The economic effect of genomic technology on the forestry industry

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Abstract:

In response to threats from climate change, such as an increased likelihood of droughts and insect outbreaks, significant investments in forestry genomics research have been made. The main advantage of genomic technology is that it greatly reduces the amount of R&D time to come up with a new product, and it is much more precise than traditional breeding techniques. However, the technology also comes with higher upfront R&D costs. Thus, whether the research effort would result in a worthwhile use of scarce research resources remains unknown. To help quantify the economic effect, we assess the welfare consequences of the forestry genomic research by estimating a timber supply model and a dynamic global forest products trade model. Using the forest industry of Alberta as our empirical setting, we find that the research program can yield an increase in total economic surplus of 400 million CAD in present value and the benefit-cost ratio of the research program is 43.9, indicating that more resources can be allocated advantageously to genomics-assisted tree breeding programs. The findings provide a justification for adopting genomic technology in the forestry sector and are useful in supporting genomics-enhanced reforestation policies and investment decisions.

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1 Introduction

Facing challenges of rapidly growing global population, increasing competition, changing climate, and environmental pressure, the idea of productivity and improving productivity has never been more important in agriculture and forestry sectors. Research in animal and plant breeding has resulted in higher yields for producers over time, especially with significant investments in genomics research in the past two decades. In Canada alone, public funding agencies have invested approximately $480 million CAD to genomics-based technologies in the agri-food and forestry sectors in the past 15 years (GenomeCanada, 2017). With all these investments being made, a key question to ask is, "What are the economic impacts of this research and development (R&D) effort?". It is crucial to carefully measure the economic rate of return of the investment in R&D to make sure a worthwhile use of scarce research resources, especially in an era of falling public funding in agricultural and forestry R&D (Clancy et al., 2016). Many studies have evaluated the economic impacts of animal and crop breeding R&D efforts based on the economic surplus theory (Alston et al., 1995). More recently, there are studies that have evaluated the economic effect of using genomic technology on the livestock sector (Weaber and Lusk, 2010) and the crop sector (Naseem and Singla, 2013). However, to the best of our knowledge, there are no studies that have estimated the economic impact of adopting genomic technology in the forestry sector. In fact, the forestry sector is uniquely suited to benefit from genomic technology because of its long breeding horizons. Traditional tree breeding takes about 30 years to finish one breeding cycle which is much longer than an animal or crop breeding cycle, making it unable to respond quickly enough to climate change and changes in the economic objectives of forest products, market demands, and management policies; however, with the use of genomic technology, the tree breeding cycle can be significantly shortened by up to 20 years. Additionally, genomic selection delivers more accurate breeding values and allows a higher intensity of selection (Schreiber and Thomas, 2017).

While genomic technology offers numerous improvements upon traditional methods, it does come with higher upfront R&D costs and it is unclear exactly how much it can improve upon traditional methods regarding quantity and quality attributes. Even though the technology is expected to significantly increase the supply of timber[1] and wood products, the change of market condition remains unknown. An increase in timber supply can reduce input (e.g., log) cost for the wood manufacturing sector; however, it may also lead to a reduced product (e.g., lumber) price. If the input price fall less than the output price, profits of the wood manufacturing sector will decrease. Thus, the overall welfare effects in response to the adoption of genomic technology in the forestry sector are unclear. The welfare consequences depend on the relative magnitude of the increase in timber supply and the decrease in wood product prices.

The primary objective of this study is to estimate the economic effect of adopting genomic technology in the forestry sector. Empirical evidence is gathered to determine whether the public investment in genomics research has resulted in a socially worthwhile use of public funds, and how economic benefits of the forestry genomics research program are distributed across consumers and producers. Our empirical setting is the forest industry of Alberta, Canada. We propose a two-step approach for estimating benefits brought by the genomics research program. The first step is to quantify the increase in harvest volume attributable to the genetic improvement of seeds through a timber supply simulation model, holding all other production parameters constant. The second step is to integrate the timber supply change information into a spatial equilibrium model which is developed and used to measure the economic surplus gain. Our judgments about economic performance are made from the viewpoint of society rather than individual forest owners or producers. The criterion we adopt for assessing the welfare effects of using genomic technology is a comparison of the net gain, the surplus of benefits over costs, that accrues to society as a whole.

The following section is a review of the forest economics literature concerning the economic evaluation techniques of a research program and economic impact analysis of timber and wood products market shocks. Section 3 introduces the theoretical framework, and section 4 presents estimation results. We wrap up with a discussion of implications of this paper and recommendations for future study.

[1]The ACE was defined as an immediate increase in today's allowable cut which is attributed to expected future increases in (timber) yields (Schweitzer et al., 1972).

2 Literature Review

2.1 Standard Economic Evaluation Techniques

Based on the welfare concept, the net benefits of a research project is usually calculated from research benefit over what would have occurred in its absence, net of the costs of doing the research (Heisey et al., 2010). The econometric method and the economic surplus method are two major methods commonly used to measure the benefits and costs of research through constructing appropriate counterfactual scenarios. The econometric analysis relates the measure of costs to the measure of benefits via statistical estimation while economic surplus analysis relates costs to benefits synthetically (Heisey et al., 2010).

Econometric approaches require estimation of econometric models, either through direct estimation of production functions or indirect estimation of profit or cost functions, to infer the impact of research on output or productivity. Hyde et al. (1992) used the econometric method to evaluate the economic benefits of forestry research. Their approach begins with industry production as a function of public and private research expenditures, and the costs of other productive inputs. Supply and demand functions were derived from the production function using Hotelling's lemma. The system of supply and demand equations were then simultaneously estimated using time series data on research expenditures and input prices. Their model permitted direct estimation of not only the net economic benefit but also the value of the marginal product resulting from research, which told us the addition to output originating from the last unit of research. Gopinath and Roe (2000) used the cost function approach to analyze research spillover and returns to agriculture R&D in three vertically linked U.S. sectors: food processing, primary agriculture, and farm machinery and equipment. Their model led to a system of 12 nonlinear equations. Gopinath and Roe's procedure allowed them to estimate private and social rates of return on research in each sector under scenarios with and without taking research spillovers from sector to sector into account. The potential problems with the econometric approaches lie in extensive demands they place on data and the fact that the approaches are confined to more aggregated data. The econometric approaches are also primarily used for *ex post* analysis.

