# EFFECT OF CROP CHARACTERISTICS AND MACHINE PARAMETERS ON BERRY LOSSES DURING WILD BLUEBERRY HARVESTING

by

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## LIST OF ABBREVIATIONS USED

AD – Anderson Darling

ANCOVA – Analysis of Covariance

ANN – Artificial Neural Network

BL – Blower Loss

BP – Back Propagated

CE – Coefficient of Efficiency

cm – Centimeter

CV – Coefficient of Variance

DAP – Diammonium Phosphate

DBE – Doug Bragg Enterprises

F – Function layer

FD – Fruit Diameter

FY – Fruit Yield

FZ – Fruit Zone

GL – Ground Loss

GLM – General Linear Model

h – Hour

ha – Hectare

I – Inputs

K – Potassium

kg – Kilogram

km – Kilometer

LS – Least squares

MAP – Monoammonium Phosphate

$Min_i$ – Minimum value of input.

$Max_i$ – Maximum value of input.

MMC – Multiple Means Comparison

MR – Multiple Regression

MSE – Mean Square Error

n – Number of Inputs

N – Nitrogen

P – Phosphorus

PD – Plant Density

PH – Plant Height

r – Coefficient of Correlation

$R^2$ – Coefficient of Determination

$R_i$ – Actual value of input

RMSE – Root Mean Square Error

RPM – Revolution Per Minute

RTK-GPS – Real Time Kinematics Global Positioning system

SAS – Statistical Analysis System

SD – Standard Deviation

SL – Shoot Loss

ST – Stem Thickness

TFY – Total Fruit Yield

TBL – Total Berry Losses

TL – Total Loss

USDA – United States Department of Agriculture

$u_i$ – Normalized value of input

VR – Variable Rate

VRG – Variable Rate Granular

W – Weight layer

$W_f$ – Weight function

Y – Output

YC – Yield Collected

## ABSTRACT

Wild blueberry crop characteristics have been changed in last two decades due to improved management practices. Currently, growers are facing increased harvesting losses (15-25%) with existing harvester due to change in crop conditions. Eight wild blueberry fields were selected to find an optimum combination of crop characteristics and machine parameters during harvesting. The harvester was operated at selected levels of ground speed and header revolutions per minute (RPM) in different categories of plant and fruit characteristics. Results indicated the optimum combination of machine and crop parameters was ground speed 1.2 km $h^{-1}$, header RPM 26, plant height 24 cm, fruit yield 4300 kg $ha^{-1}$ and plant density 570 plants/$m^2$ to reduce the berry losses during mechanical harvesting. Based on the results, it can be concluded that the suggested harvester settings in conjunction with optimum crop characteristics could reduce berry losses in order to increase farm profitability.

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# CHAPTER 1: INTRODUCTION

The wild blueberry (*Vaccinium angustifolium* Ait.) is a unique crop native to Eastern Canada and Maine, USA with over 93,000 hectares under production (Yarborough, 2013). Northeastern North America produces 148 million kg of berries annually (USDA National Agricultural Statistics Service, 2015; Yarborough, 2015). The Wild blueberry fields have typically originated from native blueberry stands found on deforested farmland by removing competing vegetation (Eaton, 1988). This crop propagates in well-drained and acidic soils (pH 3.9-5.5) having low mineral nutrients (Trevett, 1962). Newly developed wild blueberry fields normally have significant proportion of bare spots and weed patches, with gentle to severe topography (Zaman et al., 2008 and 2010). These fields are predominately managed on two-year production cycle with the perennial shoots pruned in alternative years to maximize floral bud initiation, fruit set, yield, and ease of mechanical harvesting (Eaton, 1988). The wild blueberries are not harvested until more than 90% of berries turn into blue (Kinsman, 1993).

In last three decades, improved management practices using selective herbicides, fungicides, pollination and fertilizers have resulted in taller plants, higher plant densities, and significant increases in fruit yield (Yarborough and Ismail, 1985; Litten et al., 1997; Esau et al., 2014). Farooque et al. (2014) reported that the plant height varied from 15 to 39 cm, and fruit zone ranged from 7 to 31 cm within selected wild blueberry fields. Eaton (1994) reported the range of plant density from 200 to 250 plants per square meter in Nova Scotia fields. Recently, visual observation revealed that the plant density has increased up to 400 plants per square meter. Fruit size of the wild blueberry plants normally ranges from 0.3 cm to 1.4 cm (Soule, 1969; Farooque et al., 2014). Metzger and Ismail (1976) reported that the average fruit yield was 960 kg ha$^{-1}$ during 1969 to 1974. This average increased to 1580 kg ha$^{-1}$ during 1985 to 1989 for selected wild blueberry fields (DeGomez and Smagula, 1990). The wild blueberry yield has increased by an average of 2.3 million kg each year over a 20 year (Yarborough, 2004). Since 1980s, fruit yield has increased by approximately 37 million kg in the State of Maine and 55 million kg in Atlantic Canada and Quebec (Yarborough, 2013). This increase in fruit yield demanded for mechanized harvesting of wild blueberries.

Over the past 100 years, wild blueberry fields have been harvested with hand rakes (Yarborough, 1992). The picking efficiency of the manual raking was reported to be 80% as it required skilled labor (Kinsman, 1993). Significant increase in fruit yield, high labor costs, shortage in labor quality, shorter harvesting season, uneven field topography, and variability in plant and fruit characteristics were the basis for the development of a mechanical blueberry harvester (Yarborough, 2002). Gray (1969) developed a hollow reel raking mechanism machine, which has served as the basis for today's harvester. Sibley (1992) indicated that picking efficiency of Gray's hollow reel raking machine was 80 to 85% during lab experiments, but it could pick only 30 to 35% in fields due to variability in crop characteristics and rough terrain. Hall et al. (1983) evaluated the picking efficiency of the blueberry harvester, which revealed 68% berry recovery in weedy fields and 75% in well managed fields. Rabcewicz and Danek (2010) evaluated the picking performance of a raspberry harvester and observed approximately 20% fruit loss during mechanical harvesting of raspberries. Maurin (2009) reported that higher ground speed of the harvester can cause more losses during mechanical harvesting of soybean. Farooque et al. (2014) evaluated the performance efficiency of a commercial wild blueberry harvester at different ground speeds and head revolutions. They reported that the fruit losses during mechanical harvesting ranged from 8 to 18% within selected wild blueberry fields. They also indicated an optimum combination of ground speed and header revolution can minimize berry losses during mechanical harvesting.

Currently, more than 80% of wild blueberry fields in Canada are mechanically harvested with the remaining 20% still being hand raked due to limitations in field terrain (PMRA, 2005). The wild blueberry industry is facing 15 to 25% berry losses during harvesting with the existing commercial blueberry harvester. These berry losses are partially caused by the changes in crop conditions (plant and fruit characteristics) and rough terrain. Weber and Fehr (1966) tested the soybean combined harvester at different cut of plant heights from the ground surface. They suggested that a height of cut higher than 15 cm from the ground resulted in an increased harvesting losses. Several researchers have evaluated the berry picking performance of the mechanical harvester during variable time span at different harvester settings (Soule, 1969; Hall et al., 1983; Farooque et al., 2014). To our knowledge no research has been published to report an optimum combination of machine parameters and wild blueberry crop characteristics to increase harvestable berry yield. Therefore, there is need to investigate the effect of crop characteristics on berry picking efficiency of the harvester.

There are a variety of factors are involved to contribute in fruit losses during harvesting. These include crop and machine parameters, operator skills, weather fluctuations, disease and insect damage, weed coverage, time of harvesting, lodging of crop, maintenance of the harvester and many uncontrollable factors (Salter et al., 1980; Farooque et al., 2013; Farooque, 2015). The relationships among these factors are usually non-linear, demanding for a robust technique to analyze these relationships. Harvesting process which governs the picking performance of a mechanical harvester are considered as complicated and non- linear for various cropping systems (Chen et al., 2001). Proper understanding of these relationships can suggest ideal operational settings to improve berry picking efficiency of the harvester. A predictive approach is considered to be more appropriate in cases where inputs (machine parameters and crop characteristics) and output (berry losses) are intrinsically variable. Modeling of such non-linear relationships using mathematical algorithms can provide valuable information to improve picking performance of the mechanical harvester. Modeling will also account for the variations in plant and fruit characteristics to suggest optimal machine operating parameters for effective berry recovery. The data driven model will certainly become more reliable through time and will be able to adapt to unforeseen changes in the data (Huang and Foo, 2002). Understanding and predicting the relationships between the machine operating parameters and crop characteristics can be helpful for efficient berry recovery. There is a need to investigate the interactions between crop and machine parameters that may help to suggest optimal scenarios to reduce harvesting losses during mechanical harvesting. Therefore, this research was initiated to determine the optimum combination of machine parameters and crop characteristics to reduce berry losses during harvesting. Increased harvesting efficiency will generate more revenue for the farmer's community to justify the ever increasing cost of wild blueberry production.

