Evaluation of the economic impact of adopting precision crop load management for sustainable apple production

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Abstract

Crop Load Management in Apple Production is one of the main factors determining the annual profitability of Apple orchards. Under or over-thinning the number of fruits on a tree can have serious economic consequences for growers. Finding the specific fruit load per tree is imperative to increase or achieve maximum profit per tree. Prior research uncovers a theoretical tradeoff between the fruit number left on a tree that makes it to harvest and gross economic value. The literature suggests a possible optimum range, but no specific optimum crop load target is given for Gala and Honeycrisp apple varieties in New York, Washington, Michigan, and North Carolina. Based on secondary experimental data, in this research, we studied the precise optimum point of the relationship at which maximum profit is achieved. We used independent regressions per state and variety to create a quadratic profit function that relates the dependent variable (profit) and the independent explanatory variable (fruit # per tree or crop load). The function enabled me to calculate the maximum point of the relationship where maximum profit is achieved. As expected, the relationship between fruit load and profit per tree is curvilinear bell-shaped-type. The results show different optimal treatment points for maximum profit among the states and cultivars studied. A summary of the maximum point per state and variety can be found in the results section. As expected, due to its geographical advantage, Washington state presents the highest magnitude in profit for both cultivars (Gala & Honey crisp) than all other states that are part of this experiment. Further on, a Box-Cox transformation was also performed to compare the standard quadratic regression vs. a more flexible one. The standard and Box-Cox quadratic profit functions present different corresponding maximum treatment points for profitability. Only the NY transformation gave a significant lambda value, but we failed to reject a Chi-square test for the lambda value, rendering the transformation statistically indifferent from the standard quadratic function. As expected, managing crop load does have a significant influence on apple orchard profitability. The findings of this research are intended to serve as tools for agricultural extension teams to address grower profitability with precise recommendations per state.

Keywords: Crop load, profit function, quadratic function

BIOGRAPHICAL SKETCH

Mauricio first graduated 2001 from Zamorano University in Honduras as an agricultural engineer. He then joined Lacteos de Honduras S.A. de C.V. as a cheese plant manager. In 2006 he completed his Master's in Food Technology from Wageningen University in the Netherlands. He then returned to work at Lacteos de Honduras, but this time as Product Development Manager. Mauricio then joined Cargill Mexico as a Senior Product Manager. During his stint at Cargill, Mauricio held various positions, including Senior Commercial Manager and Senior Merchant in the risk management sourcing department. While at Cargill, he completed an executive M.B.A. at Cornell University in Ithaca, NY. In 2021 Mauricio decided to return to academia and pursue an M.S. in Food & Agriculture Applied Economics from Cornell Dyson (2023).

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INTRODUCTION

Apples are the number one consumed fruit in the U.S., currently grown in 50 states using more than 382,000 acres of land. The industry comprises more than 26,000 growers producing 10.1 billion pounds of fruit annually, generating 3.2 billion U.S. dollars of farm-gate revenue (USDA, 2022). A recent USAPPLE™ industry report (USApple Industry Outlook-Foreword, 2022) states that the industry faces increasing fertilizer, labor, and freight costs. According to the same publication, trade wars are closing once-profitable foreign markets, leading to over-supply and stagnant prices domestically. Given these market pressures, growers need to identify strategies to increase profitability. In particular, improving crop load management decisions can address these concerns.

Apple trees often produce many more flowers than needed for a commercial crop. Only 3-10% of the initial population of flowers should be carried to harvest to optimize crop value and promote a constant annual production (Robinson, 2014). Although some fruitlets abscise naturally, without active crop thinning, too many remain, resulting in small fruit size. Small fruit size at harvest sharply reduces crop value. Over-thinning also has serious economic consequences, resulting in lower yield, and reduced total crop value. The difference between the optimum crop load and under-thinning or over-thinning can sometimes be a difference of thousands of dollars per acre (Robinson, 2014). Thus, growers often fail to capture the maximum crop value because they make inappropriate crop load management decisions. A more precise crop load management should enable growers to get closer to the optimum level of fruit, allowing them to move closer to the maximum potential crop value.

According to Robinson et al. (2013), crop load management is the most critical management strategy that determines the annual profitability of apple orchards. Earlier research on apples found a significant relationship between crop load and fruit size but do not measure profit implications (Wrights et al. 2006; Anthony, Serra, and Musacchi 2019). Gallardo et al. (2015) assessed the potential impacts of non-optimal crop load on profits, focusing on Honeycrisp apples employing a hedonic pricing model to estimate the relationship between Honeycrisp apple quantities and prices, but did not consider production data. To address this gap, this study aims to apply econometric techniques to model the relationship between crop load and profitability. This research uses experimental data to identify optimal crop loads at which the maximum profit occurs for Gala and Honeycrisp varieties. The analysis used 668 observations from field experiments from New York, Washington, North Carolina, and Michigan.

Accurate crop load estimation has constantly challenged tree fruit producers (Winter, 1986). Stajnko et al. (2004) state that several forecasting models based on ecological and cultivar-related parameters for yield have been tested, producing mixed results. Crop load estimation based on directly counting fruits or buds would eliminate bias or model inaccuracy, but prohibitively high labor costs render this approach unfeasible. Using econometrics techniques, this research estimates a profit function that models (predicts) the relationship between crop value (partial profit) as a function of various crop load treatments, controlling for variety and geographical location. The results are relevant for apple growers because a USDA-funded research project is developing and testing technology to help reduce the fruit counting labor requirement. This model can provide valuable information for developers of the counting technology to predict the individual tree deviation from the potential maximum crop profitability.

Literature Review

Robinson et al. (2013) argue that crop load management is the single most important yet challenging management strategy that determines the profitability of apple orchards. Poor or inadequate thinning[1] can reduce profitability substantially. The reason is that the number of fruits on a tree directly affects the yield, fruit size, and quality of harvested fruit, which largely determines the crop value. If thinning is inadequate and too many fruits are left on the tree, fruit size will be small. In that case, fruit quality will be poor, and flower bud initiation for the following year's crop may be either reduced or eliminated. Robinson et al. (2013) also state that over-thinning also carries economic perils on yield and crop value, reducing yields due to large fruit size but too few fruits per tree. Thus, Robinson et al. (2013) summarized that crop load management is a balancing act between reducing crop load sufficiently to achieve optimum fruit size without reducing total tree yield excessively (Figure 1).

Figure 1 Counterbalancing responses of Gala fruit size and yield to crop load by Robinson et al.(2013).

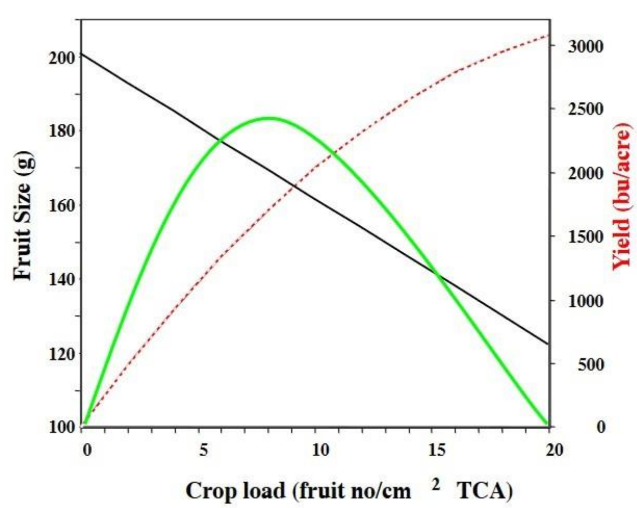
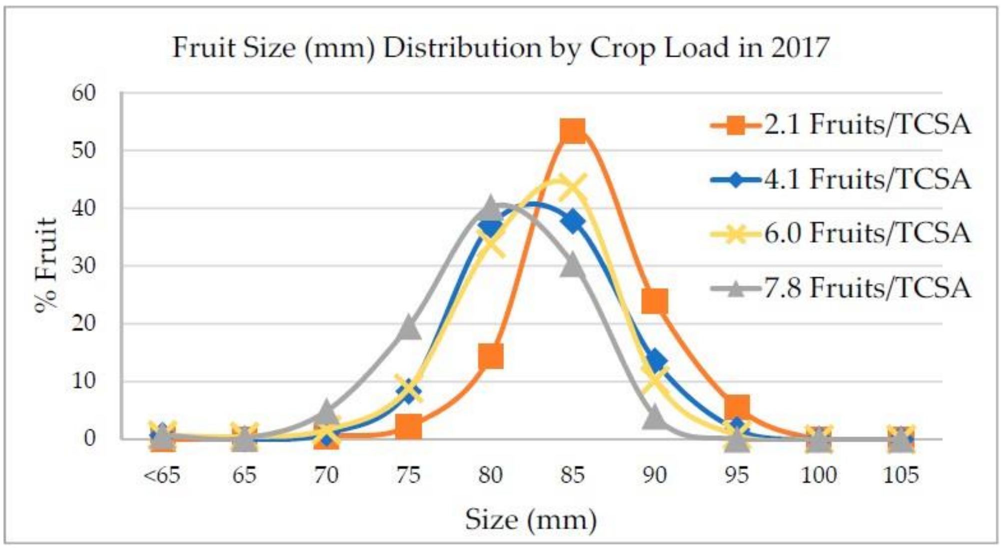


