12,500	\$1,884,609	\$942,305	\$21,426,522	4.05%
		Large-scale	18,750	\$2,157,999	\$1,078,999	\$32,641,875	3.01%
Williams Lake		Small-scale	50	\$3,106,462	\$1,553,231	-\$2,003,437	43.67%
		Medium-scale	12,500	\$3,867,126	\$1,933,563	\$20,518,228	9.09%
		Large-scale	18,750	\$4,140,515	\$2,070,258	\$31,518,477	6.16%
Hanceville	Bundled slash	Small-scale	50	\$1,840,354	\$920,177	-\$2,386,124	27.83%
		Medium-scale	12,500	\$3,043,906	\$1,521,953	\$20,903,857	6.88%
		Large-scale	18,750	\$3,481,932	\$1,740,966	\$32,174,910	5.02%
Anahim Lake		Small-scale	50	\$3,698,896	\$1,849,448	-\$2,994,041	38.18%
		Medium-scale	12,500	\$4,902,448	\$2,451,224	\$20,592,672	11.76%
		Large-scale	18,750	\$5,340,474	\$2,670,237	\$31,979,739	7.97%
Horsefly		Small-scale	50	\$1,834,954	\$917,477	-\$2,395,737	27.69%
		Medium-scale	12,500	\$3,038,507	\$1,519,253	\$18,927,570	7.64%
		Large-scale	18,750	\$3,476,532	\$1,738,266	\$29,309,548	5.53%
Williams Lake		Small-scale	50	\$3,817,471	\$1,908,735	-\$3,043,204	38.55%
		Medium-scale	12,500	\$5,021,023	\$2,510,511	\$18,227,051	13.86%
		Large-scale	18,750	\$5,459,049	\$2,729,524	\$28,537,975	9.24%

Table D-10. Required feedstock, capital cost, covered portion of the capital cost, NPV (net present value) after incentives, and the percentage of change in the NPV values for Biochar production in wet torrefaction scenarios.

Biohub location	Pathway	Biochar production scenario	Required feedstock amount (odt)	Capital cost	Covered portion of the capital cost with incentives	NPV after the direct incentives	Percentage of change in NPV
Hanceville	Ground slash	Small-scale	80	\$1,148,851	\$574,426	-\$1,287,101	30.86%
		Medium-scale	20,000	\$2,892,006	\$1,446,003	\$34,448,864	3.85%
		Large-scale	30,000	\$3,502,774	\$1,751,387	\$51,971,096	3.07%
Anahim Lake		Small-scale	80	\$3,007,393	\$1,503,697	-\$1,896,145	44.23%
		Medium-scale	20,000	\$4,750,548	\$2,375,274	\$34,577,937	6.47%
		Large-scale	30,000	\$5,361,317	\$2,680,658	\$52,152,875	4.76%
Horsefly		Small-scale	80	\$1,143,452	\$571,726	-\$1,298,812	30.56%
		Medium-scale	20,000	\$2,886,606	\$1,443,303	\$32,434,135	4.09%

		Large-scale	30,000	\$3,497,375	\$1,748,688	\$49,077,181	3.25%
Williams Lake		Small-scale	80	\$3,125,968	\$1,562,984	-\$1,949,703	44.50%
		Medium-scale	20,000	\$4,869,123	\$2,434,561	\$31,275,013	7.39%
		Large-scale	30,000	\$5,479,891	\$2,739,946	\$47,682,273	5.35%
Hanceville	Bundled slash	Small-scale	80	\$1,862,650	\$931,325	-\$2,332,571	28.53%
		Medium-scale	20,000	\$4,241,819	\$2,120,909	\$31,982,713	6.23%
		Large-scale	30,000	\$5,089,015	\$2,544,508	\$48,796,885	4.83%
Anahim Lake		Small-scale	80	\$3,721,193	\$1,860,596	-\$2,940,788	38.75%
		Medium-scale	20,000	\$6,100,361	\$3,050,180	\$31,813,509	9.26%
		Large-scale	30,000	\$6,947,557	\$3,473,779	\$48,732,643	6.73%
Horsefly		Small-scale	80	\$1,857,251	\$928,626	-\$2,349,011	28.33%
		Medium-scale	20,000	\$4,236,419	\$2,118,210	\$28,942,686	6.92%
		Large-scale	30,000	\$5,083,616	\$2,541,808	\$44,374,476	5.33%
Williams Lake		Small-scale	80	\$3,839,768	\$1,919,884	-\$2,996,196	39.05%
		Medium-scale	20,000	\$6,218,936	\$3,109,468	\$28,156,607	10.82%
		Large-scale	30,000	\$7,066,132	\$3,533,066	\$43,470,929	7.74%

Table D-11. Required feedstock, capital cost, covered portion of the capital cost, NPV (net present value) after incentives, and the percentage of change in the NPV values for AC (activated carbon) production scenarios.

Biohub location	Pathway	AC production scenario	Required feedstock amount (odt)	Capital cost	Covered portion of the capital cost with incentives	NPV after the direct incentives	Percentage of change in NPV
Hanceville	Small-diameter logs	Small-scale	1,252	\$2,850,178	\$1,425,089	\$110,744	108.78%
		Medium-scale	2,504	\$4,189,641	\$2,094,821	\$1,484,780	446.02%
		Large-scale	3,756	\$5,344,521	\$2,672,261	\$2,912,101	448.73%
Anahim Lake		Small-scale	1,252	\$3,268,252	\$1,634,126	-\$29,297	98.19%
		Medium-scale	2,504	\$4,607,716	\$2,303,858	\$1,350,208	274.96%
		Large-scale	3,756	\$5,762,595	\$2,881,298	\$2,789,863	1200.19%
Horsefly		Small-scale	1,252	\$2,904,687	\$1,452,344	\$48,634	103.59%
		Medium-scale	2,504	\$4,244,151	\$2,122,076	\$1,382,000	344.63%
		Large-scale	3,756	\$5,399,030	\$2,699,515	\$2,779,682	653.67%
Williams Lake		Small-scale	1,252	\$3,621,551	\$1,810,776	-\$178,344	90.87%
		Medium-scale	2,504	\$4,961,015	\$2,480,508	\$1,159,430	201.38%
		Large-scale	3,756	\$6,115,894	\$3,057,947	\$2,552,306	1431.74%

Table D-12. Required feedstock, capital cost, covered portion of the capital cost, NPV (net present value) after incentives, and the percentage of change in the NPV values for Pellet production scenarios.