**1.1 Objectives**

The objectives of this study are to:

1. Determine the effect of plant characteristics on the picking efficiency of the wild blueberry harvester;
2. Identify the impact of the fruit characteristics on berry losses during harvesting; and,
3. Determine the optimum combination of crop characteristics and machine parameters for effective berry recovery during mechanical harvesting using artificial neural network.

# CHAPTER 2: LITERATURE REVIEW

## 2.1 Wild Blueberry Cropping System

Canada produced record berries 100.6 million kg in 2014, which is more than 1.5 times of 2013 crop (Yarborough, 2015). USDA National Agricultural Statistics Service (2015) reported that the wild blueberry crop for Maine was totaled 47.4 million kg in 2014; it was the second largest crop since 2000. Wild blueberries are not planted like other crops but it develops by removing forests and rocks from areas that have already sufficient coverage of blueberries (Trevett, 1962). Newly developed wild blueberry fields may have 30% to 50% area of bare spots and weed patches (Zaman et al., 2010). These fields develop in well-drained, infertile and acidic (pH. 4.5 to 5.5) soil (Trevett, 1959). Wild blueberry is naturally a perennial crop but to enhance the floral bud initiation, fruit production and ease of mechanical harvesting, it is forced into biennial production system by pruning in alternating years (Hall et al., 1979).

Wild blueberry fields are managed on a two year production cycle (Eaton, 1988), pruning is the first management practice which forces the wild blueberry crop from its natural perennial production system into a biennial production system which improves plant growth and fruit yield (Hall et al., 1979). Pruning also tries to control the germination of weeds and grasses to remain plants dominant in the field (Trevett, 1962). Plants grow vegetatively in the middle of May after pruning in the sprout year, and initiate flower buds formation for the crop year from August to October (Hall et al., 1979). The crop is covered with snow during the winter dormancy period and the blueberry flower buds develop in the following spring (Eaton and Nams, 2006), and flowering occurs in May and June in the second year. The flowers are pollinated for fruit production by insects or bee hives and berries develop quickly after fertilization of ovules (Bell, 1950). The wild blueberry fruit remains quiescent during June and July, and then they further increase in size and mature until harvest. Usually wild blueberry harvesting is carried out by hand rakes or mechanical harvester in August to early September, when almost 90% berries are fully ripe (Kinsman, 1993). Wild blueberry has been harvested by metal hand rakes for many decades (Dale et al., 1994), but now more than 80% fields are harvest mechanically (Yarborough, 1992). Mechanical harvesting is more efficient when compared to hand raking as a mechanical harvester can harvest over 1 hectare per day (Kinsman, 1993).

In the Atlantic Provinces of Canada wild blueberry production has significantly increased over the past 20 years (Yarborough, 2004). Berry yield has increased due to a range of improved management practices which include; weed control, insect and disease control, fertilizer applications, pruning and pollination (Yarborough, 2007). These management practices also changed the crop characteristics, which increase in plant growth and fruit yield (Yarborough and Ismail, 1985; Eaton, 1994; Litten et al., 1997). Fruit yield has been increased two to three fold in last two decades (Yarborough, 2004) and plant height increased more than 30 cm by continuous application of fertilizer in wild blueberry fields (Percival and Prive, 2002). Visual observation reveals that management practices also enhanced the larger fruit zone, fruit size, plant density and stem thickness.

A workable wild blueberry harvester was developed in 1980s to improve harvesting efficiency (Dale et al., 1994), but significant increase in fruit yield and change in crop characteristics increased the harvesting losses in last two decades (Yarborough, 2004). Wild blueberry growers traditionally use 1.6 km $h^{-1}$ ground speed and 28 header RPM of the mechanical harvester (Sibley, 1994). By these settings wild blueberry industry is facing 15 to 25% berry losses during mechanical harvesting (PMRA, 2005). Therefore, this present study emphasizes the need to find a better settings of a harvester in conjunction with crop characteristics to reduce the harvesting losses and improve berry picking efficiency of the wild blueberry harvester.

### 2.2 Effect of Improved Management Practices on Plant Growth and Fruit Yield

More than 67% of the wild blueberry crop is grown in Quebec and Atlantic Canada, with the remaining 33% being grown in Maine, USA (Yarborough, 2013). The wild blueberry crop in Quebec in 2014 was 35 million kg, which is considerably higher than previous 5 year average of 23 million kg. In Nova Scotia, growers have improved management practices and increased number of honeybees in their fields which increased the wild blueberry crop over 28 million kg in 2014 (Janet, 2015). New Brunswick produced a record crop in 2014 that was more than 27 million kg by contribution of good pollination in wild blueberry plants (Melanson, 2015). Prince Edward Island (PEI) also had a bumper crop at 10 million kg due to increase in growing number of acres coming into production and is expected to improve berry production in future (Yarborough, 2015). However, most of the gains in yield are due to better management practices in wild blueberry fields. The improved management practices using selective herbicides, fungicides, fertilizers, pruning method and pollination have resulted in healthy and tall plants, higher plant density, and significant increases in fruit yield within wild blueberry fields (Eaton, 1994; Litten et al., 1997; Yarbrough, 2004). Over the past 20 years, all of these management practices have been combined to improve wild blueberry fruit yield by an average of 2.3 million kilogram each year (Yarborough, 2004). Growers also changed the harvesting operation from hand rakes to mechanical harvester due to significant increase of the efficiency of berry production (Dale et al., 1994).

#### 2.2.1 Land Improvement

The wild blueberry covers more than 93,000 ha under management in North Eastern North America (Yarborough, 2013). Wild blueberry fields have increased with over 12,700 ha of new fields added in past 20 years (Yarborough, 2009). Yarborough (2013) reported that the wild blueberry production area in Atlantic Canada and Main have increased and revealed that Quebec has 32,184 ha area under management. New Brunswick and Nova Scotia have wild blueberry cropping area above 13,400 ha and 16,187 ha, respectively (WBANA, 2013; Yarborough, 2013) and in PEI there is approximately 4,450 ha in production (Chris, 2008). Newfoundland and Labrador has more than 1,000 ha wild blueberry fields to produce berry fruit (Yarborough, 2013). Half of wild blueberry fields are harvested annually because of the two-year production cycle (Hepler and Yarborough, 1991). Production of wild blueberry has increased on the average by 2 to 3 fold by increase in number of hectares over the past 20 years (Yarborough, 2004). Besides the fruit production, crop characteristics have been also changed due to improvements in management practices within wild blueberry fields (Eaton, 1994; Yarborough, 2004).

### 2.2.2 Pruning

Naturally grown wild blueberry is forced perennial production system to biennial production by regular pruning for better plant growth and berry yield (Hall et al., 1979). It also helps the blueberry plants to remain dominant by controlling weeds within the fields (Trevett, 1959). Most of the fields are pruned in late fall or early spring (Warman, 1987), with no differences detected between spring versus fall pruning (Ismail and Yarborough, 1979). Pruning can be done either by burning or by flail mowing (Trevett, 1959). Ismail et al. (1981) reported that pruning was done by burning straw or a tractor-drawn oil burner in wild blueberry fields. Burning of fields has the advantage of controlling disease, insect and weeds within the fields (Warman, 1987). However, continuous burning can deplete the organic matter of the surface layer more with an oil burner than with straw burns (Smith and Hilton, 1971), since wild blueberry rhizomes usually grow 2 to 10 cm from the soil surface (Eaton and Jensen, 1997). In 1974, after the increase in oil prices, flail mowing technique was widely adopted in all wild blueberry fields and substantially reduced the production cost as compared to burning (Yarborough et al., 1986; Yarborough and Drummond, 2001).

Several studies were conducted and reported on the effect of pruning methods on plant growth and berry yield (Trevett and Durgin, 1972; Ismail and Yarborough, 1979; Ismail et al., 1981). Warman (1987) and Ismail et al. (1981) found almost double berry yield in burned plots as compared to mowed plots. Penney et al. (2008) also reported that higher mean berry yield in burned plots than in unburned plots in wild blueberry fields. Contrary to these results, mowing within 1 cm would produce equivalent berry yield to burning (Smith and Hilton, 1971; Ismail and Yarborough, 1979; Smagula and Dunham, 1995). Moreover, Ismail et al. (1981) reported that mowing produced more branched stems and a higher plant density than oil burning and also increase in total stem length (20.4 cm) as compared with burning (14.0 cm). Eaton et al. (2004) concluded that mowing at different height of cut did not affect the plant height, floral buds and fruit yield. Although mowing produced lower yields than burning; the flower buds did not differ between the two pruning techniques (Ismail and Hanson, 1982).