Figure 1 portrays experimental results showing a nonlinear relationship between yield, fruit size, and crop load (Robinson et al., 2013). The figure shows that, as crop load increases, the total yield increases (red dotted line), but fruit size decreases (black line). In other words, fruit size is small at very high crop load levels, but the total yield per tree increases. Crop value (total revenue) in this situation would be zero or less since the revenue from selling small fruits is often lower than packing and storage costs. On the other hand, when crop load is reduced to more moderate levels through thinning, crop value rises dramatically even though the total tree yield is lower. The reduction in total tree yield is offset by larger fruit sizes, which receive higher prices. Robinson et al. (2013) argue that an optimal crop load level maximizes the value of apples per tree, balancing yield and fruit size. Further reductions in the crop load beyond this optimal level would result in a lower crop value due to decreasing tree yield. Although individual fruit size would continue to increase, it does not compensate for the yield loss. Thus, figure 1 suggests a trade-off between the fruit size and the number of apples per tree, suggesting that optimal crop load management should be identified. Identifying and achieving the optimal crop load is challenging for apple growers because it is very difficult to run experimental trials of various crop load levels to assess each treatment level's economic impact. Additionally, running multiple levels of thinning experiments with multiyear-year replications to construct the appropriate curves would be an extra burden on grower operations. To address this gap in information, I have created an econometric model to determine the relationship between crop load and per-tree profit. This model can assist growers in making informed decisions about crop load recommendations and provide valuable information for developers of Information Technology (IT) solutions to assist growers in making profit-maximizing crop load management decisions.

The challenge of identifying the relationship between crop load and profit is not exclusive to apples. Multiple studies have explored this relationship in other crops like pears (Bound, 2021) and grapes (Geller & Kaan, 2013). Regarding apples, the relationship between crop load and fruit quality has been analyzed by Anthony, Serra, and Musacchi (2019). The authors performed experiments and analyses to examine the effect of crop load on yield and fruit size. The study showed that fruit quality parameters (fruit size) weakened as crop load density increased (Figure 2). That is, they found that fruit size decreased significantly at higher crop load levels. However, Anthony, Serra, and Musacchi (2019) did not examine the impact on profits.

Figure 2 Optimizing Crop Load for New Apple Cultivar: "WA38" by Anthony (2017).



Embree et al. (2007) assessed the effect of blossom density and crop load on growth, fruit quality, and return bloom in Honeycrisp apples. Their findings showed that adjusting crop load to six fruit/cm^2 TCSA (Trunk Cross Sectional Area) will induce consistent Honeycrisp production. However, similar to Anthony, Serra, and Musacchi (2019), the impact on value (i.e., profit) was not measured.

Concerning profit, Gallardo et al. (2015) assessed the potential impacts on profits when crop load is not optimal. They employed a hedonic pricing model to estimate the relationship between Honeycrisp apples quantities and prices by size category. This information was used to analyze potential changes in grower returns as production shifts to a certain fruit size. Gallardo measured the impact of fruit size on profit but did not model the relationship between the latter and crop load. Stover, Wirth, and Robinson (2001) evaluated the relationship between crop load, fruit size, and crop value at a range of crop loads following fruit thinning. However, Stover, Wirth, and Robinson's (2001) evaluation was done on a different set of cultivars (*Empire*, *Mcintosh*, *Delicious*) and did not use profit as the variable for crop value.

All these studies reinforce the need to study the specific points where crop load provides the most profit for two important apple varieties grown in the U.S.

Crop Load Management Strategies

Crop load is typically managed by reducing flower buds through pruning, inducing fruitlet abscission through spraying chemical thinning agents (plant growth regulators) over four weeks between flowering and 20mm fruitlet diameter and by hand thinning between 4-10 weeks after bloom (Robinson et al., 2013). Presently pruning is mainly done without specific attention to managing flower bud number; thus, some growers prune too little, and some over-prune. Most US apple growers practice chemical thinning, but it is highly variable and difficult to predict or control, Robinson et al. (2013). Hand thinning is costly and performed without clear guidance regarding the target number of final fruits per tree. As a result of these imprecise practices, optimizing fruit numbers within a very narrow period is difficult to achieve. Because managing crop load in apples has such a significant economic consequence and has been unpredictable, it contributes to large revenue variability among apple growers.

As mentioned in the introduction, accurate crop-load estimation has constantly challenged tree fruit producers (Winter, 1986). Stajnko et al. (2004) state that several forecasting models based on ecological and cultivar-related parameters for yield have been tested, producing mixed results. Crop-load estimation based on direct counting fruits or buds would eliminate any bias or model inaccuracy; however, a high labor input and attention to detail are required. To make fruit counting a viable option, automated technology is currently being developed to reduce the high labor requirement. Multiple projects and companies are trying to develop mechanized and automated equipment to perform crop load counting. Some systems being evaluated consist of 3-D imaging or lidar (light detection & ranging) systems mounted on rovers, all-terrain vehicles, and drones with the purpose of counting buds, flowers, or fruitlets per tree. As presented by Gongal, A. et al. (2015) to this date, the overall accuracy of these systems is close to 82%. These and other developments mark a possible route to combine precision crop load research with automated counting systems to provide actionable feedback to growers that can increase profits.

Profit Function Estimation Methods

I employed a production function methodology to analyze the relationship between crop load and value (profit). According to Beattie, Taylor & Watts (2009), production economics is concerned with the choice among (1) alternative production processes or technologies, (2) outputs or enterprise selection, and (3) resource allocation. We use a profit function to determine the input utilization to achieve maximum output. Specifically, I use a production function to determine the optimal amount of fruit or crop load treatment to maximize the partial profit per tree. Bettie, Taylor & Watts (2009) define a production function as a quantitative or mathematical description of a firm's various technical production possibilities. The production function relates the maximum output in physical or value terms to alternative levels of the inputs in physical terms (in this case, crop load).

The choice of the functional form varies according to the type of data, the type of relationship, and the intended research question to be answered. Examples of data types may include biological, nominal, ordinal, interval, and ratio, among others (Oxford Brookes University, 2023). Regarding functional forms, most studies use either Quadratic, Cobb-Douglas, or translog functions (Chalfant, 1984). Cho (2012) argues that there is no straightforward statistical test to determine which functional form is most appropriate. Thus, in many cases, researchers choose the proper form according to their research purpose and data characteristics. I employed the standard quadric functional form for this research because it allows us to estimate simple non-linear relationships. Beattie, Taylor, and Watts (2009) address the use of quadratic functions to relate one product with one-variable factors, the likes of corn yield to nitrogen fertilization rate. This study also relates one product (profit) with one factor (crop load). Additionally, the quadratic function allows for a relationship displaying Diminishing Marginal Returns (Beattie, Taylor, Watts, 2009). This function enables the visualization and calculation of the specific point at which the slope equals zero (marginal return = 0) when the curve is concave. Mathematically:

$$MPP = \partial y / \partial x = 0 \qquad (1)$$

where y denotes the quantity of output and x is the variable factor of production. *MPP* is the marginal physical productivity.

In general, regression analysis is the path to obtain the function coefficients. Stover, Wirth, and Robinson (2001) used linear regressions to predict mean fruit size and evaluate the relationship between crop load, fruit size, and crop value at a range of crop loads. Regressions operate under the assumption that data is homoscedastic and portrays a normal distribution. Given the data's biological nature, this assumption may not be valid in this study. According to Box and Cox (1964), transformations might be helpful to make the data in a relation of more stable error variance (more homoscedastic). According to the theory, the transformation results in fewer heteroscedastic residuals than those of the untransformed data (Box-Cox, 1964). A Quadratic Box-Cox form also incorporates first-order and second-order effects of input on output. The Box-Cox method contains several traditional functions such as quadratic, translog, and inverse quadratic as special embedded parametric cases. Due to all the above, the Box-Cox functional form can provide greater flexibility, making it adaptable to biological data and helping achieve a normal distribution of the residuals, which is assumed when employing a regression analysis framework.

Tauer (2000) estimated the production relation between the optimal amount of nitrogen and soil data. Using secondary data, Tauer (2000) compared the relation between variables mentioned above in the standard quadratic form and the "flexible" Box-Cox functional form. Tauer (2000) then used those estimated functions to determine optimal nitrogen application. Following Tauer (2000), this research entails a single-output and single-input biological relationship. Therefore, I utilized a Box-Cox transformation before modeling a quadratic functional form. I then compared the results of both the transformed and untransformed data forms.