Biohub location	Pathway	Pellet production scenario	Required feedstock amount (odt)	Capital cost	Covered portion of the capital cost with incentives	NPV after the direct incentives	Percentage of change in NPV
Hanceville	Ground slash	Small-scale	2,778	\$1,306,715	\$653,358	\$319,197	206.90%
		Medium-scale	100,000	\$4,838,822	\$2,419,411	\$37,705,042	6.01%
		Large-scale	506,944	\$15,214,572	\$7,607,286	\$141,602,966	4.99%
Anahim Lake		Small-scale	2,778	\$3,165,257	\$1,582,629	-\$240,312	86.71%
		Medium-scale	100,000	\$6,697,364	\$3,348,682	\$38,539,711	8.32%
		Large-scale	506,944	N/A	N/A	N/A	N/A

Horsefly		Small-scale	2,778	\$1,301,316	\$650,658	-\$157,318	80.34%	
		Medium-scale	100,000	\$4,833,423	\$2,416,712	\$27,498,483	8.42%	
		Large-scale	506,944	N/A	N/A	N/A	N/A	
Williams Lake		Small-scale	2,778	\$3,283,832	\$1,641,916	-\$895,663	64.67%	
		Medium-scale	100,000	\$6,815,939	\$3,407,970	\$26,351,754	12.91%	
		Large-scale	506,944	N/A	N/A	N/A	N/A	
Hanceville		Bundled slash	Small-scale	2,778	\$2,152,433	\$1,076,217	-\$1,081,432	49.84%
			Medium-scale	100,000	\$7,771,372	\$3,885,686	\$31,490,477	12.24%
			Large-scale	506,944	\$24,399,194	\$10,000,000	\$113,101,225	8.48%
Anahim Lake	Small-scale		2,778	\$4,010,975	\$2,005,488	-\$1,695,098	54.18%	
	Medium-scale		100,000	\$9,629,914	\$4,814,957	\$27,478,272	18.33%	
	Large-scale		506,944	N/A	N/A	N/A	N/A	
Horsefly	Small-scale		2,778	\$4,129,550	\$1,073,517	-\$1,732,259	38.26%	
	Medium-scale		100,000	\$9,748,489	\$3,882,986	\$16,253,066	26.77%	
	Large-scale		506,944	N/A	N/A	N/A	N/A	
Williams Lake	Small-scale	2,778	\$4,129,550	\$2,064,775	-\$2,424,145	46.00%		
	Medium-scale	100,000	\$9,748,489	\$4,874,245	\$15,953,749	37.00%		
	Large-scale	506,944	N/A	N/A	N/A	N/A		
Hanceville	Small-diameter logs	Small-scale	3,912	\$1,302,316	\$651,158	\$2,711,428	26.95%	
		Medium-scale	140,845	\$9,047,457	\$4,523,729	\$122,198,274	3.38%	
		Large-scale	714,006	N/A	N/A	N/A	N/A	
Anahim Lake		Small-scale	3,912	\$1,720,390	\$860,195	\$2,590,164	41.56%	
		Medium-scale	140,845	N/A	N/A	N/A	N/A	
		Large-scale	714,006	N/A	N/A	N/A	N/A	
Horsefly		Small-scale	3,912	\$1,356,825	\$678,413	\$2,574,876	30.36%	
		Medium-scale	140,845	N/A	N/A	N/A	N/A	
		Large-scale	714,006	N/A	N/A	N/A	N/A	
Williams Lake		Small-scale	3,912	\$2,073,689	\$1,036,845	\$2,345,817	64.13%	
		Medium-scale	140,845	N/A	N/A	N/A	N/A	
		Large-scale	714,006	N/A	N/A	N/A	N/A	

D.3 Enhanced first-year allowance for depreciation

The NPVs of bioproduction scenarios under the first-year allowance depreciation policy are shown in Table D-13 to Table D-18.

Table D-13. Required feedstock, NPV (net present value) after the first-year enhanced allowance measure, and the percentage of change in the NPV values for CNC (cellulose nanocrystal) production scenarios.

Biohub location	Pathway	CNC production scenario	Required feedstock amount (odt)	NPV after the enhanced first-year allowance	Percentage of change in NPV
Hanceville	Ground slash	Small-scale	12.5	-\$1,399,169	-0.06%
		Medium-scale	625	\$43,158,602	0.55%
		Large-scale	1,250	\$91,382,952	0.42%
Anahim Lake		Small-scale	12.5	-\$2,933,238	-0.03%
		Medium-scale	625	\$41,828,171	0.56%

		Large-scale	1,250	\$90,043,210	0.43%
		Small-scale	12.5	-\$1,396,710	-0.06%
		Medium-scale	625	\$43,073,997	0.55%
Horsefly		Large-scale	1,250	\$91,195,623	0.42%
		Small-scale	12.5	-\$3,033,227	-0.03%
		Medium-scale	625	\$41,642,558	0.57%
Williams Lake		Large-scale	1,250	\$89,745,559	0.43%
		Small-scale	12.5	-\$2,768,548	-0.01%
		Medium-scale	625	\$42,006,618	0.56%
Hanceville		Large-scale	1,250	\$90,126,108	0.42%
		Small-scale	12.5	-\$4,305,362	0.00%
		Medium-scale	625	\$40,680,928	0.57%
Anahim Lake		Large-scale	1,250	\$88,795,847	0.43%
		Small-scale	12.5	-\$2,766,907	-0.01%
		Medium-scale	625	\$41,902,484	0.56%
Horsefly		Large-scale	1,250	\$89,910,710	0.42%
		Small-scale	12.5	-\$4,405,986	0.00%
		Medium-scale	625	\$40,491,704	0.58%
Williams Lake		Large-scale	1,250	\$88,491,242	0.43%

Table D-14. Required feedstock, NPV (net present value) before and after the first-year enhanced allowance measure, and the percentage of change in the NPV values for CNF (cellulose nanofibril) production scenarios.