Economic surplus approaches mainly look at how research affects supply, demand,

and their resulting market outcomes. Benefits from research are measured by changes in areas that are defined as consumer and producer surpluses. The gain in surplus can then be compared against the costs of the research. Barkley (1997) analyzed the *ex post* economic impact of the wheat breeding program at the Kanas State Agricultural Experiment Station by modifying an economic surplus model from Alston et al. (1995). The author constructed a two-sector model consisting of Kansas and the rest of the world (ROW). Barkley found that the major beneficiaries of Kansas wheat improvement research were Kansas wheat producers who adopted the new varieties. Naseem and Singla (2013) did an ex ante economic impact analysis of novel traits in canola resulting from the use of genomic technology. The changes in welfare were calculated based on a stochastic economic surplus model (Alston et al., 1995). They found that the major beneficiaries of the surplus gain were consumers as well as Canadian producers and innovators. The economic surplus model does provide us a relative easy way to calculate the economic surplus gain brought by a new technology or return on R&D, and it is very useful in estimating the distribution of benefits among different stake holders. The economic surplus method can be used for *ex ante* as well as *ex post* research evaluation. The main limitations of economic surplus models include the assumptions about the exogenous parameters and little attention on the dynamic issues. Since the surplus results are calculated directly using the exogenous parameters (e.g., elasticities), the accuracy of the results highly depends on the accuracy of the magnitude of the parameters. This study adopted the economic surplus method in the sense that the demand and supply curves are calibrated instead of being econometrically estimated.

2.2 The Impacts of Market Shocks in the Forestry Sector

The spatial equilibrium (SE) model is commonly used to estimate the demand and supply curves and assess the effects of product market shocks in the forestry sector. The advantage of the SE model is that it is able to predict the new trade patterns easily over a long-term period by maximizing the total trade surplus (Adams and Haynes, 1987). The SE model also allows us to perform policy analysis under different scenarios by simply altering the parameters in the objective function or constraints.

Delcourt (1995) used a partial equilibrium trade model to exam the effects of forest policies on international trade flows of softwood lumber (SWL) and predicted changes in SWL production, consumption and prices for 7 demand regions and 8 supply regions over a 38-year period from 1987 to 2025. In the study, Delcourt (1995) considered two scenarios: 1) decrease in British Colombia (BC) production; 2) increase in supplies from alternative sources. Results of the first scenario suggested that the province experienced a net increase in welfare at little expense to its domestic consumers in short-run due to the increased global SWL price and redistribution of exports (Delcourt, 1995). Under the second scenario, producers in BC were not significantly affected by the lower prices; revenues of BC producers were actually increasing overtime (Delcourt, 1995). Abbott et al. (2009) further extended Delcourt's approach by incorporating uncertainty of parameters and incorporating a game-theoretic approach via a Cournot oligopoly game into the spatial equilibrium model, which was used to analyze the economic effects of Mountain Pine Beetle (MPB) outbreaks on BC forestry industry. Abbott et al. (2009) divided the world into 21 regions and they used the model to project the production, consumption, and trade flows in sawlogs and lumber from 2005 to 2035. Instead of exogenously shifting the intercept of the lumber supply curves, Abbott et al. (2009) adjusted the AAC overtime to reflect the impacts of MPB outbreak on timber supply. The results indicated that the timber shortage caused by MPB would negatively affect both the BC interior timber and lumber sectors in terms of producer surplus (Abbott et al., 2009). The main weakness of these two studies (Delcourt, 1995; Abbott et al., 2009) is that they did not account for the differentiated forest products and substitutes. Their models are also not real dynamic models in the sense that capital investment and harvesting decisions are not endogenous.

Chang and Gaston (2014) used a recursive dynamic spatial equilibrium model to analyze the competitiveness of Canadian SWL industry. The main contribution of their paper is that they relaxed the restrictive assumption of product homogeneity and disaggregated SWL into higher and lower grade lumber groups. Based on 2011 baseline data, the authors made assumptions about future demand and supply based on factors that may affect global SWL markets and projected global SWL trade flows from 2012 to 2021. Their results indicated that for both Canadian high grade and low grade SWL, in the near future, the annual total exports would decline significantly; SWL price would increase globally and the price increase for lower grade SWL would be greater than higher grade lumber (Chang and Gaston, 2014). Using similar spatial equilibrium modeling technique, Chang and Gaston (2015) examined the global impacts of potential changes in trade policies and supply constraints in Russia and New Zealand. They found that, compared to the baseline projection, Russian softwood log export tax reduction would cause increases in Russian log production, exports and prices over the 2012–2021 period. On the other hand, restricting New Zealand's log production would cause both export and annual production in New Zealand to drop. The weaknesses of the two papers are that the lumber supply changes were all based on assumptions, and therefore the accuracy of the simulation results depends on the accuracy of the assumptions. In their studies, changes of timber supply and harvesting decisions in different regions are also not considered.

Methodologically, our economic model was drawn heavily on the spatial equilibrium model developed by Chang and Gaston (2014). Chang and Gaston (2014) used relative old data set of year 2011 for a national level analysis; and the focus of their studies was to project the future production, consumption and trade flows of lumber in different regions. However, the purpose of our study is to analyze the welfare effects of adopting genomic technology in the forestry sector using a more updated data set. In addition, we consider the change of harvesting decisions through a timber supply model instead of exogenously shifting the wood product supply. In short, this study differs in scope and in methodology from all studies that were conducted on the forest sector.

3 Theoretical Framework

3.1 Timber Supply Model

In Alberta, essentially all forest lands are publically-owned. Though most production is organized and carried out by private entrepreneurs responding to market incentives, they are strongly influenced and constrained by decisions and regulations of the Alberta government. The final harvest levels are approved by the Government of Alberta through annual allowable cut (AAC) (Schreiber and Thomas, 2017). In order to increase the allowable harvest level, forest companies have the option to engage in a range of silvicultural activities, such as using genetically-improved seeds. The change of the AAC due to the silvicultural activities are called allowable cut effect (ACE). The ACE allows an immediately increase in annual harvest by the same amount each year for the number of years in the forest rotation if there is any improvement in growth, regardless of when its direct effect will be realized (Pearse, 1990). To represent current practice in Alberta, we construct a linear programming-based timber supply model where the objective is to maximize harvest volume for pine and spruce subject to provincial regulatory policies and resource constraints. Specifically, we employ the Woodstock Forest Modeling System and the Mosek solver.