Contribution to the Literature

Despite its importance, the literature review indicates a lack of research estimating profit functions to identify the optimal level of crop load for apples, particularly for specific varieties (e.g., Gala, Honeycrisp) and apple-producing states (e.g., New York, Washington State, North Carolina, and

Michigan). This information is valuable for stakeholders in the US apple industry, as optimal crop loads may differ across varieties and states.

My contribution to the literature is to employ econometric approaches (using a quadratic functional form and the Box-Cox transformed quadratic function) using experimental data to estimate state- and variety-specific optimal crop load management levels that maximize grower profits. I focus on Gala and Honeycrisp varieties for New York, Washington State, North Carolina, and Michigan. This information is quite valuable for developers of innovations based on digital technology to automatize this important activity in apple production.

METHODOLOGY

The methodology consists of two steps. I first calculate per-tree revenues, costs, and profits using experimental data. Subsequently, I use these experimental data calculations to econometrically estimate profit functions by variety and state.

Data:

I developed a database of 668 tree-level observations with data provided by the Cornell Horticultural research team. The data corresponds to the 2021 apple crop harvest year. The data consisted of tree-level observations of two experiments: Pruning severity, or "Experiment 1," which has 346 observations, and Crop Load, or "Experiment 2," with 322 observations. I refer to them as Pruning Experiment and Crop Load Experiment hereafter. Pruning is defined as the control of tree size or canopy size, but it can also be used to manage floral bud numbers and is recommended as the first stage of any thinning[1] program (Bound 2021). On the other hand, crop load is defined as the number of fruit left intentionally on a tree that should make it to harvest. The Pruning Experiment measured the relationship between fruit size vs. floral bud load for four states and determined the relationship between pruning severity and fruit number, yield, fruit size, and crop value in New York, Washington, Michigan, and North Carolina. The Crop Load experiment differs from the pruning experiment in that it measures the relationship between the number of fruit and the crop load (instead of bud load). An additional difference between these experiments refers to controlling for tree size in the crop load experiment. The independent variable of interest for the pruning experiment is the number of fruit per tree; conversely, for the crop load experiment, it is the number of fruit per cm^2 (TCSA). In apple production, dividing by the trunk cross-sectional area allows for comparing crop load regardless of variations in tree size within a given test (Westwood & Roberts, 1970). The data provided by the Cornell Horticultural team is described in Table 1.

Table 1 Data provided by the Cornell Horticultural team.

Data	Description
# Fruit / Tree	Units
Crop load	Fruit/cm^2 (TCSA) Only for Experiment 2
Fruit Weight	average individual fruit weight/ tree (grams)
Red Blush Area	average % of red in fruit per tree
Yield/tree	Kilos
Color classification	% of fruit per tree in each color category: Utility, USNo1., Fancy, Extra Fancy, XX-Fancy
Size Classification	% of fruit per tree in each size bucket: <128, 128-136, 136-153, 153-167, 167-190, 190-215, 215-238, 238-264, >264

Using the above data, I processed and used it to create a “pruning treatment labor cost” and a “crop load treatment labor cost” variable. The profit variable is based on the tree yield, labor input cost, and farm-gate prices. Next, I collected additional market data to calculate the revenue and profit per tree. The procedure of such calculation consisted of the following: Based on market information provided by the commercial packing house operator New York Apples Sales, we used only two classifications for color: “Process apples” (which groups color classifications ranging from process to Fancy apples) and “Extra-Fancy” which groups all color classifications pertaining to Extra Fancy and above. Therefore, operationally I grouped Utility, No.1, and Fancy under “Utility.” “Extra-Fancy” and “XX-Fancy” were grouped under the “Extra Fancy” name. Utility apples are not further classified according to size. The Extra Fancy Apples grouping was further distributed according to the sizing scale provided by the horticultural team. Each variety has its specific price table provided by Cornell Agritech Team. Per industry standards, fruit sizes were grouped under the following categories in Table 2.

Table 2 Fruit Size Classification

Size name	**Fruit Size (grams)**
138’s	<128, 128-136, 136-153
100’s	153-167, 167-190
80’s	190-215, 215-238
72’s	>238

The proportion (%) of each size category was multiplied by the total amount in kilos of Extra-Fancy per tree. The sum in kilos of each price category was multiplied by its corresponding price. All revenue per group size plus the process apples were summed up to generate the total revenue per tree. Table 3 presents the prices per fruit size classification for the apple varieties considered in this study. For example, for a tree with a color distribution of 79% “Utility,” 24% “X-Fancy,” and a total tree yield of 33.5 kilos, only the 24% of “Extra-Fancy” proportion of 33.5 kilos would be further classified according to fruit size and multiplied by its corresponding price detailed in table 3.

Table 3 Prices according to fruit size for Gala and Honeycrisp cultivars

Fruit Size	Price/Bushel (USD)	Fruit Size	Price/Bushel (USD)
Utility GALA	3.3	UtilityHoney Crisp	3.3
Gala138s count	16	HC 138s count	16
Gala100s count	19	HC 100s count	19
Gala 80s count	20	HC 80s count	20
Gala 72s count	21	HC 72s count	21

To calculate the cost as a function of crop load level, I first assigned a pruning labor cost which depends on the given pruning treatment. Based on field observations, I assigned one second per flower bud removed. Therefore, a treatment of 400 spur floral buds costs 0 (zero) because it implies no labor activity. Table 4 presents the labor time assigned for each treatment per experiment.

Table 4 Assigned Labor Time per Treatment

Pruning Treatment (Floral Buds/Tree)	**Assigned labor time (seconds)**	**Crop Load Treatment** (# Fruit/cm2 TCSA)	**Assigned labor time (seconds)**
400	0	3	350
350	50	4	300
300	100	5	250
250	150	6	200
200	200	7	150
150	250	9	100
100	300	12	50
50	350	15	0

The labor time detailed above was then converted to cost in USD by multiplying by the wage rate ($ 17/hour labor rate, which converted to $/second = 0.004722 USD/second). A labor harvest cost was also assigned for every pruning and crop load system. The labor harvest cost was calculated by taking the number of fruits per tree and multiplying that number by the wage rate (every apple harvested represents 1 second in labor harvest cost). The more fruit per tree, the higher the labor cost (because of the higher number of apples needed to harvest per tree). In this research, I define total crop value as total revenue per tree and partial profit per tree as total revenue minus crop load treatment labor cost minus tree harvest labor cost.

Econometric Model

To obtain a regression that reflects the relationship between pruning severity or crop load with profit, I started by performing a scatter plot visual analysis. The intent was to observe any possible visual relationship between the two variables of interest, partial profit, and fruit number per tree. Furthermore, I ran a correlation test between these two variables. The correlation value was above 0.6 for the pruning experiment, while the Crop load experiment showed a low correlation value of

0.05. I used independent regressions for each state (NY, WS, NC, and MI) and each apple variety (Gala & Honey Crisp) to control for geographical and cultivar-specific fixed effects. As mentioned in the literature review, I employed a simple quadratic regression relating one input with one output. The following equation represents the empirical model used for the regression estimation:

$$y_{ijz}=a+bx_{ijz}-cx^2_{ijz} \quad (2)$$

Where *y* is the output variable (partial profit), *x* is the independent variable (fruit per tree or crop load), b is the linear quadratic coefficient, c is the squared quadratic coefficient, and *a* is the line intercept. The equation subscripts refer to the following: *i* defines the state, *j* is the cultivar, and *z* refers to the type of experiment. As mentioned, the model is state, cultivar, and experiment specific. The independent variable was the number of fruit per tree for the pruning experiment and Crop Load (# fruit/cm^2 TCSA) for the crop load experiment. For both experiments, partial profit per tree served as the dependent variable.

Before running regression estimations, I generated a squared value of the treatment variable (in both experiments) to capture possible nonlinearities between crop load levels and partial profits. The quadratic regression estimation was performed in Stata, defining # fruit per tree (treatment) as the independent variable and per-tree partial profit as the dependent variable. The first derivative of the resulting quadratic regression was calculated and equaled to zero to calculate the maximum value of x (independent variable, or crop load level) where profit is maximum. This procedure was performed per state and cultivar to generate the optimal crop load level for state/variety combinations using the following equation:

$$MP_{ijz} = b - 2cx_{ijz} = 0 \qquad (3)$$

Where *MP* is the marginal profit and *c* is the quadratic coefficient estimated from equation (2). Again, dependent and independent variables are state, cultivar, and experiment-specific.