Biohub location	Pathway	CNF production scenario	Required feedstock amount (odt)	NPV after the enhanced first-year allowance	Percentage of change in NPV
		Small-scale	136	\$11,548,336	0.70%
		Medium-scale	8,974	\$1,015,715,673	0.15%
		Large-scale	18,846	\$2,159,255,347	0.12%
		Small-scale	136	\$10,225,191	0.80%
		Medium-scale	8,974	\$1,014,732,639	0.15%
		Large-scale	18,846	\$2,158,541,809	0.12%
		Small-scale	136	\$11,535,346	0.70%
		Medium-scale	8,974	\$1,014,595,560	0.15%
		Large-scale	18,846	\$2,157,336,701	0.12%
		Small-scale	136	\$10,122,080	0.80%
		Medium-scale	8,974	\$1,012,921,415	0.15%
		Large-scale	18,846	\$2,155,334,272	0.12%
		Small-scale	136	\$10,485,024	0.78%
		Medium-scale	8,974	\$1,013,562,833	0.15%
		Large-scale	18,846	\$2,156,290,961	0.12%
		Small-scale	136	\$9,140,609	0.64%
		Medium-scale	8,974	\$1,012,390,598	0.15%
		Large-scale	18,846	\$2,155,276,145	0.12%
		Small-scale	136	\$10,466,181	0.78%
		Medium-scale	8,974	\$1,012,109,795	0.15%
		Large-scale	18,846	\$2,153,414,436	0.12%
		Small-scale	136	\$9,031,814	0.61%
		Medium-scale	8,974	\$1,010,582,470	0.15%

		Large-scale	18,846	\$2,151,765,422	0.12%
--	--	-------------	--------	-----------------	-------

Table D-15. Required feedstock, NPV (net present value) after the first-year enhanced allowance measure, and the percentage of change in the NPV values for biochar production in dry torrefaction technology scenarios.

Biohub location	Pathway	Biochar production scenario	Required feedstock amount (odt)	NPV after the enhanced first-year allowance	Percentage of change in NPV
Hanceville	Ground slash	Small-scale	50	-\$1,911,832	0.00%
		Medium-scale	12,500	\$21,999,262	0.01%
		Large-scale	18,750	\$33,601,555	0.01%
Anahim Lake		Small-scale	50	-\$3,449,538	0.00%
		Medium-scale	12,500	\$21,145,941	0.01%
		Large-scale	18,750	\$32,886,117	0.01%
Horsefly		Small-scale	50	-\$1,915,790	0.00%
		Medium-scale	12,500	\$20,595,540	0.01%
		Large-scale	18,750	\$31,690,717	0.01%
Williams Lake		Small-scale	50	-\$3,556,668	0.00%
		Medium-scale	12,500	\$18,810,963	0.01%
		Large-scale	18,750	\$29,691,036	0.01%
Hanceville	Bundled slash	Small-scale	50	-\$3,306,300	0.00%
		Medium-scale	12,500	\$19,564,932	0.03%
		Large-scale	18,750	\$30,644,679	0.03%
Anahim Lake		Small-scale	50	-\$4,843,489	0.00%
		Medium-scale	12,500	\$18,432,261	0.04%
		Large-scale	18,750	\$29,628,022	0.03%
Horsefly		Small-scale	50	-\$3,313,214	0.00%
		Medium-scale	12,500	\$17,591,032	0.04%
		Large-scale	18,750	\$27,781,703	0.03%
Williams Lake		Small-scale	50	-\$4,951,940	0.00%
		Medium-scale	12,500	\$16,014,229	0.04%
		Large-scale	18,750	\$26,133,848	0.03%

Table D-16. Required feedstock, NPV (net present value) after the first-year enhanced allowance measure, and the percentage of change in the NPV values for biochar production in wet torrefaction technology scenarios.

Biohub location	Pathway	Biochar production scenario	Required feedstock amount (odt)	NPV after the enhanced first-year allowance	Percentage of change in NPV
Hanceville	Ground slash	Small-scale	80	-\$1,861,526	0.00%
		Medium-scale	20,000	\$33,178,624	0.02%
		Large-scale	30,000	\$50,433,532	0.02%
Anahim Lake		Small-scale	80	-\$3,399,842	0.00%
		Medium-scale	20,000	\$32,486,210	0.02%
		Large-scale	30,000	\$49,793,824	0.02%
Horsefly		Small-scale	80	-\$1,870,538	0.00%
		Medium-scale	20,000	\$31,166,281	0.03%
		Large-scale	30,000	\$47,542,003	0.02%
		Small-scale	80	-\$3,512,687	0.00%

Williams Lake		Medium-scale	20,000	\$29,130,876	0.03%
		Large-scale	30,000	\$45,270,812	0.02%
Hanceville	Bundled slash	Small-scale	80	-\$3,263,896	0.00%
		Medium-scale	20,000	\$30,122,272	0.05%
		Large-scale	30,000	\$46,566,971	0.04%
Anahim Lake		Small-scale	80	-\$4,801,384	0.00%
		Medium-scale	20,000	\$29,131,581	0.05%
		Large-scale	30,000	\$45,681,243	0.04%
Horsefly		Small-scale	80	-\$3,277,636	0.00%
		Medium-scale	20,000	\$27,084,631	0.05%
		Large-scale	30,000	\$42,146,949	0.05%
Williams Lake		Small-scale	80	-\$4,916,080	0.00%
		Medium-scale	20,000	\$25,422,268	0.06%
		Large-scale	30,000	\$40,367,119	0.05%

Table D-17. Required feedstock, NPV (net present value) the first-year enhanced allowance measure, and the percentage of change in the NPV values for AC (activated carbon) production scenarios.

Biohub location	Pathway	AC production scenario	Required feedstock amount (odt)	NPV after the enhanced first-year allowance	Percentage of change in NPV
Hanceville	Small-diameter logs	Small-scale	1,252	-\$1,268,654	-0.59%
		Medium-scale	2,504	-\$471,305	-9.83%
		Large-scale	3,756	\$464,343	-12.50%
Anahim Lake		Small-scale	1,252	-\$1,622,662	-0.25%
		Medium-scale	2,504	-\$805,980	-4.44%
		Large-scale	3,756	\$146,663	-31.65%
Horsefly		Small-scale	1,252	-\$1,361,463	-0.42%
		Medium-scale	2,504	-\$603,425	-6.81%
		Large-scale	3,756	\$301,841	-18.16%
Williams Lake		Small-scale	1,252	-\$1,960,813	-0.34%
		Medium-scale	2,504	-\$1,172,260	-2.50%
		Large-scale	3,756	-\$261,357	-36.37%

Table D-18. Required feedstock, NPV (net present value) after the first-year enhanced allowance measure, and the percentage of change in the NPV values for Pellet production scenarios.