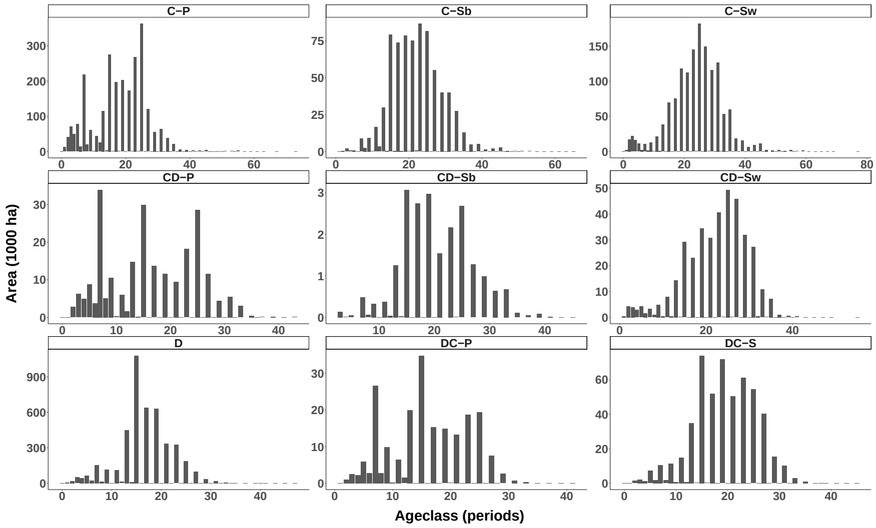

Figure 1: Starting age class distributions by species composition strata. Age classes are in five-year wide periods

The simulation process depends on a combination of the age class distribution of the initial forest inventory and the growth and yield information. We use forest inventory, growth and yield data from the Government of Alberta as our starting values, and then simulate the annual timber supply under different breeding strategies. The data was compiled from 20 Forest Management Agreement areas in the province, which covered 95% of the timber production areas in Alberta [2]. Figure 1 shows the initial age class distributions of different species composition strata. Since forests regenerated with genetically-improved seeds grow faster than the existing ones, the genetic gain can be realized by volume gain. We calculated gains in volume yield by applying the percent genetic gain to the volume given in the existing yield tables. Figure 2 presents the yield curves for existing stands and regenerated stands of different species composition strata. All yield curves are based on harvest volumes from clear-cutting. Following Abbott et al.

[2]There were over 550,000 ha in the net landbase which could not be directly assigned to a species composition stratum. These primarily represent harvest areas in the first few age classes. Due to the vintage of the AVI in relation to the time of harvest species composition calls were not yet available for these hectares (pers. comm. Nov. 17, 2017, Darren Aitkin, Manager Forest Biometrics Group, Government of Alberta).

(2009), we assume the lumber recovery rate is fixed over time, indicating that the wood product production will change in parallel with the timber supply change.

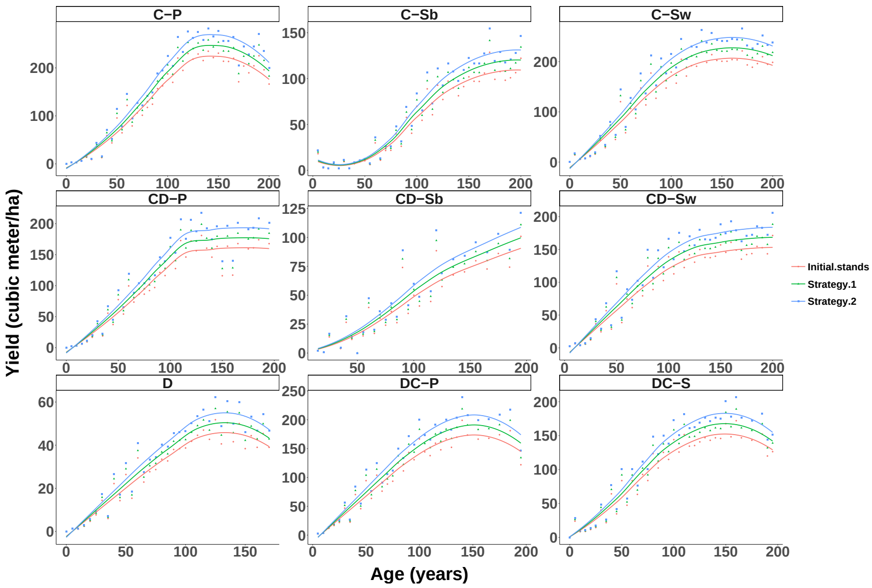

Figure 2: Yield curves by species composition strata for initial stands and regenerated stands (Stretegy 1 & 2). Strategy 1 & 2 correpond to genomic scenarios in section 3.2.5.

3.2 Economic Modeling Approach

We identify and measure economic costs and benefits of the research project based on applied welfare analysis. Pine and spruce together accounts for about 90% of Alberta merchantable volume of coniferous growing stock, and they are mainly used for the production of softwood lumber (SWL). Therefore, it is appropriate to only consider the SWL industry for the economic evaluation. Since SWL is a commonly traded commodity, we construct a global trade model (i.e., spatial equilibrium model) to evaluate the economic effect of SWL supply shifts in Alberta. This approach allows for a more detailed representation of markets and requires less restrictive assumptions (Paris et al., 2011).

3.2.1 Countries and (or) Regions

Assuming interconnected competitive markets, the model considers two net demand regions and four net supply regions. In 2015, BC accounts for 63.4% of the total SWL export in Canada and 25.6% of the total SWL export in the world (FAO, 2015). Alberta is the focus area in this study. Thus Canada is divided into 3 regions: Alberta (AB), British Columbia (BC) and the rest of Canada (ROC). The remaining export regions are grouped together as rest of the world export (ROW_ex).

The demand for SWL is dominated by the U.S. where almost 31.6% of all foreign export are destined in 2015 (FAO, 2015). In 2015, 94% of the total U.S. SWL imports are from Canada; 96% of total Alberta SWL exports are shipped to the U.S. (Figure 3). Thus U.S. is treated as an import region in this study. The remaining import regions are grouped together as rest of the world import (ROW_im).