As part of the econometric analysis, a Box-Cox transformation was performed to analyze if a more flexible functional form than a standard quadratic function applies to this specific data set (Box and Cox, 1964). The Box-Cox functional form consists of the following formula:

$$(y^{\lambda}-1)/\lambda = c + b*[(x^{\lambda}-1)/\lambda] + a*[(x^{\lambda}-1)/\lambda]^2 \qquad (4)$$

In this case, *y* is the profit per tree, and x is the crop load treatment (# of fruit per tree for experiment 1, or the crop load per tree/cm^2 TCSA for experiment 2). Lambda, along with *a*, *b*, and *c*, are the parameters to be estimated, and since lambda can take any value, this function form is more flexible than the quadratic form. If lambda equals one, the equation collapses to the quadratic functional form. If the limit of lambda approaches zero, then the functional form becomes translog.

The Box-Cox regression estimates were performed using Stata statistical software for every state and apple variety. The statistical software's "Lambda" model produces the lambda and the *a*, *b*, and *c* parameter values for transformation. The estimators were used to transform the input or independent variable (# of fruit or crop load) to obtain the new forecasted y value (i.e., partial profit per tree). The estimated output value (new forecasted y) was plotted against the original x values (independent variable) to compare against the standard quadratic production regression. The first derivative of the obtained Box-Cox quadratic curve was calculated and equaled to zero to compute the maximum profit of the treatment under the Box-Cox transformation procedure. This procedure enabled me to compare the maximum profits per treatment, state, and cultivar for both functional forms (Quadratic & Box-Cox transformed).

RESULTS & DISCUSSION

<u>Summary Statistics</u>

A descriptive statistics analysis suggests differences in means for the measured experimental parameters of fruit/tree, fruit weight, yield, and partial profit. These differences in means are observed across states, cultivars, and experiment types.

Regarding the Gala cultivar under the pruning severity experiment (Table 5), on average, Washington State exhibits the highest average partial profit per tree ($36.95). Washington State also has the highest average individual fruit weight. Likewise, in this same pruning severity experiment, a similar difference is observed for the Honeycrisp variety. That is, Washington State has the highest average partial profit per tree ($36.42) among all states. Washington State also has the highest average fruit weight among all states in the study (282.63 grams). A word of caution is necessary, as these differences are for one year only, and they can be affected by weather patterns.

Table 5 Pruning Experiment Descriptive Statistics Summary

Pruning Experiment

Location	Cultivar	Statistic	Nº fruits/tree	Fruit weight (g)	Kg/tree	Partial Profit ($)
North Carolina	Honeycrisp	Mean	120.91	276.21	32.14	13.07
		SD (σ)	51.07	38.76	11.37	5.66
Washington	Honeycrisp	Mean	124.71	282.63	31.09	36.42
		SD (σ)	57.68	76.01	8.07	13.90
Washington	Gala	Mean	200.10	202.70	38.47	36.95
		SD (σ)	82.26	31.56	12.16	11.23
New York	Honeycrisp	Mean	99.08	221.42	20.59	4.22
		SD (σ)	62.17	44.01	11.36	3.41
New York	Gala	Mean	261.57	156.87	37.91	21.96
		SD (σ)	124.96	30.15	13.77	7.71
Michigan	Gala	Mean	201.39	160.28	31.68	20.65
		SD (σ)	85.14	16.17	12.57	7.98
Michigan	Honeycrisp	Mean	88.83	160.28	22.34	11.08
		SD (σ)	35.22	16.17	6.05	3.04

Considering the Crop load experiment (Table 6), for the Gala variety, Washington State has the highest average partial profit per tree ($38.8), followed by New York ($16.44) and Michigan ($15.44). Concerning the Gala cultivar fruit weight variable, Washington state exhibits the highest average individual fruit weight among the states in this study (199.25 grams).

The descriptive statistics for the Honeycrisp variety are similar. Washington has the highest average profit per tree ($51.62), followed by Michigan ($36.68), North Carolina ($12.86), and New York ($5.46). Regarding individual average fruit weight, Washington State displays the highest average among all states, with a value of 293.28 grams, as expected. Overall, the results from the descriptive analysis of the Crop Load experiment are consistent with those of the pruning severity experiment.

Table 6 CropLoad Experiment (controlling for tree size) Descriptive Statistics Summary

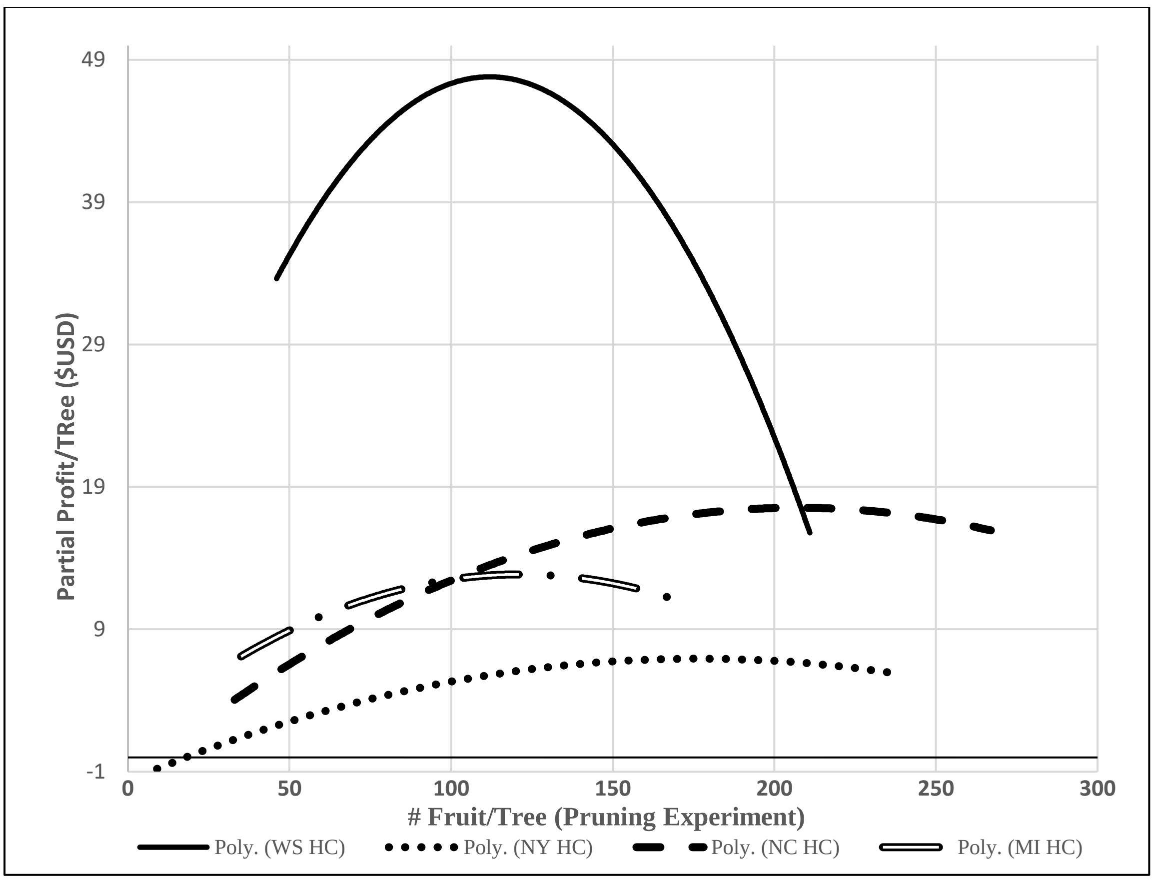
Crop Load Experiment

Location	Cultivar	Statistic	Nº fruits/tree	Fruit weight (g)	Kg/tree	Partial Profit ($)
North Carolina	Honeycrisp	Mean	141.95	261.67	36.05	12.86
		SD (σ)	44.42	42.80	9.86	5.53
Washington	Honeycrisp	Mean	107.91	293.28	30.48	51.62
		SD (σ)	31.86	46.33	6.39	11.96
Washington	Gala	Mean	205.52	199.25	39.78	38.88
		SD (σ)	72.52	25.92	12.23	12.26
New York	Honeycrisp	Mean	106.11	224.27	22.99	5.46
		SD (σ)	33.04	36.54	5.64	2.89
New York	Gala	Mean	158.41	181.89	27.86	16.44
		SD (σ)	56.45	21.39	7.82	7.88
Michigan	Gala	Mean	170.05	144.74	24.54	15.44
		SD (σ)	76.47	16.35	11.07	7.51
Michigan	Honeycrisp	Mean	68.25	276.83	17.98	36.68
		SD (σ)	33.80	38.05	7.56	15.48

Partial Profits, Pruning Severity, and Crop Load

This section focuses on the main objective of this study, the relationship between crop load and profits. Figures 3 and 4 present the relationship between partial profit per tree ($) with pruning severity (# fruit/tree), using the parameter estimate of the quadratic regression in equation (2) for each state and variety. Appendix A presents the quadratic regression results parameter estimates by cultivar and state.