### 2.2.3 Weed Management

Weed species in wild blueberry fields typically grow above the blueberry canopy and absorb most of the sunlight (Chandler and Mason, 1946); thus the floral bud numbers do not generate efficiently due to inadequate sunlight received by blueberry plants (Smagula and Ismail, 1981). Weed competition in blueberry fields can negatively affect floral bud development, hinder harvest operations, and decrease berry yield quality (Penney and McRae, 2000; Kennedy et al., 2010). More than 100 weed species, ranging from annual herbs, grasses, perennial shrubs, and woody perennials are common in all wild blueberry fields (McCully et al., 1991). Eaton (1994) found significant differences in plant height, plant density and fruit yield in weedy plots with weed free plots due to the application of fertilizers with herbicides. Yarborough and Marra (1997) observed 1000 kg ha$^{-1}$ reduction in berry yield due to presence of weeds in wild blueberry field. Patten and Wang (1994) indicated that linear reduction in cranberry yield with weed populations.

Application of herbicides can increase blueberry yield and plant growth effectively (Yarborough and Bhowmik, 1988; Penney and McRae, 2000). Prior to 1980s, growers controlled weeds by cutting, burning and directed spot application of non-selective herbicides (Jensen and Specht, 2002). However, dramatic increase in berry yield was observed with selective herbicides for wild blueberry production after 1980s (Jensen, 1985; Jensen and Kimball, 1985). According to Yarborough et al. (1986) and Eaton (1994), herbicide applications have resulted in significant decrease of weed pressure and appear to reflect greater plant stands as well as increased berry production. Traditionally, herbicides and fungicide are applied to control competing weeds and disease both in prune and production years, which encourage healthier plant and higher fruit production (Yarborough, 2004). Wild blueberry yield may increase 50 to 100% by controlling weeds within wild blueberry fields (Yarborough and Bhowmik, 1988; Percival and Dawson, 2009).

### 2.2.4 Fertilization

Wild blueberry farmers apply fertilizers after pruning in vegetative year to improve plant growth and berry yields (Percival and Sanderson, 2004). Although fertilizers have significantly affected the growth of blueberry plants, it also encourage the spread and growth of weeds within the fields (Penney and McRae, 2000). Fertilizer uptake by grasses and other weeds normally restrict the growth of blueberry plants (Yarborough and Ismail, 1985). Researchers suggested that the fertilizers and herbicides can be effectively used to improved wild blueberry growth without stimulating weeds (Hepler and Ismail, 1985; Yarborough et al., 1986; Eaton, 1994). Input of fertilizer may increase the number of floral buds as they are related to fruit development and berry yield (Jeliazkova and Percival, 2003). Sanderson and Eaton (2004) reported that the use of fertilizer resulted in significant increase of plant height, floral buds and fruit yield. Townsend and Hall (1970) examined the leaf nutrient concentrations in wild blueberry plants. They showed that nutrient concentration in the leaf increased in early fall during sprout year and decreased in same period of crop year. Nitrogen (N) plays a vital role in improving plant growth by increasing plant height and number of branches per plant (Bourguignon et al., 2006).

Generally, wild blueberry growers used nitrogen, phosphorus (P) and potassium (K) fertilizers, which have N, P and K formulation ratio such as 13-26-5, 14-18-10, or 18-46-0 (Eaton et al., 1997). N and P nutrient deficiency levels in wild blueberry plants are determined by foliar analysis (Yarborough and Smagula, 1993). Diammonium phosphate (DAP) fertilizer or monoammonium phosphate (MAP) fertilizer is normally used by growers to manage their field's fertility levels (Smagula and Yarborough, 1999). Eaton (1994) checked the long term effect of herbicides and fertilizers on blueberry growth and production from 1979 to 1991. He also measured the stem height (11 to 22 cm), plant density (200 to 250 stems per $m^2$), fruit buds (3 to 7 fruit buds per stem) and average yield (2000 to 4000 kg $ha^{-1}$). Litten et al. (1997) used DAP fertilizer in phosphorus limited soils and found an increase in the number of flower buds and yield from 4,900 to 6,235 kg $ha^{-1}$. Fruit yield increased two to three fold by continuous application of fertilizer, herbicides and pruning methods in wild blueberry fields (Eaton, 1994; Yarborough, 2004). Saleem (2012) applied fertilizer on a site-specific basis with a variable rate granular (VRG) fertilizer spreader using prescription maps based on variation in slope within wild blueberry fields. He demonstrated that variable rate (VR) fertilization in wild blueberry fields improved fruit yield.

### 2.2.5 Pollination

Wild blueberry flowers are more than 85% dependent on insect pollination for fruit set and yield (Bigras-Huot et al., 1972; Savoie et al., 1993; Morse and Calderone, 2000). Growers usually pollinates their fields in July of crop year in order to improve the berry production (Campbell, 2008). Numerous species of insect search in nectar and pollen from flowers and in return, the insects unintentionally pollinate the flowers (Yarborough, 2002). An appropriate pollination requires viable seeds for well-developed blueberry fruits (Perron, 1985). Wood (1961) showed that a better fruit set could be obtained in wild blueberries by using honeybees. Karmo (1974) encouraged the use of honeybees in Nova Scotia's and Maine's wild blueberries fields, to improve pollination and better fruit development. Four to eight hives are appropriate to pollinate the area of 1 ha (Ismail, 1987). Yarborough (2004) indicated that blueberry yield increased by 785 kg $ha^{-1}$ in Maine's fields with the use of honeybee hives. Moreover, in Nova Scotia yield increased by 192 kg $ha^{-1}$ with each honeybee colony, the growers increased number of hives by four colonies in one hectare (Eaton and Nams, 2012). Over the last 20 years, use of honeybee pollination has substantially increased in all growing wild blueberry fields (Drummond, 2012). Although some growers are using alternate pollinators (e.g bumble bees and alfa-alfa bees) to diversify, honeybees still remain the dominant pollinator because of price and availability (Stubbs and Drummond, 2001).

## 2.3 Wild Blueberry Harvesting

### 2.3.1 Harvesting by Hand Raking

The wild blueberry fruits stay on the plant fully ripe until the maturity of greener berries (Dale, 1999), which is usually not harvested until almost 90% berries change their color into blue (Kinsman, 1993). Generally, harvesting occurs in early or mid-August and completed within three to four weeks (Trevett, 1959; Yarborough, 1997). Wild blueberries must be harvested prior to the first frost (Kinsman, 1993). Wild blueberry crop is harvested either by hand raking or mechanically. For several decades, this unique crop was harvested using metal hand rakes. In last two decades, wild blueberry acreages and crop characteristics have changed by involvement of improved management practices within fields, which shifted the harvesting operation from hand rakes to mechanical harvester (Yarborough, 2004). Kinsman (1993) indicated that the blueberry rakers also faced a major problem by the presence of weed species within the field, which reduced raking speed and/or picking efficiency. To overcome these unresolved issues, research on the development of the mechanical harvester started in late 1940s (Rhodes, 1961).

### 2.3.2 Mechanical Harvesting of Wild Blueberries

Harvesting of the wild blueberry represents the major expense in the blueberry production system (Yarborough, 1992). A significant increase in berry yield as well as change in harvesting scenarios, encouraged the development of a viable mechanical harvester (Holbein, 1991; Dale et al., 1994). The fundamental factors for the development of a mechanical harvester were: issues surrounding hand raking, uneven field topography, plant stature, and issues surrounding weeds. Many researchers attempted to develop a mechanical harvester prior to the 1980s for wild blueberry crop (Rhodes, 1961; Soule, 1969; Grant and Lamson, 1972; Richard, 1982). Hall et al. (1983) determined that a workable machine could not be adopted because of difficulties surrounding both the harvester itself as well as site-specific field conditions.

In 1947, research on the development of mechanical harvester was started at Agricultural Engineering Department, University of Maine, USA (Kinsman, 1993). A stationary comb concept was developed in 1957 to pick blueberries and an external vacuum collector was attached for the berry collection (McKiel, 1958). Hayden Separator Company (Massachusetts, USA) designed a harvester that was similar to cranberry picker machine (Dale et al., 1994), consisting of a series of six raking combs which raked the berries in the opposite direction of the machine movement (Rhodes, 1961). This machine revealed poor picking performance and also ploughed the soil during harvesting operation (Rhodes, 1961). Hollow reel raking mechanism was developed by Gray (1969), which also served as the basis for today's harvesters (Dale et al., 1994). Soule (1969) indicated that Gray's harvester was able to pick 80 to 85% in the lab experiment, however harvesting efficiency dropped to 30 to 35% in the field. MacAulay (1975), after a few modifications was able to increase the picking performance of Gray harvester. In mid 1970s, a modified cranberry harvester showed 56% harvesting efficiency, similar to hand raking, but 3.8 times faster than hand harvest (Yarborough, 1992). In 1979, a successful harvester was developed by the Bragg Lumber Company in Collingwood, NS. This harvester increased the picking head width and hydraulic control systems for head height, head rotational speed, speed control for conveyors, and belts (Yarborough, 1992; Dale et al., 1994). There was an ongoing effort to develop a smaller, more efficient harvester that produces better fruit quality equivalent to hand-raking (Yarborough, 2002).