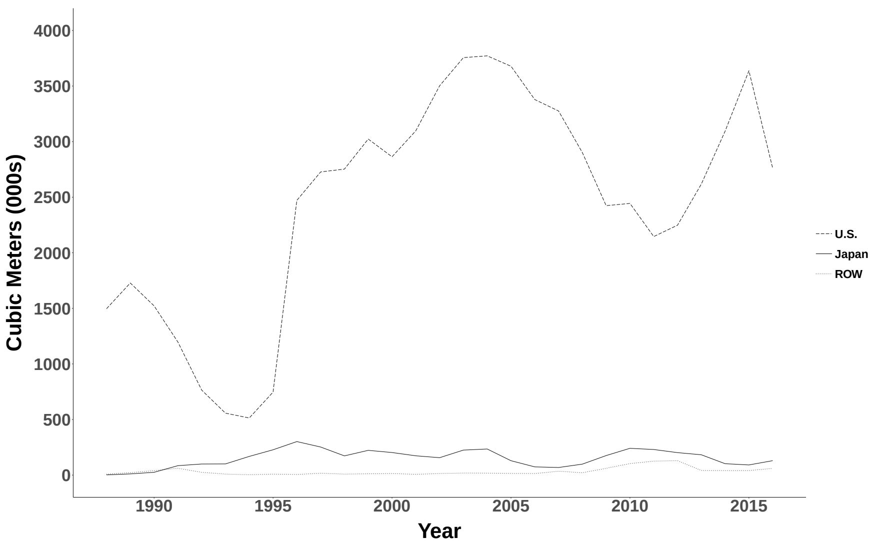

Figure 3: Alberta softwood lumber exports to major markets, 1988-2016.

3.2.2 Derivation of Net Demand and Supply Estimation

The model considers n net demand regions and m net supply regions. Both supply and demand functions are assumed to be linear and therefore have constant slope[3]. According to Delcourt (1995), linear demand and supply are easy to be integrated and are robust in determining an equilibrium. In the demand function, factors that could affect the lumber consumption, such as the housing market, interest rates, income growth, population and technology, are not explicitly included, but included as an intercept shifter. Similar to the demand function, the lumber supply function is also defined as the relationship between the quantity produced and the price. Investment in enhanced silviculture, technical change and government policy can all cause changes in future lumber supply. These factors are also included as intercept shifters in the model. To reduce model complexity,

[3]A change in slope may pose a problem in solving for equilibrium values (Chang and Gaston, 2014)

cross-effects between products were not considered in this study.

Suppose the net demand region i (i=1, . . . , n) and the net supply region j (j=1, ..., m) of SWL have the following linear domestic demand and supply functions:

$$q_i^d = a_i + b_i \rho_i^d \tag{1}$$

$$q_i^s = c_i + d_i \phi_i^s \tag{2}$$

$$q_j^d = a_j + b_j \rho_j^d \tag{3}$$

$$q_j^s = c_j + d_j \phi_j^s \tag{4}$$

where a_i, b_i and a_j, b_j are the intercepts and slopes of the domestic demand function in regions i and j, respectively; c_i, d_i and c_j, d_j are the intercepts and slopes of the domestic supply function in regions i and j, respectively; q_i^d, q_i^s and q_j^d, q_j^s represent the domestic consumption and production in regions i and j, respectively; and ρ_i^d, ϕ_i^s and ρ_j^d, ϕ_j^s represent the domestic demand and supply prices in regions i and j, respectively.

The intercepts and slopes of eq.(1)-(4) can be calculated based on the base-year data of production, consumption, mean market prices, and the own-price elasticities of domestic supply and demand for SWL, which are expressed as follows:

$$b_i = e_i^d \left(\frac{q_i^d}{p_i^d} \right) \tag{5}$$

$$a_i = q_i^d - b_i \rho_i^d \tag{6}$$

$$d_i = e_i^s \left(\frac{q_i^s}{\phi_i^s} \right) \tag{7}$$

$$c_i = q_i^s - d_i \phi_i^s \tag{8}$$

$$b_j = e_j^d \left(\frac{q_j^d}{p_j^d} \right) \tag{9}$$

$$a_j = q_j^d - b_j \rho_j^d \tag{10}$$

$$d_j = e_j^s \left(\frac{q_j^s}{\phi_j^s} \right) \tag{11}$$

$$c_j = q_j^s - d_j \phi_j^s \tag{12}$$

where e_i^d, e_i^s and e_j^d, e_j^s represent the own-price elasticities of domestic demand and supply of the SWL in region i and j, respectively. To derive the net demand and supply functions, net demand and supply elasticities are required and can be calculated as follows:

$$
\begin{aligned}
\varepsilon_i^d &= e_i^d\left(\frac{q_i^d}{M_i}\right) - e_i^s\left(\frac{q_i^s}{M_i}\right) && (13)\\
\varepsilon_j^s &= e_j^s\left(\frac{q_j^s}{X_j}\right) - e_j^d\left(\frac{q_j^d}{X_j}\right) && (14)
\end{aligned}
$$

where ε_i^d is the net demand elasticity in region i and ε_j^s is the net supply elasticity in region j. M_i is the import quantity of SWL in region i, and X_j is the export quantity of SWL in region j. The intercepts and slopes of the net demand and net supply functions can be derived as follows:

$$
\begin{aligned}
\alpha_i &= \frac{(c_i - a_i)}{(b_i - d_i)} && (15)\\
\beta_i &= \frac{1}{\left[\varepsilon_i^d\left(\frac{M_i}{\rho_i^d}\right)\right]} && (16)\\
\gamma_j &= \frac{(c_j - a_j)}{(b_j - d_j)} && (17)\\
\delta_j &= \frac{1}{\left[\varepsilon_j^d\left(\frac{X_j}{\phi_j^s}\right)\right]} && (18)
\end{aligned}
$$

We assumed that changes in consumption and production for each time period were measured by changing the intercepts of domestic demand and supply functions. Specifically, the intercepts of domestic demand and supply functions are defined as below:

$$
\begin{aligned}
a_{i(t+1)} &= a_{it} + q_{it}^d(R_i^D)[(t+1) - t] && (19)\\
c_{i(t+1)} &= c_{it} + q_{it}^s(R_i^S)[(t+1) - t] && (20)\\
a_{j(t+1)} &= a_{jt} + q_{jt}^d(R_j^D)[(t+1) - t] && (21)\\
a_{j(t+1)} &= a_{jt} + q_{jt}^s(R_j^S)[(t+1) - t] && (22)
\end{aligned}
$$

where $t+1$ is the year of next period and t is the year of the current period. R_i^D and R_j^D are the expected annual SWL demand changes (%) in regions i and j, respectively. R_i^S and R_j^S are the expected annual SWL supply changes (%) in regions i and j, respectively.