Figure 3 Relationship between Partial Profit and # Fruit /tree for New York, Washington, Michigan, and North Carolina-Honeycrisp cultivar



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The number of fruit per tree is the independent treatment variable, and partial profit is the dependent variable. Consistent with Robinson et al. (2013), the results suggest a non-linear relationship between the treatment and the dependent variable for both apple varieties. These estimates allow me to calculate the optimal level of each treatment to maximize partial per-tree profits. Figure 3 (Honeycrisp variety)indicates that over-pruning and under-pruning negatively impact profitability. Recall that moving along the x-axis from right to left is associated with a more severe pruning treatment, resulting in a lower fruit count per tree but a higher individual fruit weight. Thus, the maximum point reveals the right balance between pruning severity to maximize profits. Over-pruning results in lower revenue and profits. Similarly, if a farmer prunes too little, an excess number of fruits will reduce individual fruit size due to the limited amount of energy (carbohydrates) available per individual fruit. Smaller fruit size is classified as lower quality fruit, leading to revenue penalties and lower profits.

Consistent with the descriptive analysis, Figure 3 indicates that Washington State has the highest level of profits among all states, followed by North Carolina, Michigan, and New York. The regression results provide strong evidence that Washington State operates at a higher profitability/tree range than the rest of the states in this study. The quadratic regression allows me to estimate the treatment levels that yields the maximum profit point, that is, the highest point of the regression curve (or the point where the slope of the line = 0, if concave). The maximum point for every curve is the primary research outcome expected from this study. I see notable differences between states for the pruning experiments regarding both varieties of apples. Washington State obtains the maximum point of the profit curve when pruning leaves 116 fruit per tree. Therefore, this is the point at which maximum profit/tree is achieved as a function of the number of fruit per tree obtained via pruning severity. North Carolina resulted in a maximum treatment point of 207 fruit per tree, while New York state has 176 fruit/tree. Thus, the results indicate that optimal pruning levels for Honeycrisp Apples are state specific. In summary, the # fruit per tree at which we obtain the maximum profit varies geographically.

Figure 4 Relationship between Partial Profit and # Fruit /tree for New York, Washington, Michigan, and North Carolina—GALA cultivar

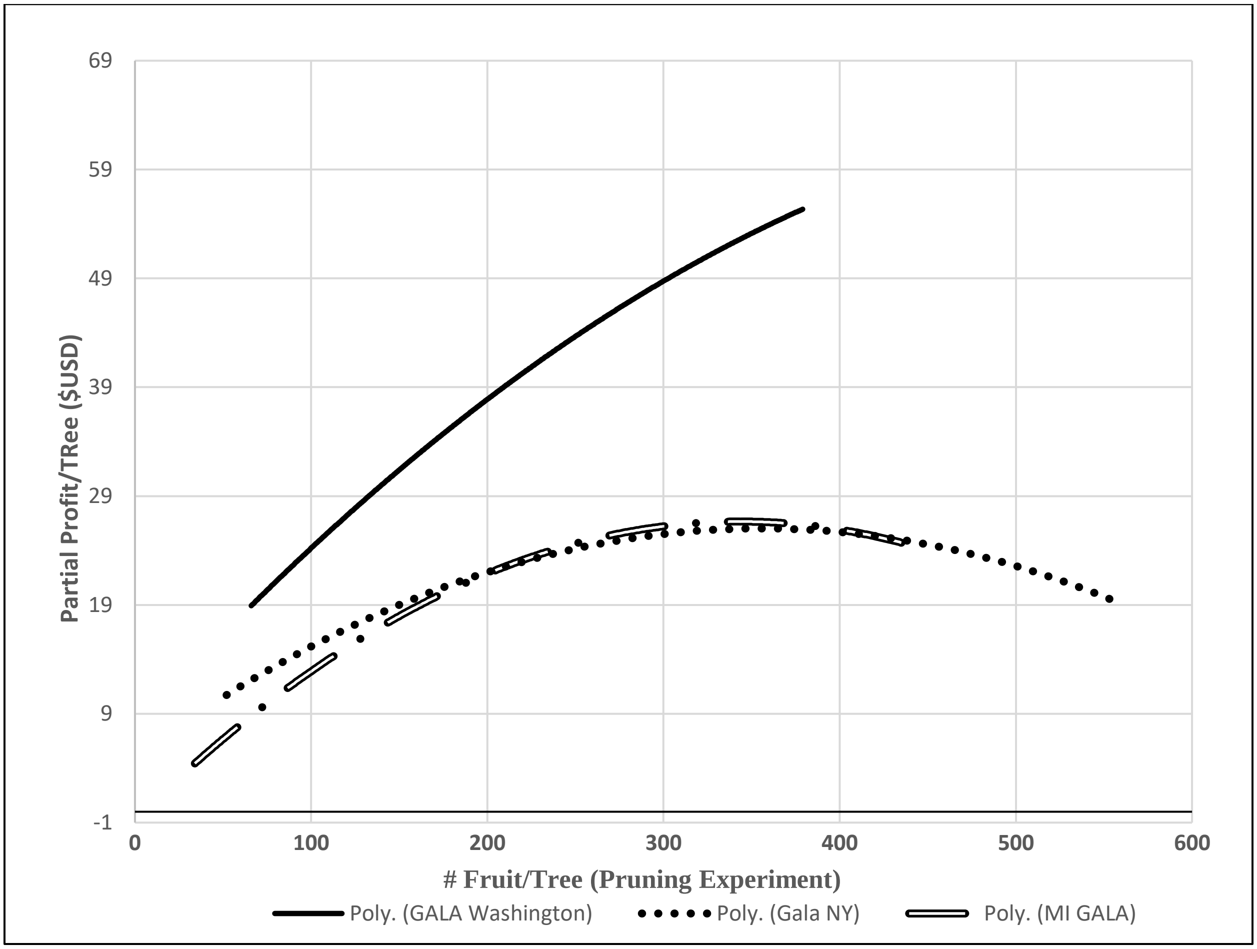

Figure 4 shows the results of the pruning experiment for the Gala variety (See Appendix A for the quadratic regressions parameter estimates used to calculate these curves). Washington State has the highest partial profit curve, followed by Michigan and New York. The highest point in partial profit per tree for Washington State is achieved at 637 fruit per tree. New York State reaches the highest point in partial profit at 355 fruit/tree. As expected, Washington State Gala apples operate in a higher profitability per tree range than other states. This is similar to the Honeycrisp findings. Regardless of apple cultivar, an obvious pattern indicates that Washington State operates in a higher profit range than the rest of the states considered in this study.

Figures 5 and 6 present the results of the Crop Load experiment for Honeycrisp and Gala apples, respectively (Appendix A presents the quadratic regression results for this experiment). The results of the crop load experiment for the Honeycrisp variety (Figure 5) are consistent with Robinson et al. (2013). That is, the relationship between crop load (fruits/cm^2 TCSA[1]) and profitability per tree is nonlinear. Increasing crop load increases profits up to a certain level, but further increases in crop load beyond this level diminish profits (due to lower fruit quality in terms of size). Likewise, profitability decreases if we remove too many fruits per tree. Figure 5 indicates that Washington State and Michigan have the highest partial profit per tree (depending on the crop load level), followed by North Carolina and New York. Thus, the crop load experiment suggests differences in optimal levels across states for Honeycrisp apples (Figure 5 and Table 8 below). North Carolina achieves its maximum profit with the lowest crop load, followed by Washington, New York, and Michigan. Washington State can reach a higher profit magnitude with a lower crop load level.