Biohub location	Pathway	Pellet production scenario	Required feedstock amount (odt)	NPV after the enhanced first-year allowance	Percentage of change in NPV
Hanceville	Ground slash	Small-scale	2,778	-\$299,792	-0.40%
		Medium-scale	100,000	\$35,579,660	0.04%
		Large-scale	506,944	\$134,919,794	0.03%
Anahim Lake		Small-scale	2,778	-\$1,808,482	-0.01%
		Medium-scale	100,000	\$35,592,842	0.04%
		Large-scale	506,944	N/A	N/A
Horsefly		Small-scale	2,778	-\$800,402	-0.02%
		Medium-scale	100,000	\$25,375,487	0.05%

	Williams Lake	Large-scale	506,944	N/A	N/A
		Small-scale	2,778	-\$2,535,123	0.00%
		Medium-scale	100,000	\$23,352,474	0.06%
		Large-scale	506,944	N/A	N/A
Hanceville	Bundled slash	Small-scale	2,778	-\$2,156,073	0.00%
		Medium-scale	100,000	\$28,091,073	0.13%
		Large-scale	506,944	\$104,380,282	0.11%
Anahim Lake		Small-scale	2,778	-\$3,699,804	0.00%
		Medium-scale	100,000	\$23,257,381	0.15%
		Large-scale	506,944	N/A	N/A
Horsefly		Small-scale	2,778	-\$2,805,776	0.00%
		Medium-scale	100,000	\$12,856,049	0.28%
		Large-scale	506,944	N/A	N/A
Williams Lake		Small-scale	2,778	-\$4,488,921	0.00%
		Medium-scale	100,000	\$11,680,448	0.31%
		Large-scale	506,944	N/A	N/A
Hanceville	Small-diameter logs	Small-scale	3,912	\$2,159,934	1.13%
		Medium-scale	140,845	\$118,575,480	0.32%
		Large-scale	714,006	N/A	N/A
Anahim Lake		Small-scale	3,912	\$1,853,879	1.32%
		Medium-scale	140,845	N/A	N/A
		Large-scale	714,006	N/A	N/A
Horsefly		Small-scale	3,912	\$1,999,288	1.22%
		Medium-scale	140,845	N/A	N/A
		Large-scale	714,006	N/A	N/A
Williams Lake		Small-scale	3,912	\$1,453,247	1.68%
		Medium-scale	140,845	N/A	N/A
		Large-scale	714,006	N/A	N/A

D.4 BC output-based pricing system

To calculate the emission limits for each product, as given in Eq. 1-1, the production-weighted average emissions intensity (PWAEI) is required. PWAEI is defined as the total emissions of a sector (or product grouping) divided by its total production (Government of Canada, 2018).

According to the guidelines of the BC output-based pricing system (Government of BC, 2024c), PWAEI is only provided for wood pellets, with a value of 0.1048 t CO₂-eq per tonne of pellets. For the other products, PWAEI values were estimated by reviewing a selection of studies from the literature. Based on reported material and energy use, as well as process inputs, an average value was calculated and used as the PWAEI for each product.

For CNC the PWAEI value is estimated at 5,420 g CO₂-eq/kg CNC by averaging the values in Table D-19 to Table D-23.

Table D-19. Inputs and emissions of CNC (cellulose nanocrystal) production with acid recovery.

Inputs	Unit	Amount/kg of CNC	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the factor (g CO ₂ -eq/kg CNC)
Steam	MJ	18.49 ^{a,b}	0.180 ^c	3,327.95
Electricity	kWh	3.47 ^a	0.0115 ^c	39.91
Water-OR treatment	kg	95.88 ^a	0.00108 ^a	104
Bleached wood pulp	kg	1.98 ^a	0.778 ^a	1,540
Total				5,011.85
a) (Rajendran et al., 2023b)				
b) (Thermodynamics of Steam, n.d.)				
c) (BC Building Code, 2018)				

Table D-20. Inputs and emissions of CNC (cellulose nanocrystal) production without acid recovery.

Inputs	Unit	Amount/kg of CNC	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the factor (g CO ₂ -eq/kg CNC)
Steam	MJ	11.89 ^{a, b}	0.180 ^c	2,140.76
Electricity	kWh	3.38 ^a	0.0115 ^c	38.87
Water-OR treatment	kg	130.62 ^a	0.00108 ^a	141
Bleached wood pulp	kg	1.98 ^a	0.778 ^a	1,540
Total				3,860.63
a) Rajendran et al., 2023b)				
b) (Thermodynamics of Steam, n.d.)				
c) (BC Building Code, 2018)				

Table D-21. Inputs and emissions of CNC (cellulose nanocrystal) production with sulfuric acid hydrolysis.

Inputs	Unit	Amount/kg of CNC	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the factor (g CO ₂ -eq/kg CNC)
Electricity	kWh	1.4 ^a	0.0115 ^b	16.1
Dissolving pulp	kg	3.33 ^a	0.588 ^c	1960
Wastewater	kg	66.67 ^a	0.000588 ^c	39.2
Solid waste	kg	2.33 ^a	0.00824 ^c	19.2
Total				2,034.53
a) (Zargar et al., 2022)				
b) (BC Building Code, 2018)				
c) (SimaPro 9.6, 2024)				

Table D-22. Average inputs and emissions of CNC (cellulose nanocrystal) production of two acid hydrolysis processes.

Inputs	Unit	Amount/kg of CNC	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the factor (g CO ₂ -eq/kg CNC)
Electricity	MJ	0.67 ^a	0.0032 ^b	2.15
Heat	MJ	174.25 ^a	0.05 ^b	8712.25

Sulfate pulp	kg	1 ^a	0.588 ^c	588
Total				9,302.40
a) (Kane et al., 2023)				
b) (BC Building Code, 2018) – considering that 1 kWh = 3.6 MJ				
c) (SimaPro 9.6, 2024)				

Table D-23. Inputs and emissions of CNC (cellulose nanocrystal) production with chemical acid hydrolysis.

Inputs	Unit	Amount/kg of CNC	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the factor (g CO ₂ -eq/kg CNC)
Electricity	kWh	500 ^a	0.0115 ^b	5750
Sulfate pulp	kg	1.94 ^a	0.588 ^c	1140.72
Wastewater	ml	0.005 ^a	0.000000588 ^c	0.00000294
Total				6,890.72
a) (Kane et al., 2023)				
b) (BC Building Code, 2018) – considering that 1 kWh = 3.6 MJ				
c) (SimaPro 9.6, 2024)				

The NPVs of CNC production scenarios under the BC output-based pricing policy are shown in Table D-24.

Table D-24. NPV (net present value) comparison of CNC (cellulose nanocrystal) production scenarios with and without carbon pricing.