Since the intercept parameters of the domestic demand and supply functions were updated for each year, the intercept parameters of the net demand and supply functions in the model were also changed accordingly.

3.2.3 Positive Mathematical Programming

Samuelson (1952), first, and Takayama and Judge (1971), after him, have shown that the optimal trade flow could be determined using the mathematical programming model. The specification of a spatial trade model among regions corresponds to the maximization of a quasi-welfare function (QWF) subject to constraints regarding the demand and the supply of the various regions. The QWF objective function is defined as the sum of all regional demand integrals less the sum of all regional supply integrals and interregional transportation costs (eq. 23), which corresponds to the maximization of the sum of consumer and producer surpluses netted out of total transaction costs (Samuelson, 1952; Takayama and Judge, 1971).

$$Max \sum_{i=1}^{n} \int_0^{M_i} D_i(M_i)\, \mathrm{d}M_i - \sum_{j=1}^{m} \int_0^{X_j} S_j(X_j)\, \mathrm{d}X_j - \sum_{i=1}^{n} \sum_{j=1}^{m} t_{ij} Q_{ij} \tag{23}$$

where D_i and S_j are the demand and supply of SWL for the regions; Q_{ij} is the quantity of SWL exported from region j to region i; t_{ij} is the per unit transportation cost of SWL from region j to region i. The transportation costs among different regions are considered to obtain the competitive optimum solution for regional prices and quantities and interregional flows when total economic welfare (trade surplus) of all markets is maximized. To be used in the algorithm of the objective function, the net demand and supply equations are assumed in its inverted form. The inverse demand and supply functions are derived from the domestic demand and supply functions in each region as follows:

$$P_i^d = \alpha_i - \beta_i M_i \ , i = 1, \ldots .n \tag{24}$$

$$P_j^s = \gamma_j - \delta_j X_j \ , j = 1, \ldots .m \tag{25}$$

where α_i and β_i denote the intercept and slope of the net demand function of SWL, and the variables P_i^d and M_i represent the demand (import) price and total quantity demand (imports) of SWL for region i, respectively. γ_j and δ_j are the intercept and slope of the net supply function of SWL, and the variable P_j^s and X_j denote the supply (export) price and total supply (exports) of the product k for region j. Therefore, the integrals of eq.(23) can be expressed in terms of quadratic function in eq.(26) along with the related constraints in eqs(27)-(30):

$$Max \sum_{i=1}^{n}[\alpha_i M_i - \frac{1}{2}\beta_i (M_i)^2] - \sum_{j=1}^{m}[\gamma_j X_j + \frac{1}{2}\delta_j (X_j)^2] - \sum_{i=1}^{n}\sum_{j=1}^{m} t_{ij} Q_{ij} \tag{26}$$

subject to

$$\sum_{i}^{n} Q_{ij} \leq X_j \tag{27}$$

$$\sum_{j=1}^{m} Q_{ij} \geq M_i \tag{28}$$

$$M_i, X_j, Q_{ij} \geq 0 \tag{29}$$

$$\sum_{i=1}^{n} M_i - \sum_{j=1}^{m} X_j = 0 \tag{30}$$

Constraint (27) ensures that the SWL supply of region j is greater or equal to the total export of SWL in region j. Constraint (28) ensures that the total SWL import of region i is at least as big as what is consumed in region i; constraint (29) ensures prices and quantities are positive; and constraint (30) ensures that the markets clear.

The standard mathematical model proposed by Samuelson (1952) and Takayama and Judge (1971) was critiqued by Paris et al. (2011) for the discrepancy between the equilibrium solution and the observed demand, supply and level of trade flows. The cause of the discrepancy problem can be attributed to the imprecision of unit transaction cost. To generate solutions that perfectly reproduce observed supply and demand quantities as well as prices and trade flows for a given base year, we adopt the calibration method proposed by Paris et al. (2011), which is an extension of the positive mathematical programming method (Howitt, 1995). Specifically, the unit transaction costs are further adjusted by either adding or subtracting the shadow price from the level of the given costs (Paris et al., 2011).

Following Paris et al. (2011), van Kooten and Johnston (2014) and Chang and Gaston (2014), the calibration process was implemented in three steps. First, the objective function (eq.23) is solved, subject to all the constraints (eqs.27-30) and an additional calibration constraint (eq.31).

$$Q_{ij} = Q'_{ij} \tag{31}$$

where Q'_{ij} represents the observed trade flow of lumber between export region j and import region i. After solving the model, the dual (shadow) prices λ_{ij} was generated. Second, the shadow prices generated in the first step were used to adjust the original transportation costs in the objective function to achieve the "effective" transaction costs between export and import regions. The new objective function is showed as follows:

$$Max \sum_{i=1}^{n} \int_{0}^{M_i} D_i(M_i)\,\mathrm{d}M_i - \sum_{j=1}^{m} \int_{0}^{X_j} S_j(X_j)\,\mathrm{d}X_j - \sum_{i=1}^{n}\sum_{j=1}^{m}(t_{ij} + \lambda_{ij})Q_{ij} \tag{32}$$

Finally, the modified objective function (eq.32) was solved again subject to the original constraints (eqs.27-30) in order to calibrate the spatial equilibrium model perfectly to the observed trade flows, quantities of production and consumption and prices. The model is solved by using the Microsoft Excel software package called What's Best!. It allows users to try different trade scenarios, perform sensitivity analysis or impose additional constraints with little difficulty (Chang and Gaston, 2014).

To define the initial equilibrium of the model, values are assigned for all elasticities as well as initial prices and quantities shown in eqs(5)-(12). Table 1 reports the regional SWL production, consumption and mean price values and Table 2 reports the trade flow data between regions. The base-year prices of SWL in each region are derived from the weighted means of the unit values of exports or imports (Chang and Gaston, 2014). Following van Kooten and Johnston (2014), positive mathematical programming is used to calibrate the spatial equilibrium model to actual SWL trade flows among trade regions so that the transportation cost represent the shadow price which consider factors that are not included in the transportation cost (e.g., heterogeneous lumber quality, tariff, etc).