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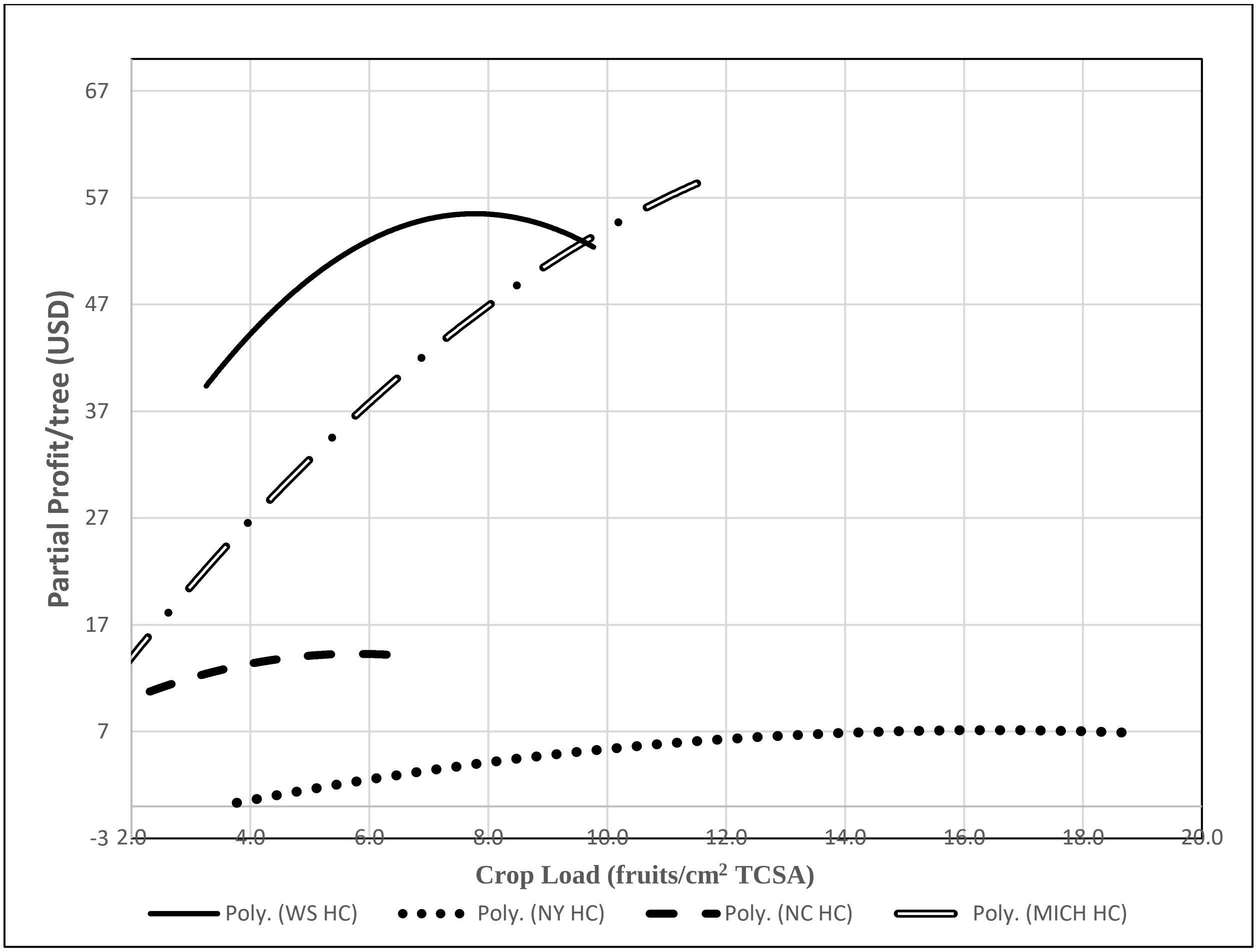
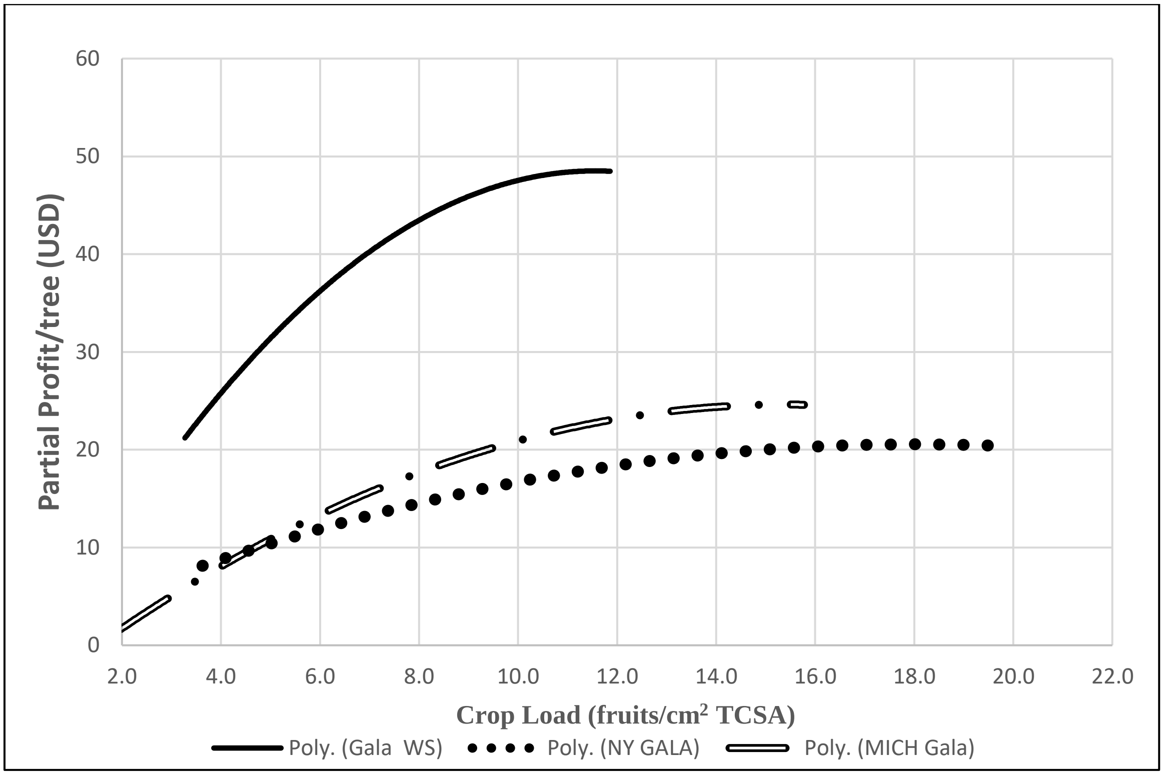
[1] "TCSA" = Truck Cross Sectional Area

Figure 5 Relationship between Partial Profit and Crop load for New York, Washington, Michigan, and North Carolina—Honeycrisp cultivar



Regarding the Gala cultivar for the Crop Load experiment (Figure 6), the relationship between crop load and profits is nonlinear, demonstrating that profit will be negatively impacted if the crop load level is too low or too high. As expected, we see a marked difference in partial profitability between states. Washington state has a higher profitability magnitude, followed by Michigan and New York, the last two at very similar levels.

Figure 6 Relationship between Partial Profit and Crop load for New York, Washington, Michigan, and North Carolina-GALA cultivar



Washington State has competitive advantages in apple production, thus exhibiting the highest profits. Yakima (the main apple production region) receives more natural light (Daily Light Integral-DLI) than the other states in the experiment. Specifically, Yakima enjoys an average range of 30-35 D.L.I., while New York State hovers only 25-30 D.L.I. (Korczynski, Logan, and Faust 2002). On average, Washington State orchards have 20% more photosynthetically active radiation (energy) available for plant vegetative and fruit growth than New York State orchards. Subsequently, this geographic advantage results in higher profits due to a larger yield, even when controlling for pruning or crop load treatment.

Profit Functions

I used equation (1) to model the relationship between profit and the experiment-specific independent variable. For function coefficients, please refer to Appendix 1. I summarize the results from the regressions as follows: (1) For New York Gala apples, the crop load experiment, all coefficients are statistically insignificant, making this regression unsuitable to predict a statistically significant maximum profit point. (2) Washington State (crop load experiment Honeycrisp variety), all coefficients in this particular regression are statistically significant, rendering the coefficients not applicable for a quadratic profit function. (3) Concerning North Carolina, the pruning experiment regression has a very low R-squared, making only the crop load experiment regression applicable to calculate a profit function. (4) For Michigan, we find a relatively high r-squared value for most regressions compared to New York. (5) Except for the crop load experiment for the Gala variety, Washington State presents the highest intercept values compared to all other states, in line with the higher profit curve lines seen in the initial results sections.

Maximum Profit Crop Load levels

I employed equation (3) to estimate the treatment point at which maximum profit is achieved. The procedure was performed for each state, cultivar, and experiment. A summary of optimum treatment points for each apple variety and experiment is summarized in Table 7. The table suggests that the profit-maximizing treatment level varies by cultivar and state.

Table 7 Treatment point at which maximum profit occurs

Treatment Point with Maximum Partial Profitability					
Exp 1 Pruning Severity (# Fruit/Tree)			Exp 2 Crop Load (fruit/cm2 TCSA)		
	Gala	**Honeycrisp**		**Gala**	**HC**
WS	637	116	**WS**	11.56	7.77*
NY	355	176	**NY**	18*	16.43
NC	-	207	**NC**	-	5.76
Mi	356	121	**Mi**	15.38	16.74

* Non-significant

Pruning experiment - Concerning the Gala cultivar, New York requires more severe pruning (less fruit/tree) to achieve maximum profitability compared to Washington State. On the other hand, for the Honeycrisp variety, Washington State requires the most severe pruning among all states in the study. New York and Michigan share similar pruning requirements for the Gala variety to maximize profit. Regarding the Honey Crisp variety, Michigan demands the most severe pruning treatment to attain maximum profit.