Biohub location	Pathway	CNC production scenario	Required feedstock amount (odt)	NPV under BC OBPS (selling credits) ^a	Percentage of change
Hanceville	Ground slash	Small-scale	12.5	-\$1,397,579	0.05%
		Medium-scale	625	\$42,950,888	0.06%
		Large-scale	1,250	\$91,055,655	0.06%
Anahim Lake		Small-scale	12.5	-\$2,931,648	0.02%
		Medium-scale	625	\$41,620,456	0.06%
		Large-scale	1,250	\$89,715,913	0.06%
Horsefly		Small-scale	12.5	-\$1,395,120	0.05%
		Medium-scale	625	\$42,866,283	0.06%
		Large-scale	1,250	\$90,868,326	0.06%
Williams Lake		Small-scale	12.5	-\$3,031,638	0.02%
		Medium-scale	625	\$41,434,844	0.07%
		Large-scale	1,250	\$89,418,262	0.06%
Hanceville	Bundled slash	Small-scale	12.5	-\$2,767,636	0.03%
		Medium-scale	625	\$41,800,962	0.06%
		Large-scale	1,250	\$89,802,248	0.06%
Anahim Lake		Small-scale	12.5	-\$4,304,450	0.02%
		Medium-scale	625	\$40,475,271	0.07%
		Large-scale	1,250	\$88,471,988	0.06%
Horsefly		Small-scale	12.5	-\$2,765,995	0.03%
		Medium-scale	625	\$41,696,827	0.06%

Williams Lake		Large-scale	1,250	\$89,586,850	0.06%
		Small-scale	12.5	-\$4,405,074	0.02%
		Medium-scale	625	\$40,286,047	0.07%
		Large-scale	1,250	\$88,167,382	0.06%

For CNF, the PWAEI value is estimated at 663 g CO₂-eq/kg CNF by averaging the values in Table D-25 to

Table D-28.

Table D-25. Inputs and emissions of CNF (cellulose nanofibrils) production with enzymatic pre-treatment.

Inputs	Unit	Amount/kg of CNF	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the factor (g CO ₂ -eq/kg CNF)
Pulp	kg	1 ^a	0.588 ^b	588
Heat	MJ	9.6 ^a	0.05 ^b	480
Electricity for refinement	MJ	0.44 ^a	0.0032 ^c	1.41
Electricity for treatment	MJ	8 ^a	0.0032 ^c	25.56
Total				1094.96
a) (Arvidsson et al., 2015)				
b) (SimaPro 9.6, 2024)				
c) (BC Building Code, 2018) – considering that 1 kWh = 3.6 MJ				

Table D-26. Inputs and emissions of CNF (cellulose nanofibrils) production with carboxymethylation pre-treatment.

Inputs	Unit	Amount/kg of CNF	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the factor (g CO ₂ -eq/kg CNF)
Pulp	kg	1 ^a	0.588 ^b	588
Heat	MJ	2.3 ^a	0.05 ^c	115
Electricity for treatment	MJ	8 ^a	0.0032 ^c	25.56
Total				728.56
a) (Arvidsson et al., 2015)				
b) (SimaPro 9.6, 2024)				
c) (BC Building Code, 2018) – considering that 1 kWh = 3.6 MJ				

Table D-27. Inputs and emissions of CNF (cellulose nanofibrils) production with mechanical pre-treatment.

Inputs	Unit	Amount/kg of CNF	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the factor (g CO ₂ -eq/kg CNF)
Electricity	kWh	22.69 ^a	0.0115 ^b	260.95
Water	L	50.22 ^a	0.00087 ^c	43.69
Total				304.64
a) (Arfelis et al., 2023)				
b) (BC Building Code, 2018) – considering that 1 kWh = 3.6 MJ				
c) (SimaPro 9.6, 2024)				

Table D-28. Inputs and emissions of CNF (cellulose nanofibrils) production with enzymatic pre-treatment.

Inputs	Unit	Amount/kg of CNF	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the factor (g CO ₂ - eq/kg CNF)
Electricity	kWh	44.51 ^a	0.0115 ^b	511.87
Water	L	33.98 ^a	0.00087 ^c	29.56
Distilled water	L	13.3 ^a	0.00087 ^c	11.57
Total				553
a) (Arfelis et al., 2023)				
b) (BC Building Code, 2018) – considering that 1 kWh = 3.6 MJ				
c) (SimaPro 9.6, 2024)				

The NPVs of CNF production scenarios under the BC output-based pricing policy are shown in Table D-29.

Table D-29. NPV (net present value) comparison of CNF (cellulose nanofibrils) production scenarios without BC output-based carbon pricing.

Biohub location	Pathway	CNF production scenario	Required feedstock amount (odt)	NPV under BC OBPS (direct payment and credit purchase) ^a	Percentage change in NPV (Before carbon price vs. BC OBPS direct payment and credit purchase)
Hanceville	Ground slash	Small-scale	136	\$11,398,183	-0.61%
		Medium-scale	8,974	\$1,009,611,144	-0.45%
		Large-scale	18,846	\$2,147,070,852	-0.45%
Anahim Lake		Small-scale	136	\$10,075,037	-0.69%
		Medium-scale	8,974	\$1,008,628,109	-0.45%
		Large-scale	18,846	\$2,146,357,314	-0.45%
Horsefly		Small-scale	136	\$11,385,193	-0.61%
		Medium-scale	8,974	\$1,008,491,030	-0.45%
		Large-scale	18,846	\$2,145,152,206	-0.45%
Williams Lake		Small-scale	136	\$9,971,927	-0.69%
		Medium-scale	8,974	\$1,006,816,885	-0.45%
		Large-scale	18,846	\$2,143,149,777	-0.45%
Hanceville	Bundled slash	Small-scale	136	\$10,334,477	-0.67%
		Medium-scale	8,974	\$1,007,437,933	-0.46%
		Large-scale	18,846	\$2,144,064,831	-0.45%
Anahim Lake		Small-scale	136	\$9,012,363	-0.77%
		Medium-scale	8,974	\$1,006,265,698	-0.46%
		Large-scale	18,846	\$2,143,050,015	-0.45%
Horsefly		Small-scale	136	\$10,315,634	-0.67%
		Medium-scale	8,974	\$1,005,984,895	-0.46%
		Large-scale	18,846	\$2,141,188,306	-0.45%
			Small-scale	136	\$8,907,299

Williams Lake	Medium-scale	8,974	\$1,004,457,570	-0.46%
	Large-scale	18,846	\$2,139,539,292	-0.45%

For biochar, the PWAEI value is estimated at 186 g CO₂-eq/kg biochar by averaging the values in Table D-30 to Table D-33.

Table D-30. Inputs and emissions of biochar production using slow pyrolysis.