Recently, it has been demonstrated that mechanical harvesting operation has been done more than 80% in wild blueberry fields and rest of fields are still being used hand rakes due to severe slopes or rough terrain (PMRA, 2005). In Atlantic region of Canada, there are more than 2,000 wild blueberry harvesters are in operation, with single, double or triple picking heads. Since 1960, several studies have been performed for the testing evaluation of wild blueberry harvester (Rhodes, 1961; Abdalla, 1963; Soule, 1969; Hall et al., 1983; Sibley, 1994; Farooque et al., 2014). Limited research has been conducted to improve picking efficiency of the wild blueberry harvester in relation with crop characteristics and machine operating parameters.

### 2.4 Effect of Plant and Fruit Parameters on Harvesting Losses

The wild blueberry harvesting losses has been increased with existing harvesters due to changes in crop characteristics (plant height, plant density, stem thickness, fruit yield, fruit zone and fruit size). These losses are function of machine operating and plant growth prospects of wild blueberry crop (Farooque et al., 2014; Farooque, 2015). Soule and Gray (1972) indicated that the picking performance of a wild blueberry harvester was better in weed-free fields as compared to weedy and rough fields. Hall et al. (1983) showed that the DBE blueberry harvester picking efficiency was 68% in weedy fields but 76% in smooth weed free fields. Sibley (1994), through engineering modifications, improved the efficiency of DBE blueberry harvester for better fruit recovery. Farooque et al. (2013) mounted multiple ground-based sensors onto a commercial wild blueberry harvester to sense the plant height, fruit yield, and topographic features in real-time. The information obtained from this system could help to estimate fruit loss during mechanical harvesting. Farooque et al. (2014) reported that the berry losses during mechanical harvesting were linear function of fruit yield indicating an increase in berry losses with the increase in berry yield. They suggested that an optimum ground speed and header revolution in accordance with the crop parameters can significantly enhance the picking performance of a blueberry harvester.

Many researchers have evaluated the performance of different mechanical harvesters for effective crop recovery. Chen et al. (2012) found better fruit removal and less fruit damage with vibratory shaker for sweet cherry, which reduced 5 to 10% fruit losses than mechanical harvester. Philbrook et al. (1991) observed 37% grain losses of soybean in the areas with more dense and lodged plants. Rabcewicz and Danek (2010) obtained 1 to 5% raspberries fruit losses on the ground due to shattering of raspberry plants during mechanical harvesting. Weber and Fehr (1966) observed 5 to 12% yield losses at different cuts of plant heights from the ground surface with the soybean combined harvester. Maurin (2009) suggested that the higher ground speed of the harvester with an inadequate cutting height of the soybean can cause more losses during mechanical harvesting. In soybean harvesting, the picker bars should make contact with the top one-third of the plant to achieve a better yield (Huitink, 2013). Lodging can result in declination of picking efficiency and increase in harvest losses (Woods and Searingin, 1977). Holshouser (2011) reported that the harvest losses can vary from 3 to 10% due to lodging in soybean fields. In highbush blueberry losses often reached 20 to 30% due to over ripe berries missed or spill away on the upright bush with commercial mechanical harvesters (Mainland, 1993; Takeda et al., 2008). In wild blueberries, limited research has been reported in order to improve harvesting efficiency.

Therefore, this study is emphasizing the need to study the harvesting dynamics in spatially variable crop characteristics of wild blueberry. That would be able to identify an optimum operating condition in accordance to field variability, which could be possible to increase the harvestable yield and farm profitability.

**2.5 Modelling Approach**

There are many factors that affect the harvest losses during picking operations. These include machine settings, crop characteristics, field conditions, climatic conditions, and operator skills (Salter et al., 1980). Operator has to adjust the harvester's settings during harvesting according to crop conditions in the field (Hiregoudar et al., 2011). Harvesting losses reveal complex interactions and non-linear behavior between crop and machine dynamics during machine operation (Adams et al., 1998; Bryant et al., 2000). Therefore, an appropriate model or a mathematical approach is always useful for better understanding of these complicated systems, which act as tool for evaluating agricultural and environmental problems to improve crop productivity (Minasny and McBratney, 2002). Solomatine and Ostfeld (2008) indicated that a data-driven modelling technique is used to find relationships between the system state variables without considering physical behavior of the system. Data driven modelling approach enhances the efficiency of machine by computational methods and algorithms, which replace much time consuming human activity with automatic techniques and increase the level of automation (Simon and Langley, 1995). Artificial Neural Network (ANN) one of the example of data driven modelling approach, which has been recognized as a powerful tool capable of performing better than conventional statistical models, particularly in those case where functional relationships are multiple and non-linear (Chen et al., 2001). These distinguish characteristics have led to ANN model being extensively used in several engineering research (Sablani et al., 1995; Chen et al., 1998).

ANN modelling technique was used in the field experiments in 1980s, but research has been increasing significantly in last decade (Pahlavan et al., 2012). The main interest in ANN models is due to its generic nature, flexibility and best approximation capabilities (Cybenko, 1989; Hornik et al., 1989). ANN models are developed for data classification, optimization, prediction, and other purposes of the complex systems (Maier and Danday, 2000). This technique was developed on basis of natural neurons in living organisms to solve complex computational problems (Bishop, 1994). The ANN modelling approach is an interconnected nodes network. Furthermore, its artificial neurons/nodes are connect or transmit the information from input layer to output layer, where the model altering it according to the data used to calibrate the nodes by weights manipulation and adjustment (Maier and Danday, 2000). Final output is achieved through processing of information; each node has direct communication link with correspondence nodes with an associated weight function. Simply these nodes are connected to each other in such way: observations (input layer), intermediate nodes (hidden layers or black-box) and final output (output layer) (Setiono et al., 2000). Hornik et al. (1989) explained the hidden layer "black-box" singularity, it typically receive adjusted weight inputs from the input or previous hidden layer, do transformations on receiving inputs, and pass to the next adjacent layer, which can be final output or another hidden layer. The purpose of weights adjustment is reduce the discrepancy between predicted and actual values (Wilby et al., 2003). Bishop (1994) indicated that gradient descent method based on the delta rule is used to compensate the errors and weight adjustment during training the model. The minimum value of mean square error (MSE) or root mean square error (RMSE) indicates a well-trained ANN model (Anyaeche and Ighravwe, 2013). McCulloch and Pitts (1943) determined the transfer function and learning algorithms those are associated with data between the layers. Kaul et al. (2005) indicated that linear function is an appropriate to transfer data from the input layer to the hidden layer, whereas sigmoid functions used to transfer data between the hidden layers to output layer. Several procedures (an appropriate network selection, training algorithm, suitable network structure, epoch size, analyzing trained model, post-processing and validation of model) are involve to develop a best trained model for any application of ANN (Bishop, 1995; Haykin, 1999). Over-training of model can be reduce the efficiency of model (Qin, 1999). Bishop (1995) suggested that over-training of network can be avoided by including regularization theory, which tries to smooth network predictions and cross validation via an independent dataset (Braddock et al., 1998). Improving network generalization by using the adequate-size network can avoid the over-fitting or under-fitting network problems (Huang and Foo, 2002).

ANN modelling has been used in several applications such as, various managerial problems (Hakimpoor et al., 2011), yield predictions (Alvarez, 2009), disease estimation (Batchelor et al., 1997), forecasting growth stages (Clapham and Fedders, 2004), agrochemicals assessment (Yang et al., 1997), flood forecasting (Wright and Dastorani, 2001), rainfall-runoff predictions (Sobri et al., 2012), stream flow estimations (Wright et al., 2002), and water level prediction (Patrick et al., 2002; Huang et al., 2003). Shahin et al. (2001) concluded that ANN has the better performing potential as compared to other traditional predictive methods in geotechnical engineering. In decision making cancer studies, ANN model revealed a better quality result over other non-linear forecasting models (Paulo et al., 2006). Moreover, the ANN has wide application in industrial area. For example, Saanzogni and Kerr (2001) applied feed-forward ANN in evaluating milk production, Fast and Palme (2010) investigated the use of the ANN in condition and diagnosis of a combined heat and power plant. Braga (2000) accurately predicted spatial patterns of corn yield in relation to agronomic variables, topographic features and seasonal variability using a BP-ANN model. Farooque (2015) used artificial neural network (ANN) and multiple regression (MR) techniques to identify the factors responsible for fruit losses in wild blueberry fields. Results of his study indicated that the ANN model was able to predict fruit losses accurately and reliably as functions of several input variables. Literature search shows limited work regarding the application of the ANN for berry losses in wild blueberry cropping system. This situation emphasizes the need to develop a predictive model by employing the ANN modelling for quantification of fruit losses as a function of machine parameters, plant and fruit characteristics. This practice will enable us to predict optimal harvesting scenarios to enhance berry picking efficiency.