Crop Load Experiment – For the Gala cultivar, results indicate that Washington State requires less crop load levels to maximize profits compared to other states. Also, results suggest that the Washington State Honey Crisp variety requires less fruit load than Gala to achieve maximum profit potential. The North Carolina Honeycrisp cultivar requires less crop load than other states to maximize profit. Washington and North Carolina show a similar lower range of crop load treatment to maximize profits. New York and Michigan present a similar and less severe crop load requirement to achieve maximum profit. Michigan's Honeycrisp variety shows a higher crop load requirement than all the other states to maximize profits. Washington State's Gala cultivar obtains the maximum profit at 11.56 fruit/cm^2 TCSA, NY obtains the maximum point at 18 fruit/cm^2 TCSA, and Michigan at 15.38 fruit/cm^2 TCSA. These results suggest that Washington State requires less fruit density or crop load to achieve its maximum profit compared to other states.

Overall, the results presented in Table 8 align with Robinson's (2008) recommendation of having less crop load levels for the Honey Crisp variety than for the Gala variety, particularly for young trees. The results for the crop load experiment of the Honeycrisp cultivar share some similarities with Wright et al. (2006), who show that the optimum crop load range (in terms of fruit "quality") is 3-6 fruit/cm^2 TCSA. The findings from both experiments indicate that the Gala cultivar requires higher crop loads to maximize profits than the Honeycrisp cultivar. This means that Honeycrisp apples need higher labor input resulting in higher costs.

In addition to the analysis by state, I estimated a pooled regression model aggregating across states to assess possible statistical differences across coefficients in this study (Table 7). I included state-level fixed effects to control for differences across state and e interactions with the linear and quadratic crop load independent variables. For all regressions, I used New York State as the base case.

Table 8 Pooled regressions output, per experiment and cultivar

Pruning Experiment (pooled regression)

	Honey Crisp	Gala
Intercept	-1.67	5.03*
	(1.93)[a]	(2.827)[a]
Linear (x)	.097**	.118***
	(.039)[a]	(.022)[a]
Quadratic (x^2)	-.0002*	-.0001***
	(.0001)[a]	(.000)[a]
Washington Variable	3.88	2.705
	(5.01)[a]	(5.62)[a]
North Carolina Variable	0.109	
	(3.200)[a]	
Michigan Variable	3.143	(8.256)*
	(4.339)[a]	(4.346)[a]
Washington x Fruit per tree	.277**	0.061
	(.092)[a]	(.055)[a]
Washington x Fruit per tree^2	(. 001)***	0
	(.000)[a]	(.000)[a]
NorthCarolina x Fruit per tree	0.087	
	(.056)[a]	
NorthCarolina x Fruit per tree^2	(. 0001)	
	(.000)[a]	
Michigan x Fruit per tree	0.09	0.06
	(.098)[a]	(.039)[a]
Michigan x Fruit per tree^2	0	0
	(.000)[a]	(.000)[a]
No. Observations	168	178
R-Squared $_{(adj)}$	0.673	0.735

* p < 0.1%, ** p < 0.05, *** p < 0.01,
a = (Standard Error)

Crop load Experiment (pooled regression)

	Honey Crisp	Gala
Intercept	-4.31	1.08
	(8.08)[a]	(6.04)[a]
Linear (x)	1.39	2.16*
	(1.498)[a]	(1.16)[a]
Quadratic (x^2)	-.042	-.06
	(.065)[a]	.052[a]
Washington Variable	12.07	-5.68
	(16.29)[a]	(11.09)[a]
North Carolina Variable	8.76	
	(11.80)[a]	
Michigan Variable	3.56	-6.7
	(8.85)[a]	(7.26)[a]
Washington x Crop Load	10.88**	7.03**
	(4.82)[a]	(3.002)[a]
Washington x Crop Load^2	(0.75)**	(0.34)*
	(.356)[a]	(.192)[a]
NorthCarolina x Crop Load	2.02	
	(4.95)[a]	
NorthCarolina x Crop Load^2	-0.25	
	(.60)[a]	
Michigan x Crop Load	6.43***	1.77
	(1.94)[a]	(1.57)[a]
Michigan x Crop Load^2	(0.191)*	-0.068
	(.114)[a]	(.082)[a]
No. Observations	182	140
R-Squared $_{(adj)}$	0.9	0.77

* p < 0.1%, ** p < 0.05, *** p < 0.01,
a = (Standard Error)

Table 8 suggests that for the Honeycrisp pruning experiment, the coefficient of the interaction between Washington State and the pruning variable (# of Fruit per tree) significantly differs from New York's. Washington's linear and quadratic coefficient demonstrates higher profitability, consistent with Figure 3. The rest of the states show no statistically significant differences in the linear and quadratic coefficients compared to New York State (at the 95% confidence level). These results are consistent with the state-level results in Figure 3 because Washington is the only state statistically different from the rest. These results indicate that profits are much more sensitive to crop load decisions in Washington than in other states.

Similarly, Table 8 shows statistically significant differences between Washington and the other states for the crop load experiments (Honeycrisp cultivar). This is consistent with the state-level graphical representations depicted in Figure 5. Washington's coefficients have a greater value compared to New York's. Michigan's results also indicate a statistically significant difference in profit function compared to New York. North Carolina's Honeycrisp profit function shows no statistically significant differences from New York (at the 95% confidence level).

I now focus on the pooled results for Gala apples. As seen in Figures 5 and 6, for the pruning and the crop load experiment, the pooled regressions show significant differences in the profit functions coefficient between Washington and New York, with Washington having a higher profit function than New York. These results are similar to the Honeycrisp findings. The profit functions for the rest of the states show no statistically significant differences from New York (at the 95% confidence level).

Box-Cox Regressions

I explored the relevance of applying Box-Cox transformation to the estimated state-level profit functions (equation 4). Table 9 presents the estimated lambda transformation coefficient by state, variety, and experiment. The results indicate that the only case warranting the Box-Cox transformation is the crop load experiment for the Gala cultivar in New York. Therefore, I only performed a transformation procedure for the NY Gala variety.

Table 9 Box-Cox lambda coefficient, per state and cultivar

Box-Cox lambda Coefficient Summary					
Experiment 1 (Pruning)			Experiment 2 (Crop Load)		
State	**Gala**	**Honey Crisp**	**State**	**Gala**	**Honey Crisp**
NY	.143	.020	NY	.64***	-.38*
	(.001)[a]	(.000)[a]		(.123)[a]	(.000)[a]
WS	-0.27	0.501	WS	-0.43	0.043
	(.082)[a]	(.228)[a]		(.004)[a]	(.128)[a]
Mi	0.091	-0.833	Mi	0.08	-0.017
	(.070)[a]	(.000)[a]		(.000)[a]	(.000)[a]
NC	N/A	0.12	NC	N/A	0.07
		(.000)[a]			(.006)[a]

* $p < 0.1\%$, ** $p < 0.05$, *** $p < 0.01$,

a : chi^2 H_0 : Test Lambda = 1

Only the Gala cultivar for New York State provided a significant lambda value. However, when using a 95% confidence threshold, we fail to reject the null hypothesis of the chi^2 test that the lambda value is equal to one. This means that the Box-Cox transformation may not be statistically different from the quadratic function.

Table 10 compares the linear and quadratic coefficients of the Box-Cox transformation and the quadratic regression for the Gala cultivar from New York. The results are qualitatively similar, but the parameters are significantly different between the two approaches, proving the value of using the Box-Cox transformation in specific cases (e.g., Gala apples in New York).

Table 10 Function comparison Box-Cox vs. Standard quadratic for New York Gala

New York Crop Load Experiment Profit Function Comparison		
	Gala	
Coefficient	**Box Cox**	**Quad**
Intercept	.094	1.08
	-	(6.91)[a]
Linear (x)	2.52	2.16
	-	(1.32)[a]
Quadratic (x^2)	-.196	-.06
		(.06)[a]
R-Squared (adj)		.16
Lambda	.643	
Chi^2 H_0 Test: lambda=1	.123	
No. Observations	51	51

* p < 0.1%, ** p < 0.05, *** p < 0.01,
a = (Standard Error)

I use results from Table 10 to plot the profit function for Gala apples in New York for the Box-Cox and quadratic specifications (Figure 7). The Box-Cox transformation curve results in an almost perfect bell-shaped curve compared to the quadratic function. The Box-Cox curve demonstrates that the profit-maximizing crop load for Gala apples in New York is smaller than in the quadratic function. In other words, the Box-Cox transformation results in a function that better represents and explains the relationship between crop load and partial profit for the crop load experiment of Gala apples in New York.