Table 1: Regional softwood lumber production, consumption, prices and demand & supply elasticities in base year 2015 used to define initial equilibrium.

Region	Production (million m^3)	Consumption (million m^3)	Mean price (CAD$ m^{-3})	Demand elasticity	Supply elasticity
Net supply regions					
AB	9.27	5.50	171	-0.34	1
BC	31.18	4.98	221	-0.34	1
ROC	22.53	11.14	181	-0.34	1
ROW_ex[a]	101.55	40.51	350	-0.34	1
Net demand regions					
U.S.	54.34	86.70	204	-0.34	1
ROW_im	164.71	234.74	332	-0.34	1

† The source used for elasticity estimates is from Cardellichio (1989) for all regions. All other info in the table was estimated by the authors using data from FAO (2015), CANSIM table 303 0064 (Statistics Canada, 2015), and National forest database (2015). [a] Including Austria, Chile, Finland, Latvia, New Zealand, Romania, Russian Federation, Sweden, Belarus, Brazil, and Ukraine.

Table 2: Product group trade flows in base year 2015 (millon m^3).

	Import region		
Export Region	U.S.	ROW_im	Total
AB	3.64	0.13	3.77
BC	15.53	10.67	26.20
ROC	11.27	0.12	11.38
ROW_ex	1.93	59.11	61.04
Total	32.36	70.03	102.39

† The trade flows in the table was estimated by the authors using data from the Canadian International Merchandise trade database (2015), and UN Comtrade database (2015).

3.2.4 Dynamics

A genetic improvement program will entail a sequence of improvements in genetic gain over time. Thus, it is important to identify the timing of a supply shock and the timing of the shock's effect. Although the change in supply that occurs in a certain year is assumed to be sustained at a constant level throughout time, the effect of the shock varies over time as the market is able to adjust to the change throughout time. Based on the proposed genomic scenarios (Figure 5), this study estimates the economic effects of 21 years from 2016 to 2036.

3.2.5 Projecting the Future Supply and Demand of Softwood Lumber

We first construct a plausible scenario of what would have happened to the benefits in question if the research being evaluated not been performed, and use this scenario as the basis for comparison. With this approach, any net increase in benefits relative to the baseline are considered additional.

Business As Usual (BAU)

To project the future supply and demand of SWL, we exogenously shift intercepts of domestic supply and demand curves in each region. The model's ability to analyze alternative scenarios allows the examination of a variety of different future conditions affecting domestic supply and demand conditions (Delcourt, 1995). Assumptions about the annual changes in demand and supply curves are made based on historical mean annual change (%) and expected annual (%) change in the future.

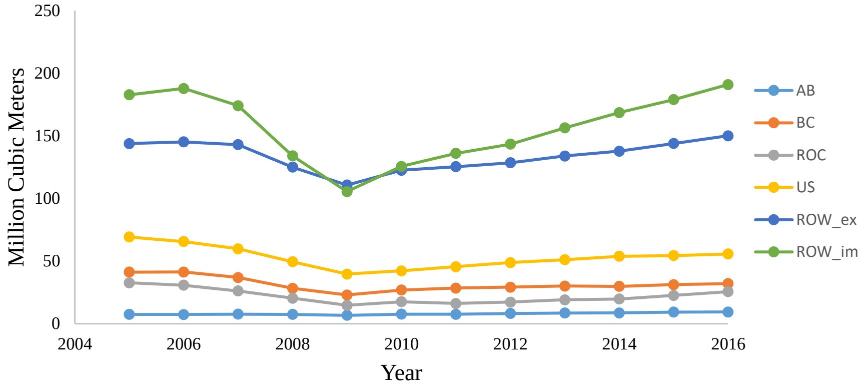

Figure 4: Historical SWL production in all regions, 2005-2016.

Figure 4 shows the historical SWL production in all regions from 2005 to 2016. The historical mean annual change is negative in BC (-2%), ROC (-1%), and U.S.(-1%), but positive in AB (2%), ROW_ex (1%) and ROW_im (1%). For ROC, ROW_ex and ROW_im, we assume that the annual changes follow the historical trends. However, for BC, according to the Forest Analysis & Inventory Branch of the Ministry of Forests, a drop in timber supply of 25% over the next twenty years will occur due to mountain pine beetle (MPB) infestation, from 76.71 million cubic metres in 2016 to 56.91 cubic metres in 2035. Thus, the annual reduction in supply for BC is assumed to be 1.25%. For U.S., though historically the mean annual production is -1%, U.S. SWL production is expected to increase in the future due to U.S. export duties on Canadian lumber in 2017 and the increase of plantation forests in U.S. south (Chang and Gaston, 2014). Therefore, we assume the mean annual change in U.S. SWL production is 0%.

Following Chang and Gaston (2014), we assume that there is no change in SWL demand in Canada over time. The annual increase in SWL demand of the rest of world import (Row_im) and export regions (Row_ex) is assumed to be 1.5% due to population increase and economic growth. In U.S., the annual increase in demand of SWL is assumed to be 3% due to the growing U.S. demand in housing. We summarize assumptions about future mean annual supply and demand changes (%) in SWL products for all regions except Alberta under the BAU scenario in Table 3.

Table 3: Assumptions about future mean annual supply and demand changes (%) for softwood lumber products in all regions except Alberta, 2016-2036.

	Change in Demand (%)	Change in Supply (%)
Export Regions		
BC	0	-1.25
ROC	0	-1
ROW_ex	1.5	1
Import Regions		
U.S.	3	0
ROW_im	1.5	1

† The assumptions are based on reported data from FAO (2009), the British Columbia Ministry of Forests and Range (2007), McKenney et al. (2016) and Chang and Gaston (2014).

In Alberta, annual allowable cut is increasing in recent years due to the new management strategies in regards to mountain pine beetle infestation. However, in the near future, timber supply is expected to reduce back to the pre-MPB infestation level as a result of MPB surge cuts ending and land-base reductions (Schreiber and Thomas, 2017). This indicates a 25% reduction in timber supply. In addition, since 2018, Alberta government (2016) requires mandatory use of improved seed for reforestation in the province which can lead to allowable cut effect for forest companies. Considering all these facts, we assume SWL supply in Alberta decreases 25% from 2021 to 2036.