# CHAPTER 3: MATERIALS AND METHODS

## 3.1 Site Selection

To achieve the objectives of this study, four wild blueberry fields were selected in central Nova Scotia and New Brunswick to examine the effect of plant characteristics on picking efficiency of the wild blueberry harvester. These fields were in the Earltown (Field A) (45.60°N, 63.09°W; 1.9 ha), Tracadie (Field B) (47.28°N, 65.14°W; 1.6 ha), Debert-I (Field C) (45.45°N, 63.45°W; 1.01 ha) and East Mine (Field D) (45.43°N, 63.48°W; 3.88 ha) in 2011, 2012, 2013 and 2014, respectively (Fig. 3-1).

Four separate wild blueberry fields were selected in central Nova Scotia to examine the effect of fruit characteristics on berry losses during harvesting. These four fields were in the Londonderry (Field E) (45.48°N, 63.57°W; 3.20 ha), Highland Village (Field F) (45.24°N, 63.40°W; 2.57 ha), Hardwood Hill (Field G) (45.42°N, 63.52°W; 2.05 ha,) and Debert-II (Field H) (45.44°N, 63.45°W; 1.01) in 2011, 2012, 2013 and 2014, respectively (Fig. 3-2). Over the past decade, these fields had been under commercial management and received biennial pruning by mowing along with weed, and disease management practices.

## 3.2 Experimental Design

### 3.2.1 Effect of Plant Characteristics

Three levels of ground speed (1.2, 1.6 and 2.0 km $h^{-1}$) and header rotational speed (RPM) (26, 28 and 30 RPM) of the harvester were selected for this study. Plant height (PH) was classified into two different classes, *i.e.*, tall plants > 25 cm and short plants ≤ 25 cm. Similarly, blueberry plant density (PD) was also categorized as, low PD (PD ≤ 530 plants/$m^2$) and high PD (PD > 530 plants/$m^2$). Four different combinations of PH and PD were established in each field during harvesting. These combinations were tall plant - low plant density, tall plant - high plant density, short plant - low plant density and short plant - high plant density.