Figure 7 Profit Functions Plot Box-Cox & Standard Quadratic for New York Gala cultivar

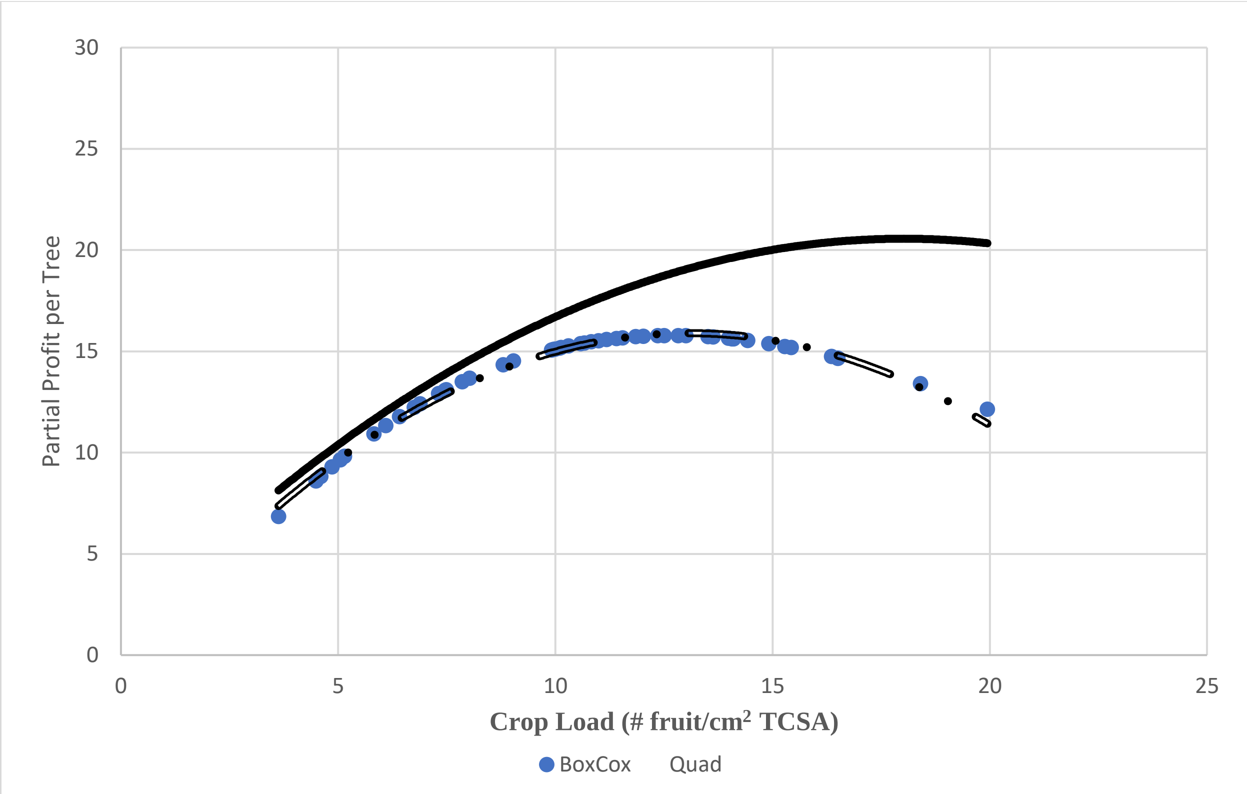


Table 11 indicates that the Box-Cox transformed regression provides a different profit-maximizing crop load level compared to the estimated optimal crop load from the quadratic function. The Box-Cox transformed regression specifies a lower crop load point (13.126 Fruit/cm^2 TCSA) at which maximum partial profit is achieved (a 27% reduction compared to the quadratic function). This would imply a more severe thinning field input to achieve this desired crop load. However, under the conditions of this experiment, both the quadratic and the Box-Cox transformed functions comparison might be inconclusive, given that the data refers to only one observation year.

Table 11 Maximum treatment point comparison Box-Cox vs. Standard quadratic New York Gala

Functions Maximum Treatment Point Comparison

	New York	
Variety	**Box-Cox** (fruit/cm^2 TCSA)	**Quad** (fruit/cm^2 TCSA)
Gala	13.12	18.02

CONCLUSIONS & IMPLICATIONS

The findings of this research are intended to serve as tools for agricultural extension teams to help apple growers improve profits through improved crop load decisions. To achieve this objective, I econometrically estimated a nonlinear relationship between pruning severity/crop load and partial profits for various varieties, states, and types of experiments. These nonlinear specifications allow me to test whether leaving too much or too few fruits per tree results in reduced profitability, as hypothesized by the literature. The maximum points of the profit functions indicate the level of pruning (or thinning) required to maximize per-tree profits for each variety-state combination. This information is essential for growers as crop load management decisions impact farm profitability.

Results indicate that climate and geographical location affect the optimum pruning or crop load levels. I showed that there are different maximum treatment points per variety and state, resulting in different partial profit maximum points between the four states of the study (NY, WA, Mi, and NC). As expected and due to its geographical characteristics, Washington State has a very different profit function than the other states, and this state operates at a higher profit than the rest. Additionally, Washington State requires a more severe pruning or thinning input to achieve maximum profit than the other states included in the study.

As stated in prior studies, crop load management has a significant economic impact on apple-growing operations. In this study, the economic implications of optimum crop load and optimum fruit size are observable and quantifiable and justify a managed approach to apple tree crop load. When coefficients are significant, the profit functions help calculate the crop load level that maximizes profits. My results also show the benefits of using the Box-Cox transformation for specific cases (e.g., Gala apples in New York). However, in this study, I found that the quadratic profit function is appropriate to calculate profit-maximizing crop load levels for most states and for Gala and Honeycrisp apples.

To improve model accuracy, I recommend incorporating new yearly harvest data into the model to increase the sample size. As new harvest year data are included, additional comparisons of the Box-Cox to the quadratic functions can be conducted. As more observations are added to the model, I anticipate changes in the results. The findings from this thesis, combined with relevant technology development, should help provide tools to standardize crop load management in US apple orchards. Apple growers who adopt precision crop load management should achieve higher levels of profitability than those who do not.

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APPENDIX A

NEW YORK				
	Pruning severity (# Fruit/Tree)		Crop Load (# fruits/cm2 TCSA)	
Coefficient	**Gala**	**Honey Crisp**	**Gala**	**Honey Crisp**
Intercept	5.03	-1.66	1.08	-4.31
	(3.25)[a]	(1.35)[a]	(6.91)[a]	(2.93)[a]
Linear (x)	0.11***	.097**	2.16	1.39**
	(4.46)[a]	(0.03)[a]	(1.32)[a]	(.54)[a]
Quadratic (x^2)	-0.0001	-0.0003	-0.06	-0.04
	(.00005)[a]	(0.0001)[a]	(.06)[a]	(0.02)[a]
R-Squared (adj)	0.30	0.40	0.16	0.33
No. Observations	74	40	51	45

* p < 0.1%, ** p < 0.05, *** p < 0.01,

a = (Standard Error)

Washington State				
	Pruning severity (# Fruit/Tree)		Crop Load (# fruits/cm2 TCSA)	
Coefficient	**Gala**	**Honey Crisp**	**Gala**	**Honey Crisp**
Intercept	7.74	2.22	-4.60	7.76
	(4.70)[a]	(6.08)[a]	(3.52)[a]	(24.89)[a]
Linear (x)	.18***	0.38***	9.19**	12.27
	(.048)[a]	(0.11)[a]	(3.52)[a]	(8.06)[a]
Quadratic (x^2)	-0.0001	-0.002***	-.40	-0.79
	(.0001)[a]	(0.0004)[a]	(.234)[a]	(.62)[a]
R-Squared (adj)	0.77	0.42	0.58	.09
No. Observations	40	24	33	33

* p < 0.1%, ** p < 0.05, *** p < 0.01,

a = (Standard Error)

North Carolina				
	Pruning severity (# Fruit/Tree)		Crop Load (# fruits/cm2 TCSA)	
Coefficient	**Gala**	**Honey Crisp**	**Gala**	**Honey Crisp**
Intercept	-	-1.55	-	-5.61
	-	(3.01)[a]	-	(2.47)[a]
Linear (x)	-	.18***	-	3.93**
	-	(.048)[a]	-	(.65)[a]
Quadratic (x^2)	-	-.0004**	-	-.128**
	-	(0.0002)[a]	-	(0.04)[a]
R-Squared (adj)	-	.038	-	.73
No. Observations	-	64		44

* p < 0.1%, ** p < 0.05, *** p < 0.01,

a = (Standard Error)

Michigan				
	Pruning severity (# Fruit/Tree)		Crop Load (# fruits/cm2 TCSA)	
Coefficient	**Gala**	**Honey Crisp**	**Gala**	**Honey Crisp**
Intercept	-3.22	1.49	-5.61**	-.75
	(2.68)[a]	(2.61)[a]	(2.47)[a]	(3.14)[a]
Linear (x)	.178***	.19	3.93	7.82***
	(.03)[a]	(.060)[a]	(.65)[a]	(1.08)[a]
Quadratic (x^2)	-.0002***	-.0008**	-0.13***	-0.23***
	(.0001)[a]	(.0003)[a]	(.039)[a]	(.081)[a]
R-Squared (adj)	.68	.3142	.73	.87
No. Observations	64	40	56	60

* p < 0.1%, ** p < 0.05, *** p < 0.01,

a = (Standard Error)