Genomic Scenarios

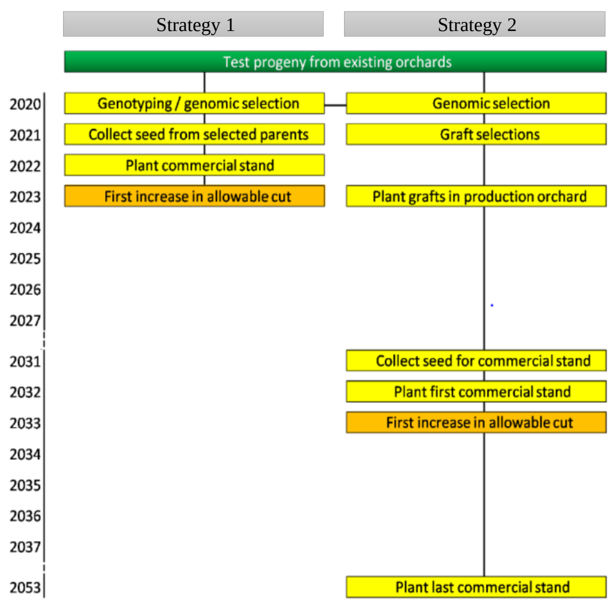

Figure 5: Implementation of the genotyping and genomic selection technology. Adapted from the genomics-assisted tree breeding research program application form.

Using genomic technology, we can increase the genetic gain of current improved seed. Figure 4 shows two different strategies of applying genomic technology to tree improvement programs, which can lead to two different levels of genetic gain. Genetic gain is defined as predicted increase in volume for selected trees over unselected (i.e., wild) trees. The average genetic gain of current improved seed is about 5%. In strategy 1, genomic selection is applied to existing orchards to select the best genotypes for near term production which can result in improved seeds with 10% genetic gain in 2023; in strategy 2, the genomic tool is used to select individuals for second generation orchards which gives us improved seeds with 20% genetic gain in 2033 (Barb Thomas, Associate Professor, Department of Renewable Resources, University of Alberta, pers. comm., 15 Dec 2017). Each strategy is analyzed by incorporating the ACE results from the timber supply model into the economic model.

3.2.6 Economic Benefits to AB

To arrive at a cumulative estimate of the value of the genomic research program today, we calculate the discounted net economic benefit for the entire stream of research gains (NPV^{NEB}), which is the discounted sum of producer and consumer surpluses net of R & D expenditures from 2016 to 2036 (eq. 33).

$$NPV^{NEB} = \sum_{t=0}^{T} (1+\rho)^{-n} (PV_t^{CS} + PV_t^{PS} - E_t) \tag{33}$$

where NPV^{NEB} is the net present value of the economic benefits of the research program; ρ is the discount rate; PV_t^{CS} is the present value of consumer surplus in year t; PV_t^{PS} is the present value of producer surplus in year t; E_t is the R & D cost in year t.

4 Results

4.1 Timber Supply Simulation

Table 4 reports the extent of the allowable cut effect (ACE) for BAU and different genomic scenarios (i.e., strategy 1 & 2). All ACEs are positive since mature reserves are available for immediate AAC increases. As expected, the ACE increases as the level of genetic gain increases. Since we assume a fixed lumber recovery factor over time, SWL supply has the same percentage change as timber supply. For BAU scenario, ACE causes 3.2% increase in SWL supply in 2018; for strategy 1, ACE causes 7% increase in SWL supply in 2023; for strategy 2, ACE causes 13.5% increase in SWL supply in 2033. Since we assume that the SWL production would decrease annually by 1.6% from 2021 to 2036 in AB due to MPB infestation, ACEs induced by the research program can compensate the negative effect of MPB infestation. The calculated lumber supply changes in Table 4 serve as inputs to shift the SWL supply curve in the economic model.

Table 4: Simulated annual allowable cuts (AACs) and allowable cut effects (ACEs) in Alberta.

Scenarios	AAC(M m^3)	ACE(M m^3)	Timber supply change (%)
Business as usual	19.1	0.6	3.2
Strategy 1	19.8	1.3	7.0
Strategy 2	21.0	2.5	13.5

4.2 Spatial Equilibrium Model Simulation

Table 5: Calibrated SWL production, consumption, trade, and prices for the trade model and comparisons with the actual levels in base year 2015.

	Production		Consumption		Trade		Price	
Region	Million (m^3)	% of actual level	Million (m^3)	% of actual level	Million (m^3)	% of actual level	CAD$ (m^{-3})	% of actual level
Export								
AB	9.27	100	5.5	100	3.77	100	171	100
BC	31.18	100	4.98	100	26.2	100	221	100
ROW	22.53	100	11.14	100	11.38	100	181	100
ROW_ex	101.55	100	40.51	100	61.04	100	350	100
Import								
U.S.	54.33	100	86.7	100	32.36	100	204	100
ROW_im	164.71	100	234.74	100	70.03	100	332	100

† Note: Adjustment (shadow price) were used to calibrate the model to the observed trade flow.

Table 5 presents calibrated SWL production, consumption, trade and prices for the spatial equilibrium model in the base year of 2015. The production, consumption, trade and price levels of 2015 are precisely duplicated using positive mathematical programming, and therefore, they provide a good foundation for projecting global SWL market conditions during the 2016-2036 period.

We summarize projected present values (PV) of total surplus results for different ad hoc scenarios in Figure 6. We used a discount rate of 8% which is comparable to the discount rate of private investments; social discount rates tend to be 2-4% as they represent a return on both social and financial returns (McWilliams, 2015). It is obvious in Figure 6 that the PV of total surplus under all genomic scenarios are greater than the BAU scenario, which means the adoption of genomic technology can lead to significant increase in the expected present value of total surplus. When estimated under the BAU scenario, the PV of total surplus are projected to be $21.8 billion. In terms of the genomic scenarios, strategy 1 can increase the PV of total surplus by $0.3 billion and strategy 2 can increase the PV of total surplus by $0.4 billion. Thus, the proposed genomic research program yields an increase in total economic surplus of at least $11.5 million per year in PV. This annual benefit is large relative to the annual average costs of roughly $0.5 million in PV for the research program.