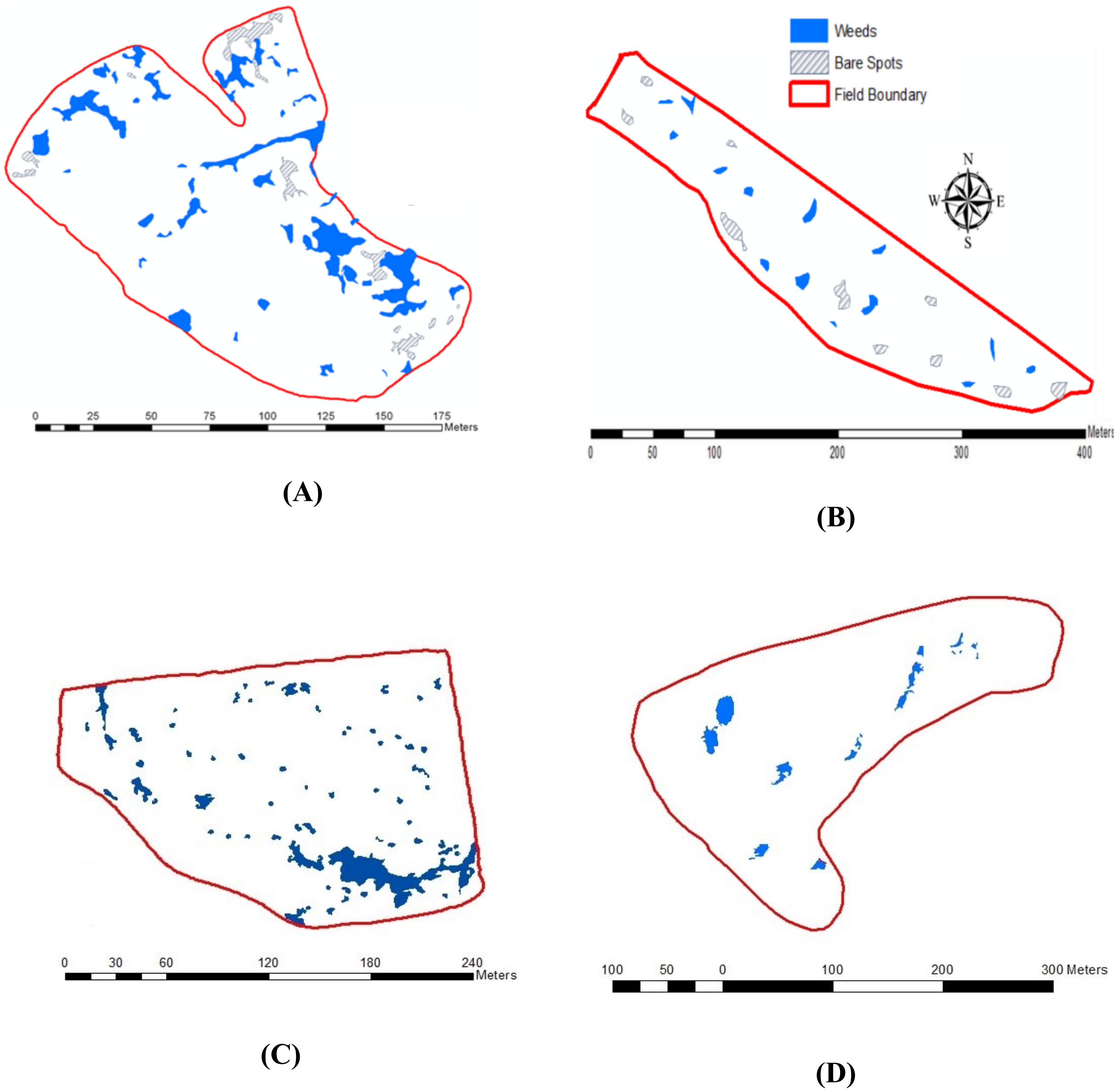



**Figure 3-1:** Layouts of selected wild blueberry fields, (A) Earltown, (B) Tracadie, (C) Debert-I, and (D) East Mine.

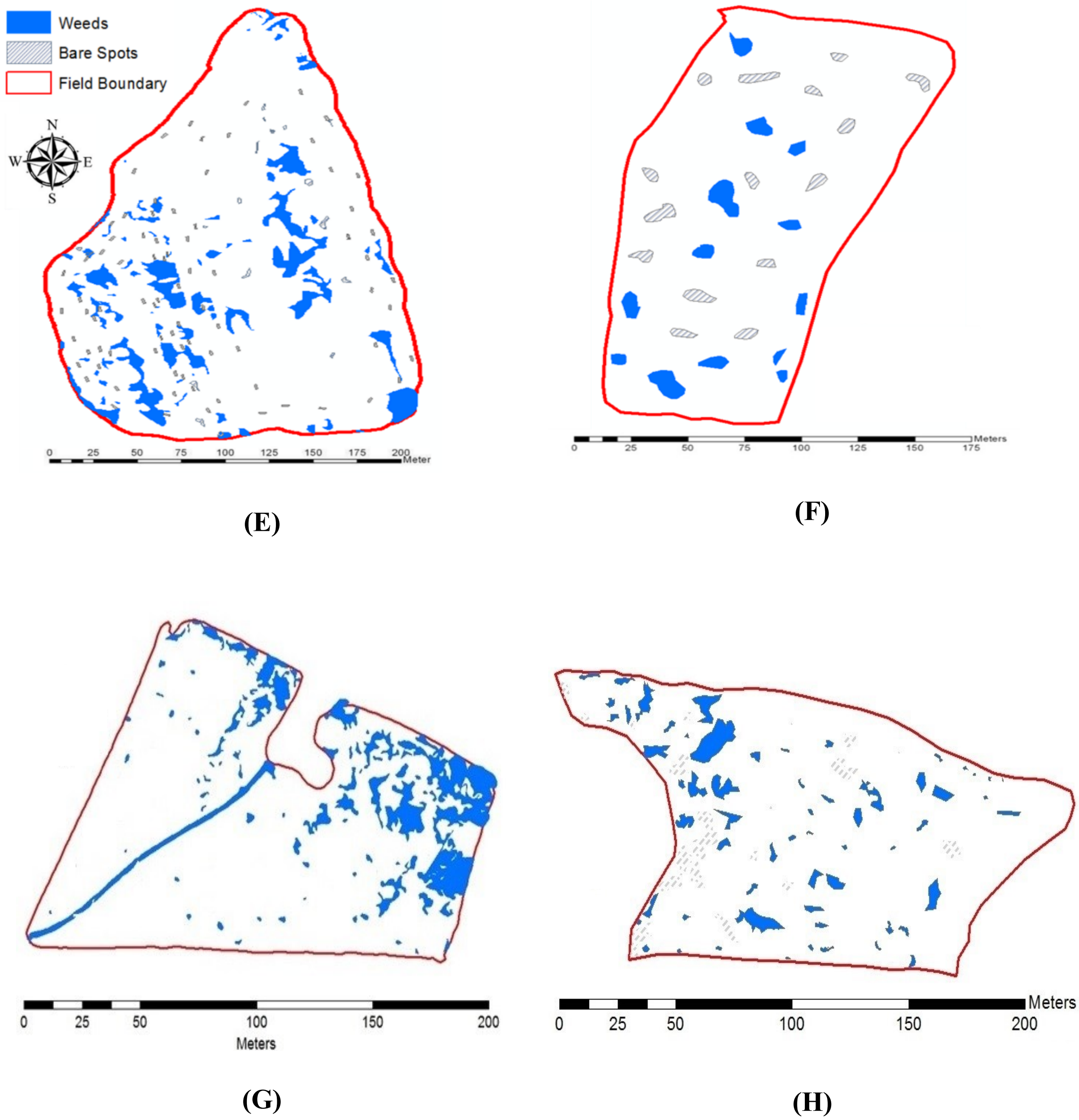



**Figure 3-2:** Layouts of selected wild blueberry fields, (E) Londonderry, (F) Highland Village, (G) Hardwood Hill and (H) Debert-II.

A 3 × 3 factorial design was used to examine the effect of harvester's ground speed and header RPM on berry losses for each combination of plant characteristics. Stem thickness (ST) was also measured for each combination of PH and PD, and used as a covariate for data analysis. The data were collected in four consecutive years from selected fields. The year of data collection was treated as a block or replicate in data analysis. Thirty six plots were constructed randomly in each field. The wild blueberry harvester was operated at nine treatment combinations of ground speed and header RPM for each combination of PH and PD.

### 3.2.2 Effect of Fruit Characteristics

The experimental design used to determine the effect of fruit characteristics was similar to that used for plant characteristics. For this experiment, fruit zone (FZ) and fruit yield (FY) were categorized into different classes, which were low FZ (FZ $\leq$ 17 cm), high FZ (FZ > 17 cm), and low FY (FY $\leq$ 3000 kg ha$^{-1}$), high FY (FZ > 3000 kg ha$^{-1}$), respectively. Thirty six plots were selected randomly in each field to accommodate nine treatment combinations of ground speed and header RPM for each of four combinations (low fruit yield - low fruit zone, low fruit yield - high fruit zone, high fruit yield - low fruit zone, and high fruit yield - high fruit zone) of fruit characteristics. Fruit diameter (FD) was used as a covariate for each combination of fruit characteristics. The picking performance of the blueberry harvester was examined in relation to four different combinations of fruit characteristics and machine operating parameters.

## 3.3 Harvesting Operation

A Commercially available single head wild blueberry harvester designed by the DBE, Ltd. mounted on a 62.5 kW John Deere tractor was used in all selected fields during harvesting (Fig. 3-3). Farooque et al. (2014) outlined the operating mechanism of wild blueberry harvester. A Hydraulic control system is mounted inside the tractor cabin to control the rotating head speed and direction of head rotation, head height, cleaning brush and conveyors. The harvester head contains sixteen teeth bars with equally spaced sixty seven bowed teeth on each bar mounted to the edge of the head. All teeth bars are fixed with cam followers and rotate by the shape of cam. The picker bars pick the berries during harvesting with different tip velocities at selected levels of ground speed and header RPM. Operator can change or adjust the rotational speed (RPM) of the head and its movement through the plants by hydraulic control system.

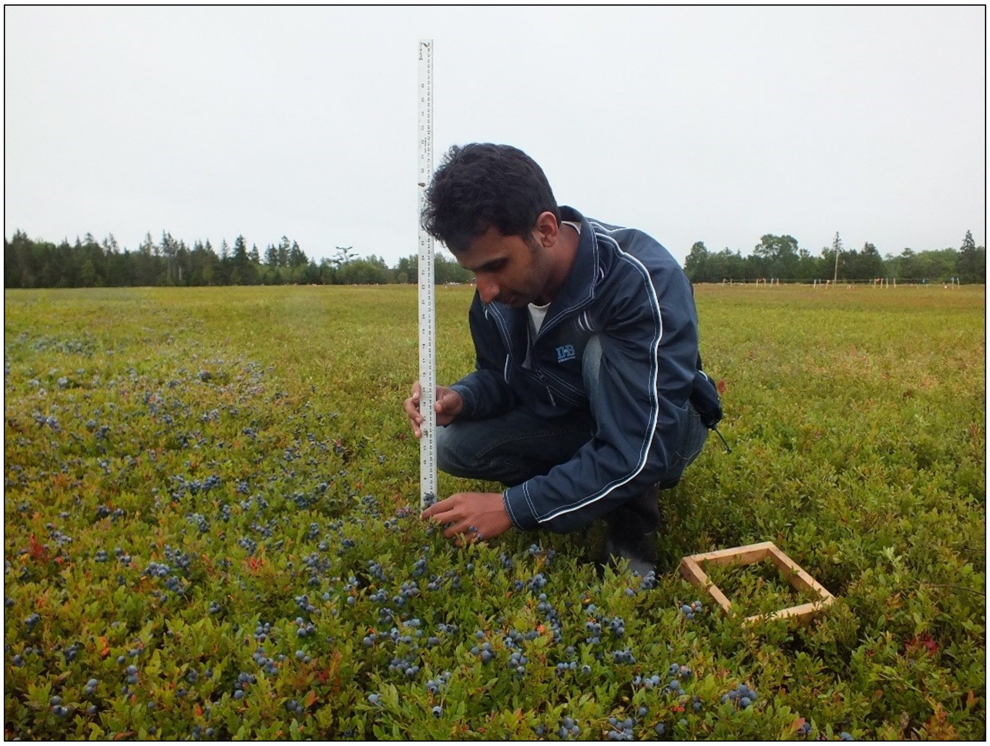
**Figure 3-3:** Single head wild blueberry harvester.

The proper harvesting operation can be achieved by altering the header RPM, which could provide moderate lift for effective berry recovery while reducing berry losses. The picking performance of the harvester head is increased by a cleaning brush rotating at the top of the picking head which removes debris and any other foreign material stuck between the teeth bars. The picker bars throw down the picked berries onto the inside conveyer and side conveyor transport harvested berries to the storage bin behind the harvester. The blower fan installed at the end of side conveyer is used to blow off leaves and any debris from the berries prior to drop in storage bin. The harvester head height from the ground is maintained by a guide wheel in the front of the harvester head. Based on the PH and FZ of the wild blueberry crop, the operator is able to change the height of the harvester's head manually in order to increase the efficiency berry picking.

### 3.4 Data Collection

Wild blueberry fields have substantial variability in fruit yields and other crop characteristics within and between fields. Newly developed wild blueberry fields may have significant proportion of bare spots and weed patches distributed throughout the fields (Zaman et al., 2010). Real Time Kinematic Global Positioning System (RTK-GPS) was used to mark selected yield plots. Field boundaries, bare spots and weed patches were also mapped using RTK-GPS. Yield plots (0.91 m x 3.0 m; same as the width of harvester head) were randomly constructed for each combination of plant and fruit characteristics (Fig 3-4). Five readings of PH and FZ were taken manually with simple ruler from each plot within selected fields as shown in Figure 3-5 (a and b). Similarly, ST and FD was recorded from each plot using Vernier caliper (Fig. 3-6, a and b). A 15 cm × 15 cm (0.025 $m^2$) wooden quadrat was used to estimate PD from each selected plot (Fig. 3-7).

**Figure 3-4:** Setting up yield plots in wild blueberry fields.



**(a)**

**(b)**

**Figure 3-5:** Manual measurement of (a) plant height and (b) fruit zone within selected plots.


**(a)**


**(b)**

**Figure 3-6:** Manual recording of (a) stem thickness and (b) fruit diameter within selected plots.

**Figure 3-7:** Calculation of plant density prior to harvest the plot.

## 3.5 Quantification of Harvesting Losses

### 3.5.1 Pre-harvest Berry Losses

A wooden quadrat having dimensions same as the yield plot (0.91 m × 3.0 m) was placed on all selected plots to collect pre-harvest berry losses in each field. Pre-harvest berry losses were collected manually prior to harvest the selected plots within selected fields. The purpose of estimating pre-harvest loss was to determine the losses actually caused by mechanical harvester during harvesting of selected plots.