Inputs	Unit	Amount/ kg of biochar	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the average EF (kg CO ₂ /kg biochar)
Ash, to landfill	kg	0.000564 ^a	0.0194 ^b	1.09416E-05
Electricity	kWh	0.964 ^a	0.0115 ^c	0.0111
Total				0.01
a) (Peters et al., 2015)				
b) (SimaPro 9.6, 2024)				
c) (BC Building Code, 2018)				

Table D-31. Inputs and emissions of biochar production using Biochar Solutin Incorporated (BSI)

Inputs	Unit	Amount/ kg of biochar	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the average EF (kg CO ₂ /kg biochar)
Diesel	L	0.018 ^a	3.007 ^b	0.0541
Propane	L	0.008 ^a	1.5477 ^c	0.0124
Total				0.07
a) (Bergman et al., 2022)				
b) (Akhtari et al., 2021)				
c) (Ministry of Environment and Climate Change Strategy, 2021)				

Table D-32. Inputs and emissions of biochar production using Air Curtain Burner (ACB)

Inputs	Unit	Amount/ kg of biochar	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the average EF (kg CO ₂ /kg biochar)
Diesel	L	0.128 ^a	3.007 ^b	0.3849
Propane	L	0.001 ^a	1.5477 ^c	0.0015
Total				0.39
a) (Bergman et al., 2022)				
b) (Akhtari et al., 2021)				
c) (Ministry of Environment and Climate Change Strategy, 2021)				

Table D-33. Inputs and emissions of biochar production

Inputs	Unit	Amount/ kg of biochar	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the average EF (kg CO ₂ /kg biochar)
Gasoline	GJ	0.001518 ^a	65.22 ^b	0.099
Natural gas	GJ	0.002782 ^a	50 ^b	0.139
Crude oil	GJ	0.000565 ^a	13333 ^b	0.0423
Total				0.28
a) (Homagain et al., 2015)				
b) (Government of BC, 2023)				

The NPVs of biochar production scenarios under the BC output-based pricing policy are shown in Table D-34 and

Table D-35.

Table D-34. NPV (net present value) comparison of biochar production (wet torrefaction) scenarios with BC output-based carbon pricing.

Biohub location	Pathway	biochar production scenario	Required feedstock amount (odt)	NPV under BC OBPS (selling credits and direct payments)	Percentage of change
Hanceville	Ground slash	Small-scale	80	-\$1,861,492	0.00%
		Medium-scale	20,000	\$33,175,894	0.02%
		Large-scale	30,000	\$50,430,818	0.02%
Anahim Lake		Small-scale	80	-\$3,399,808	0.00%
		Medium-scale	20,000	\$32,483,479	0.02%
		Large-scale	30,000	\$49,791,110	0.02%
Horsefly		Small-scale	80	-\$1,870,504	0.00%
		Medium-scale	20,000	\$31,163,550	0.02%
		Large-scale	30,000	\$47,539,289	0.02%
Williams Lake		Small-scale	80	-\$3,512,653	0.00%
		Medium-scale	20,000	\$29,128,145	0.02%
		Large-scale	30,000	\$45,268,098	0.02%
Hanceville	Bundled slash	Small-scale	80	-\$3,263,947	0.00%
		Medium-scale	20,000	\$30,097,396	-0.03%
		Large-scale	30,000	\$46,531,897	-0.03%
Anahim Lake		Small-scale	80	-\$3,277,687	0.00%
		Medium-scale	20,000	\$27,059,754	-0.04%
		Large-scale	30,000	\$42,111,874	-0.03%
Horsefly		Small-scale	80	-\$4,801,435	0.00%
		Medium-scale	20,000	\$29,106,704	-0.04%
		Large-scale	30,000	\$45,646,168	-0.04%
			Small-scale	80	-\$4,916,131

Williams Lake	Medium-scale	20,000	\$25,397,392	-0.04%
	Large-scale	30,000	\$40,332,044	-0.04%

Table D-35. NPV (net present value) comparison of biochar production (dry torrefaction) scenarios with BC output-based carbon pricing.

Biohub location	Pathway	biochar production scenario	Required feedstock amount (odt)	NPV under BC OBPS (selling credits)	Percentage of change
Hanceville	Ground slash	Small-scale	50	-\$1,911,373	0.02%
		Medium-scale	12,500	\$22,081,460	0.38%
		Large-scale	18,750	\$33,725,200	0.38%
Anahim Lake		Small-scale	50	-\$3,449,079	0.01%
		Medium-scale	12,500	\$21,228,139	0.40%
		Large-scale	18,750	\$33,009,762	0.38%
Horsefly		Small-scale	50	-\$1,915,331	0.02%
		Medium-scale	12,500	\$20,677,738	0.41%
		Large-scale	18,750	\$31,814,362	0.40%
Williams Lake		Small-scale	50	-\$3,556,209	0.01%
		Medium-scale	12,500	\$18,893,160	0.45%
		Large-scale	18,750	\$29,814,681	0.43%
Hanceville	Bundled slash	Small-scale	50	-\$3,305,867	0.01%
		Medium-scale	12,500	\$19,637,865	0.41%
		Large-scale	18,750	\$30,755,025	0.39%
Anahim Lake		Small-scale	50	-\$4,843,056	0.01%
		Medium-scale	12,500	\$18,505,194	0.43%
		Large-scale	18,750	\$29,738,367	0.40%
Horsefly		Small-scale	50	-\$3,312,781	0.01%
		Medium-scale	12,500	\$17,663,965	0.45%
		Large-scale	18,750	\$27,892,049	0.43%
Williams Lake		Small-scale	50	-\$4,951,506	0.01%
		Medium-scale	12,500	\$16,087,163	0.50%
		Large-scale	18,750	\$26,244,193	0.46%

For AC, the PWAEI value is estimated at 5,044 g CO₂-eq/kg AC by averaging the values in Table D-36 to Table D-38.

Table D-36. Inputs and emissions of AC (activated carbon) production.