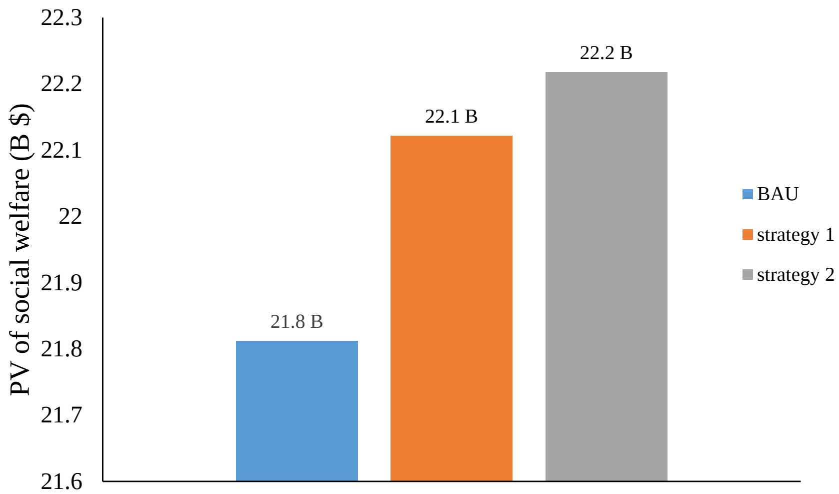

Figure 6: Present value of total surplus, Alberta, 2016-2036, r=8%.

Since we have better cost information for strategy 2, we focus our following discussion on comparing the results of BAU and strategy 2 scenarios. We present results of changes in mean annual quantities, price and welfare in Table 6. We can see that with the exception of the significant impacts on Alberta, the adoption of genomic technology in Alberta plays a minor role in global SWL markets. The overall global mean annual total surplus increases by $280 million, although the change amount is only 0.09% of the global total surplus. The mean annual impacts on production, consumption, trade, price, consumer surplus, producer surplus and total surplus are less than 1.2% in all regions except Alberta. In Alberta, comparing with the BAU scenario, adopting genomic technology results in large gains to Alberta SWL producers and relative small gains to Alberta consumers. As we can see from Table 6, with the use of genomic technology, the mean annual production in Alberta is projected to increase 14.2% which leads to a mean annual increase of producer surplus by 30.3% and a mean annual increase of net exports by 30%. However, the mean annual consumption increase in Alberta is only about 0.2%, and the mean annual consumer surplus gain is projected to be 0.3%. The reason of larger producer surplus gain and smaller consumer surplus gain is that Alberta only produces about 2% of world SWL, and therefore the increased supply of Alberta SWL will only affect the price marginally over time (-0.3%). Thus, in a competitive market, Alberta producers can act almost as price takers and enjoy benefits from the increasing timber supply and SWL production.

Table 6: Projected mean annual changes (%) in production, consumption, trade quantities and welfare between BAU and strategy 2 scenarios over the period 2016-2036.

Region	Production	Consumption	Trade	Price	Consumer Surplus	Producer Surplus	Total Surplus
Export							
AB	14.2	0.2	30.0	-0.3	0.3	33.3	14.0
BC	-0.4	0.1	-0.5	-0.3	0.2	-0.7	-0.4
ROC	-0.5	0.2	-1.2	-0.3	0.3	-0.9	-0.2
ROW_ex	-0.2	0.1	-0.3	-0.2	0.1	-0.4	-0.1
Import							
U.S.	-0.3	0.1	0.7	-0.3	0.2	-0.6	0.1
ROW_im	-0.2	0.1	0.7	-0.2	0.1	-0.4	0.0

For strategy 2 genomic research, two parts of costs are considered. The first part is the research cost which includes genotyping and phenotyping of the training population and the model development. The second part is is the operational cost which inludes seedling production from selections of progeny. The research cost is estimated to be about $1.25 Millions per year from 2017 to 2020 (Barb Thomas, Associate Professor, Department of Renewable Resources, University of Alberta, personal communication, 15 Dec 2017). The operational cost is closer to 70 thousand dollars per year per tree improvement program (Schreiber and Thomas, 2017) and there are currently 15 pine and spruce tree improvement programs in Alberta. Thus, the operational cost is estimated to be about $1.05 Millions per year at the provincial level from 2021 to 2036. The calculated benefit-cost ratio is 43.9; that is, for each dollar of funds invested in the genomics-assisted tree breeding research program, almost $44 of benefits resulted. This measure again provides evidence that the economic rate of return to genomic research in the forestry sector is high.

5 Conclusions

This study investigated the economic effect of adopting genomic technology in the forest sector in Alberta based on the welfare economic theory. We first construct a timber supply model to project the potential allowable cut effect (ACE) and then incorporate the simulated ACE results into a spatial equilibrium model. The spatial equilibrium model is calibrated to 2015 observed bi-lateral trade flows of SWL using positive mathematical programming. The main findings of this study are: 1) using genomic technology can significantly increase the aggregate timber supply; 2) the adoption of genomic technology leads to a significant increase in the projected present value of total surplus in the case of Alberta; 3) the impact of Alberta SWL supply shocks on global markets is extremely small, but important for Alberta; 4) SWL producers achieve considerable proportion of the surplus gain while consumers are not affected significantly. A conclusion we draw from this study is that under the consistent threats from climate change and the predicted future timber supply shortfall, integrating genomic technology into current tree improvement programs will be beneficial from the socio-economic point of view. We believe this study provides valuable information to forest companies and governments in Alberta regarding decisions on adopting the new technology. Nevertheless, the illustrated research method is generally applicable for forestry in other regions of the world as well.

It is critical to understand that the economic factors considered in the analyses are believed to be conservative because we only consider the genetic gain in volume. Tree breeding programs offer a multitude of additional benefits which are not quantified in this analysis, such as increased diameter growth, more uniform stands of trees, and many additional non-market values (Keegan, 1976). In addition, some of the limitations of this study should be noted. First, the effect of timber processing capacity limitations on the supply behavior is not captured. Second, as these analyses are performed during the first year of the research project, they can only identify anticipated project outputs, the potential pathway to adoption and impact, and approximate timelines. Uncertainties associated with these factors limit the conclusions that can be made at this time concerning impacts. Several extensions can be topics for future research. Notable among them includes incorporating the capacity constraints of factories into the model and estimating the non-market values associated with the research program.

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