### 3.5.2 Yield Collection and Fruit Losses during Harvesting

The harvester was operated at all nine selected treatment combinations of ground speed and header RPM to collect fruit yield quantity and berry losses from each plot within selected fields. The picker bars were cleaned from any foreign debris prior to harvesting the plot and also, previously harvested berries were transported to the storage bin. Just before harvesting the selected plots, the harvester head was raised up and moved back (approximately, 5 m) to achieve the selected treatment combination of ground speed and header RPM of the wild blueberry harvester. The harvester head was dropped down at the beginning of each plot to harvest the berry yield and raised up again after harvesting the plot. Fruit yield was collected by attaching a bucket to the harvester's conveyer belt at storage bin during harvesting (Fig. 3-8a). The post-harvest berry losses (i.e., ground loss (GL), shoot loss (SL), and blower loss (BL)) were collected after harvesting the selected plots. Berries knocked onto the ground (GL) due to the impact of the harvester head were collected manually from each plot using a wooden quadrat (Fig. 3-8b). The unharvest berries left on the plants (SL) after harvesting were also collected and weighed. Berry losses through the blower fan was collected by attaching a bucket under the blower fan during harvesting of each plot. Collected berries from each plot were cleaned from leaves and debris.


**(a)**


**Figure 3-8:** (a) Collection of fruit yield by attaching a bucket with conveyor during harvesting; (b) After harvest losses collection within selected plots.

The cleaned berries were placed in labeled Ziploc bags and weighed using a balance (Denver Instruments Inc., NY, USA) to quantify the amount of berry losses and fruit yield. The collected data of fruit yield and berry losses was recorded in kilograms (kg) and reported as (kg $ha^{-1}$). Total loss (TL) for each plot was estimated by adding up the GL, SL and BL. The percentage of losses was calculated using the following equations.

$$\text{Shoot losses (\%)} = \frac{\text{SL}}{\text{TFY}} \text{ X } 100 \quad --------- (1)$$

$$\text{Ground losses (\%)} = \frac{GL}{\text{TFY}} \text{ X } 100 \quad ---------- (2)$$

$$\text{Blower losses (\%)} = \frac{\text{BL}}{\text{TFY}} \text{ X } 100 \quad ---------- (3)$$

$$\text{Total losses (\%)} = \frac{\text{TBL}}{\text{TFY}} \text{ X } 100 \quad ----------- (4)$$

$$\text{TFY} = \text{YC} + \text{SL} + \text{GL} + \text{BL} \quad ------------- (5)$$

$$\text{TBL} = \text{SL} + \text{GL} + \text{BL} \quad --------------- (6)$$

Where,

TFY = Total fruit yield collected from the harvested plot;

YC = Yield collected by the harvester from the harvested plot;

SL = Shoot losses due to berries left on the plants after harvesting;

GL = Ground losses after harvesting;

BL = Blower losses.

TBL = Total berry losses.

### 3.6 Statistical Analysis

Minitab 17 (Minitab Inc. NY, USA) and SAS 9.3 (SAS Institute Inc., NC, USA) statistical software were used to perform the statistical analysis. Minimum, maximum, mean, standard deviation, coefficient of variation and skewness of the collected data were determined using descriptive statistics. Normality of the collected data was checked at the 5% level of significance using the Anderson-Darling (AD) test. Residual versus fitted plots were developed to verify the constant variance of the error terms. The violation of model assumptions led to suitable transformation of original data to induce normality and constant variance of the error terms. Independence of the error terms was achieved through randomization of treatments within selected field. Factorial analysis of covariance (ANCOVA) using general linear model (GLM) procedure was performed to study the joint effect of crop characteristics and machines operating parameters on berry losses during mechanical harvesting of the wild blueberry. Least square (LS) means was used as the method to perform multiple means comparison (MMC) of significant different treatments.

### 3.7 Artificial Neural Network Modeling

The purpose of collecting data of crop characteristic, machine parameters, and berry losses was to develop a mathematical model that could be able to find an optimum combination of crop characteristics and machine parameters during harvesting. The modeling approach in this study utilized the Artificial Neural Network (ANN) concept, which has non-linear and multiple processing capabilities, and also known as a powerful tool capable of performing better than conventional statistical models (Farooque, 2015). In order to understand the complex interactions among the crop characteristics and machine operating parameters, the ANN model was developed to predict berry losses as function of several variables collected in wild blueberry fields. The idea behind this modelling technique was to consider only part of data which is on the 'boundaries' of the domain where data are given to make a relationship(s) between the datasets. These relations lead to find the best connects between the specific datasets. This mathematical approach requires minimum two datasets (Anyaeche and Ighravwe, 2013); first one for development (training and internal validation) and the latter for external validation. Therefore, collected data were combined and utilized as 70% for training and 30% for validation during experimentation. Points, which were outside of the range of input variables were removed (or avoid the extrapolation error) from validation data. However, the validation data covered all variability in collected crop characteristics data.

#### 3.7.1 Input and Output Variables

For the development of the ANN model, crop characteristics including plant height, plant density, stem diameter, fruit yield, fruit zone, fruit diameter and machine operating parameters were chosen as input variables. Berry losses was selected as output variable. Inputs and output data were normalized to improve the performance of ANN model. The following equation was used for the normalization of the data and the values ranging from 0 to 1 (Farooque, 2015).

$$u_i = \frac{(R_i - Min_i)}{(Max_i - Min_i)} \qquad ----------- (7)$$

Where

$u_i$ = Normalized value of input; $R_i$ = Actual value of input; $Min_i$ = Minimum value of input. $Max_i$ = Maximum value of input.

### 3.7.2 Development of ANN Model

Peltarion Synapse (Peltarion Systems®, Netherlands), a commercially available software, was used to predict an optimum combination between crop characteristics and machine operating parameters of wild blueberry harvester for minimum berry losses. It is a user friendly software and consists of different architectures of the network, variety of training algorithms, transfer functions, and the ability to articulate the critical network parameters such as, learning rate, momentum rule and epoch size. Using the capabilities of the software, all the data were mixed after normalization by mixture tool of the software. The 70% (n = 468) of the normalized data were utilized for training, a small portion of the training data (~15%; n = 72) was reserved for verification or internal validation and 30% (n = 198) for external validation during the model development. A back-propagated artificial neural network (BP-ANN) was used to improve the model adequacy by adjusted weights. The ANN model converts the input nodes into final output (H) by weight transfer function. The process repeats until all the given inputs nodes resulted into the final layer of output. The network first predicts a target value by the estimation of output value from the inputs, and then adjusts the weights in order to reduce the errors between the network output and the target values. Minimum error corresponds to well-trained model. The model also uses 'gradient descent method' (Bishop, 1994; Hornik et al., 1989) for error minimization process in networking. In this neuron based structure, every input parameter is connected to the one hidden layer which is considered enough to model majority of continuous non-linear function (Fig. 3-9). According to

Torrecilla et al. (2004), more hidden layers in architecture may cause over-fitting or under-fitting of the model.