Inputs	Unit	Amount/kg of AC	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the factor (g CO ₂ -eq/kg AC)
Natural gas	kWh	21.24 ^a	0.180 ^b	3,822.70

Water/wastewater	kg	3.03 ^a	0.87 ^c	2.63
Total				3825.34
a) (Liao et al., 2020)				
b) (BC Building Code, 2018)				
c) (SimaPro 9.6, 2024)				

Table D-37. Outputs of AC (activated carbon) production using pyrolysis and chemical activation with ZnCl₂

Outputs	Unit	Amount/kg of AC	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the factor (g CO ₂ -eq/kg AC)
CO ₂	kg	0.57 ^a	1	570
CH ₄	kg	0.16 ^a	28 ^b	4,480
Wastewater	kg	10.6 ^a	0.87 ^c	9
Total				5,059
a) (Heidari et al., 2019)				
b) (Government of BC, 2023)				
c) (SimaPro 9.6, 2024)				

Table D-38. Outputs of AC (activated carbon) production using pyrolysis and chemical activation with H₃PO₄

Outputs	Unit	Amount/kg of AC	Emission factor (kg CO ₂ -eq/unit)	Emissions based on the factor (g CO ₂ -eq/kg AC)
CO ₂	kg	0.107 ^a	1	107
CH ₄	kg	0.219 ^a	28 ^b	6,132
Wastewater	kg	9.2 ^a	0.87 ^c	8
Total				6,247
a) (Heidari et al., 2019)				
b) (Government of BC, 2023)				
c) (SimaPro 9.6, 2024)				

The NPVs of AC production scenarios under the BC output-based pricing policy are shown in Table D-39.

Table D-39. NPV (net present value) comparison of AC (activated carbon) production scenarios with output-based carbon pricing.

Biohub location	Pathway	AC production scenario	Required feedstock amount (odt)	NPV under BC OBPS (direct payment and credit purchase)	Percentage change in NPV (Before carbon price vs. BC OBPS direct payment and credit purchase)
Hanceville		Small-scale	1,252	-\$1,885,649	-49.51%
		Medium-scale	2,504	-\$1,570,243	-265.93%

	Small-diameter logs	Large-scale	3,756	-\$1,135,889	-314.04%
Anahim Lake		Small-scale	1,252	-\$2,239,865	-38.38%
		Medium-scale	2,504	-\$1,908,274	-147.28%
		Large-scale	3,756	-\$1,451,923	-776.66%
Horsefly		Small-scale	1,252	-\$1,982,284	-46.21%
		Medium-scale	2,504	-\$1,708,500	-202.42%
		Large-scale	3,756	-\$1,301,862	-452.98%
Williams Lake		Small-scale	1,252	-\$2,581,686	-32.11%
		Medium-scale	2,504	-\$2,292,192	-100.43%
		Large-scale	3,756	-\$1,875,110	-878.39%

For pellets, the PWA EI is given as 0.1048 t CO₂-eq per tonne of wood pellets in (Government of BC, 2023). The NPVs of pellets production scenarios under the BC output-based pricing policy are shown in Table D-40.

Table D-40. NPV (net present value) comparison of pellet production scenarios without BC output-based carbon pricing.

Biohub location	Pathway	Pellet production scenario	Required feedstock amount (odt)	NPV under BC OBPS (selling credits) ^[1]	Percentage of change
Hanceville	Ground slash	Small-scale	2,778	-\$276,333	7.45%
		Medium-scale	100,000	\$36,287,343	2.03%
		Large-scale	506,944	\$138,533,552	2.71%
Anahim Lake		Small-scale	2,778	-\$1,784,330	1.33%
		Medium-scale	100,000	\$36,300,526	2.03%
		Large-scale	506,944	N/A	N/A
Horsefly		Small-scale	2,778	-\$775,696	3.07%
		Medium-scale	100,000	\$26,083,171	2.84%
		Large-scale	506,944	N/A	N/A
Williams Lake		Small-scale	2,778	-\$2,510,076	0.99%
		Medium-scale	100,000	\$24,060,157	3.09%
		Large-scale	506,944	N/A	N/A
Hanceville	Bundled slash	Small-scale	2,778	-\$2,130,793	1.17%
		Medium-scale	100,000	\$28,738,246	2.43%
		Large-scale	506,944	\$107,722,321	3.32%
Anahim Lake		Small-scale	2,778	-\$3,674,246	0.69%
		Medium-scale	100,000	\$23,904,554	2.94%
		Large-scale	506,944	N/A	N/A
Horsefly		Small-scale	2,778	-\$2,779,969	0.92%
		Medium-scale	100,000	\$ 13,503,221	5.33%
		Large-scale	506,944	N/A	N/A
Williams Lake		Small-scale	2,778	-\$4,463,114	0.57%
		Medium-scale	100,000	\$12,327,621	5.86%
		Large-scale	506,944	N/A	N/A
Hanceville		Small-scale	3,912	\$2,154,651	0.88%
		Medium-scale	140,845	\$118,877,980	0.57%

	Small diameter logs	Large-scale	714,006	N/A	N/A
Anahim Lake		Small-scale	3,912	\$1,848,596	1.03%
		Medium-scale	140,845	N/A	N/A
		Large-scale	N/A	N/A	N/A
Horsefly		Small-scale	3,912	\$1,994,005	0.95%
		Medium-scale	140,845	N/A	N/A
		Large-scale	N/A	N/A	N/A
Williams Lake		Small-scale	3,912	\$1,448,088	1.32%
		Medium-scale	140,845	N/A	N/A
		Large-scale	N/A	N/A	N/A

Appendix E (Market Analysis)

In this section, the details of the demand estimations for each bioproduct are provided.

E.1 Biochar

According to recent market reports (Research and Markets, 2025b), the global biochar market size was USD 2.2 billion in 2024 and is projected to reach USD 6.3 billion by 2033, as shown in Table E-1.

Using an exchange rate of 1 USD = 1.39 CAD, the equivalent values are:

Table E-1. Global market size for biochar in 2024 and 2033 (Research and Markets, 2025b), with equivalent values in CAD.

Year	Market size (USD billion)	Market size (CAD billion)
2024	2.2	3.06
2033	6.3	8.75

Assuming an average biochar price of 650 CAD per tonne (Godfrey et al., 2023), the corresponding global market size can be estimated as shown in Table E-2.

Table E-2. Estimated global biochar demand derived from market size and average price.

Year	Market size (CAD)	Price (CAD/tonne)	Market size (tonne)
2024	3,058,000,000	650	4,704,615
2033	8,757,000,000	650	13,472,308

This reflects an compound annual growth rate (Fernando, 2026) of approximately 12.4%, calculated as shown in Eq. E- 1, where n is the number of years.

$$Growth\ rate = \left(\frac{\text{value in year } n}{\text{value in year } 1} \right)^{\frac{1}{n}} - 1 = \left(\frac{13,472,308}{4,704,615} \right)^{\frac{1}{9}} - 1 = 12.4\% \quad \text{Eq. E- 1}$$

In 2024, Canada's biochar market size was USD 80.26 million (Data Bridge Market Research, 2025), representing approximately 3.65% of the global market. For this analysis, it is assumed that Canada's share remains constant over the forecast period.

Assuming that the global biochar market continues to grow at an average annual rate of 12.4%, and that Canada's market share remains constant throughout the forecast period, the biochar market size over the 20-year planning horizon can be estimated as shown in Table E-3.

Table E-3. Estimated global and Canadian biochar market size (tonnes) from 2024 to 2043, assuming a constant 12.4% annual global growth rate and a stable 3.65% Canadian market share.

Year	Global Market Size (tonne of biochar) considering growth rate	Canada's Market Size (tonne of biochar)
2024	4,704,615	171,633
2025	5,288,016	192,916
2026	5,943,762	216,839
2027	6,680,824	243,729
2028	7,509,287	273,952
2029	8,440,484	307,924
2030	9,487,156	346,109
2031	10,663,621	389,028
2032	11,985,974	437,270
2033	13,472,308	491,494
2034	15,142,956	552,443
2035	17,020,774	620,949
2036	19,131,454	697,950
2037	21,503,870	784,500
2038	24,170,481	881,783
2039	27,167,767	991,130
2040	30,536,735	1,114,036
2041	34,323,476	1,252,183
2042	38,579,795	1,407,461
2043	43,363,924	1,581,995

E.2 Activated Carbon

The global activated carbon (AC) market volume was approximately 3.7 million tonnes in 2024 and is projected to reach 5.8 million tonnes by 2030, reflecting a compound annual growth rate (CAGR) of about 8% (Research and Markets, 2025a).

Assuming that this growth rate continues until 2043, and that Canada's market share remains constant at 2.1% (*Activated Carbon Market Size, Trend & Industry Share | 2034, 2025*), the estimated market size (or potential demand) for activated carbon in Canada is summarized in Table E-4.

Table E-4. Estimated global and Canadian activated carbon (AC) market size (tonnes) from 2024 to 2043, assuming an 8% annual growth rate and a stable 2.1% Canadian market share.

Year	Global Market Size (tonne of AC) considering growth rate	Canada's Market Size (tonne of AC)
2024	3,700,000	77,700
2025	3,996,000	83,916
2026	4,315,680	90,629
2027	4,660,934	97,880
2028	5,033,809	105,710

2029	5,436,514	114,167
2030	5,871,435	123,300
2031	6,341,150	133,164
2032	6,848,442	143,817
2033	7,396,317	155,323
2034	7,988,022	167,748
2035	8,627,064	181,168
2036	9,317,229	195,662
2037	10,062,608	211,315
2038	10,867,616	228,220
2039	11,737,026	246,478
2040	12,675,988	266,196
2041	13,690,067	287,491
2042	14,785,272	310,491
2043	15,968,094	335,330

E.3 Nanocellulose

According to recent market reports (Markets and Markets, 2024), the global nanocellulose market size was approximately USD 0.6 billion in 2024 and is projected to reach USD 3.4 billion by 2032.

Using an exchange rate of 1 USD = 1.39 CAD, the equivalent values are shown in Table E-5.

Table E-5. Global market size for nanocellulose in 2024 and 2032 (Markets and Markets, 2024), with equivalent values in CAD.

Year	Market size (USD billion)	Market size (CAD billion)
2024	0.6	0.83
2032	3.4	4.73

Assuming an average nanocellulose price of 50,000 CAD per tonne (Godfrey et al., 2023), the corresponding global demand can be estimated as shown in Table E-6.

Table E-6. Estimated global nanocellulose demand derived from market size and average price.

Year	Market size (CAD)	Price (CAD/tonne)	Market size (tonne)
2024	834,000,000	50,000	16,680
2032	4,726,000,000	50,000	94,520

This reflects an average annual growth rate of approximately 23.7%, calculated as in Eq. E- 2:

$$Growth\ rate = \left(\frac{834,000,000}{4,726,000,000} \right)^{\frac{1}{8}} - 1 = 23.7\% \quad \text{Eq. E- 2}$$

Assuming this growth rate remains constant until 2043, and that Canada's market share (by revenue) remains at 7.7 % (Grand View Research, 2022), the projected market size (or potential demand) for nanocellulose is summarized in Table E-7.

Table E-7. Estimated global and Canadian nanocellulose market size (tonnes) from 2024 to 2043, assuming an 23.7% annual growth rate and a stable 7.7% Canadian market share

Year	Global Market Size (tonne of nanocellulose) considering growth rate	Canada's Market Size (tonne of nanocellulose)
2024	16,680	1,284
2025	20,633	1,589
2026	25,523	1,965
2027	31,572	2,431
2028	39,055	3,007
2029	48,311	3,720
2030	59,761	4,602
2031	73,924	5,692
2032	91,444	7,041
2033	113,116	8,710
2034	139,924	10,774
2035	173,086	13,328
2036	214,108	16,486
2037	264,851	20,394
2038	327,621	25,227
2039	405,267	31,206
2040	501,316	38,601
2041	620,127	47,750
2042	767,098	59,067
2043	948,900	73,065

E.4 Pellets

According to the Wood Pellet Association of Canada (Wood Pellet Association of Canada, 2024), pellet mills have a total national production capacity of approximately 4.85 million tonnes per year. In addition, six pellet plants have been proposed across Canada, with a combined capacity of approximately 730,200 tonnes per year. The development of these facilities indicates continued potential for moderate expansion in Canada's pellet production sector. This additional 730,200 tonnes per year will be considered as the anticipated demand for pellets.

E.5 Estimating the Williams Lake market demand

Based on the most recent available data, the harvest volume in the Williams Lake Timber Supply Area (TSA) was 1,964,085 m³ in 2022 (British Columbia Ministry of Forests, 2024). In comparison, the total recorded harvest volume in Canada in the same year was 131,555,231 m³

(Natural Resources Canada, 2022). Accordingly, the Williams Lake TSA accounts for approximately 1.5% of the national harvest volume. This proportion can be used as a reasonable basis for estimating or scaling Canada's overall market demand for forest-based bioproducts to the regional context of the Williams Lake TSA. Therefore, the final potential demands are calculated by multiplying the estimated Canadian market demands, reported in Table E-3, Table E-4, and Table E-7, by 1.5%.

For the pellet production, given that the majority of Canada's pellet capacity is located in British Columbia (Wood Pellet Association of Canada, 2024), the total harvest volume in BC is used to derive the demand allocation ratio for the Williams Lake TSA. In 2022, the total harvest volume in BC was 47,700,000 m³ (Economics and Trade Branch Ministry of Forests, 2022). Based on this, the Williams Lake TSA accounts for approximately 4.1% of the provincial harvest volume. This proportion is therefore used to estimate the pellet demand attributable to the Williams Lake TSA.