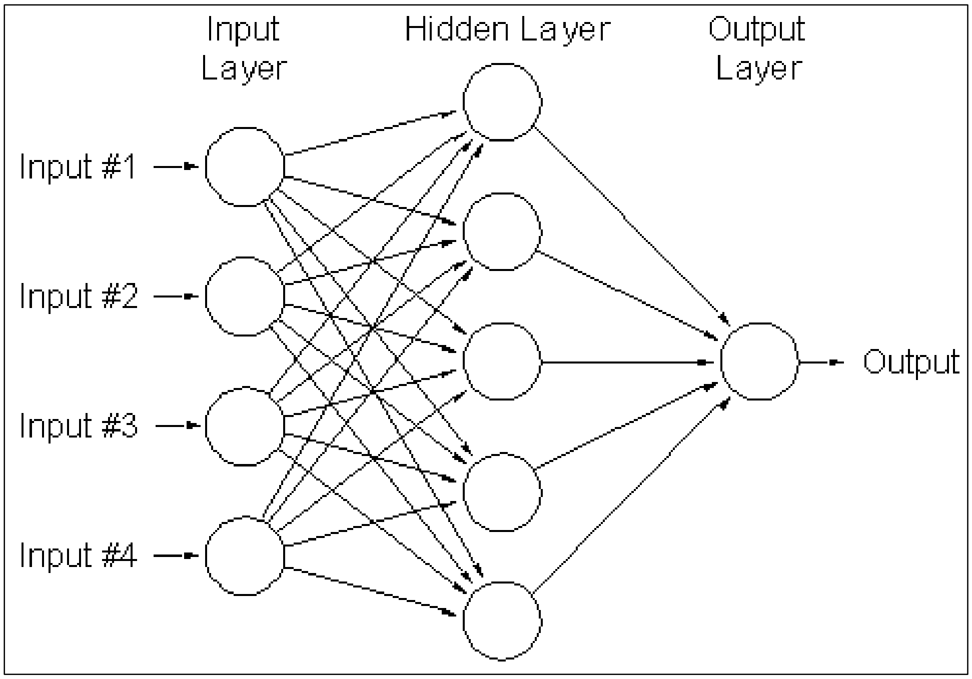



**Figure 3-9:** Structure of ANN model

For the prediction of berry losses during wild blueberry harvesting, six different architectures were developed and tested to find a suitable mathematical function to process the data. Five mathematical functions were tested including tanh sigmoid, sine, exponential, morlet and logistic sigmoid function. Peltarion Synapse is multi-function software and allowed one to use desired mathematical functions, learning rate and momentum rule. This attribute of the software enhances the performance of the developed networks in terms of the mean square error (MSE), root mean square error (RMSE) and coefficient of efficiency (CE). All networks were run at an epoch size of 1000 with the learning rate of 0.1 and momentum rule of 0.7 for each selected mathematical functions during model development. The best mathematical function was considered for selected parameters on berry losses in order to have minimum MSE and RMSE. Once completing these steps, model was configured at the optimum settings of the network (weight layers, function layers, nodes per hidden layer, epoch etc.) for prediction of berry losses during harvesting. Optimal configuration of the ANN architecture was achieved by best values of $R^2$, MSE, RMSE and CE. The best selected ANN model was operated at different epoch values at an interval of 1000 in order to determine the optimal epoch size. Majority of errors were influenced by epoch size while structuring the network of ANN model (Madadlou et al., 2009). The performance of the developed ANN model was assessed for internal and external validations when the network has been structured and trained. A trained architecture was extracted using the post-processor techniques of the software to estimate the berry losses during harvesting. After development and prediction of ANN model for berry losses, the processed data were categorized into four different classes of berry losses (< 10%, 10-15%, 15-20% and > 20%), to determine the optimum combination of crop characteristics and machine parameters during mechanical harvesting. Furthermore, the extracted file could be used for automate the wild blueberry harvester to improve the berry picking efficiency.

# CHAPTER 4: EFFECT OF PLANT CHARACTERISTICS ON PICKING EFFICIENCY OF THE WILD BLUEBERRY HARVESTER

## 4.1 Introduction

The wild blueberry is a fruit commodity native to northeastern North America. The wild blueberry fields have been developed after eradication of competing vegetation, removal of trees, stumps and rocks (Eaton, 1988). Unlike other fruit crops, wild blueberry plants emerge naturally from native stands on deforested agricultural land (Hall et al., 1979). Wild blueberries are not planted on large scale, but spread via underground rhizomes (Eaton, 1950). This crop is managed on two-year production cycle, one being a sprout year and the other a crop year. Plants are pruned after harvesting during the crop year either by burning or mowing (Yarborough, 2004). Pruning of this crop, in alternate years, encourages plant growth and vigor, increases flower buds and enhances fruit yield (Eaton, 1950). Fruit development occurs in the crop year of the biennial production cycle, which is stimulated by pollination. The wild blueberries are typically harvested manually or mechanically during August of the crop year (Hall et al., 1979).

For several decades, the wild blueberries was harvested by traditional hand rakes (Yarborough, 1992). Hand rakers experienced increased harvesting losses due to significant increase in fruit production with improved management practices (Dale et al., 1994). The other factors contributing towards increased hand raking losses were availability of quality labor at reasonable price, harvesting expenses and short harvesting season. This dilemma of manual harvesting spurred the demand for a reliable mechanical harvester (Kinsman, 1993). Many mechanical harvesting systems were developed during 1950's to 1980's to reduce the reliance on the manual harvesting (Rhodes, 1961; Richard, 1982). However, a viable commercial machine was not available to the wild blueberry industry due to many unsolved technical difficulties such as rough terrain, inability to achieve acceptable harvesting efficiencies and mechanical damage to the fruit (Soule, 1969; Hall et al., 1983). Gray (1969) used the concept of rotating picking head and developed a hollow reel raking mechanism for mechanical harvesting of wild blueberry crop. Sibley (1992) narrated that picking efficiency of this machine was 80 to 85%. Due to the limitations in field terrain, this harvester could only harvest 30 to 35% berries during harvesting. Yarborough (1992) reported that the Darlington cranberry harvester modified for wild blueberry crop, which showed 56% picking performance as compare to Gray's harvester. Dale et al. (1994) indicated that Doug Bragg Enterprises (DBE) Limited improved the design of a wild blueberry harvester by increasing the width of picking head. DBE further improved the picking head by adding hydraulic control systems for head height adjustment and head rotational speed, and also incorporated a speed control system for conveyors and belts for effective transportation of the harvested crop in the storage bin. Hall et al. (1983) evaluated the DBE blueberry harvester, reporting that the picking performance of this machine was 68% in weedy fields and 76% in weed free managed fields. Sibley (1992) evaluated the wild blueberry harvester in relation to different ground speeds and head revolutions, to examine the impact of harvester operating parameters on picking efficiency. Many researchers have evaluated the performance of several mechanical harvesters for fruit picking efficiency (Hall et al., 1983). However, limited research has been conducted to include the plant characteristics impact on harvesting the wild blueberry. Ampatzidis et al. (2012) compared the picking efficiency of a mechanical harvester with manual harvesting of sweet cherries. Results of their study revealed that the mean picking efficiency of the mechanical harvester was 40 to 50% greater than the hand harvesting of cherries. Philbrook et al. (1991) observed field losses in soybean in the southeastern USA. They found 37% soybean losses in more dense and lodged plants. Weber and Fehr (1966) reported 5 to 12% yield losses with the soybean combined harvester at different cut of plant heights from the ground surface. They also suggested that a height of cut greater than 15 cm from the ground resulted in an increased harvesting losses.

Maurin (2009) showed that the inadequate cutting height of the soybean harvester resulted in more losses during mechanical harvesting. The author also reported that higher ground speed of the harvester can cause more losses during mechanical harvesting of soybean. Farooque et al. (2014) evaluated the performance efficiency of a commercial wild blueberry harvester for berry losses during harvesting. Results of their study indicated that there is an optimum combination of ground speed and header revolutions which can minimize berry losses during mechanical harvesting.

Over the past 20 years, land management, pruning, pollination, and extensive use of agrochemicals and fertilizers have resulted in healthy plants, higher plant density and significant increase in fruit yield (Yarborough and Ismail, 1985; Litten et al., 1997). However the importance of plant characteristics on the picking efficiency of wild blueberry has not been investigated. There is a need to conduct research on quantifying the berry losses as a function of crop and machine parameters, which emphasize the need to study the harvesting dynamics in spatially variable crop characteristics. Therefore, the objective of this study was to determine the effect of plant characteristics on picking efficiency of a commercial wild blueberry harvester.

### 4.2 Materials and Methods

To achieve the objective of this study, four wild blueberry fields were selected to examine the effect of plant characteristics on picking efficiency of a commercial wild blueberry harvester. The selected fields were in the Earltown (Field A) (45.60°N, 63.09°W; 1.9 ha), Tracadie (Field B) (47.28°N, 65.14°W; 1.6 ha), Debert-I (Field C) (45.45°N, 63.45°W; 1.01 ha) and East Mine (Field D) (45.43°N, 63.48°W; 3.88 ha). The fields A, B, C and D were selected in 2011, 2012, 2013 and 2014, respectively. The selected fields had been under commercial management by mowing for the past several years along with the conventional weed, disease and nutrient management. Yield plots (0.91 m × 3.0 m; same as the width of harvester) were randomly constructed at each site.

Field boundaries, bare spots/weed patches and yield plots were mapped with a real-time kinematics global positioning system (RTK-GPS).

The experimental design used for this study was a 3 × 3 factorial design with three levels of harvester's ground speed (1.2, 1.6 and 2.0 km $h^{-1}$) and header revolutions per minute (26, 28 and 30 RPM). Two classes of plant height (tall plants > 25 cm and short plants ≤ 25 cm) and plant density (low plant density ≤ 530 plants/$m^2$ and high plant density > 530 plants/$m^2$) were used for experimental design. The randomly selected plots were constructed at each site in a way to establish four categories of the plant characteristics, *i.e.,* tall plant - low plant density, tall plant - high plant density, short plant - low plant density, and short plant - high plant density. All nine treatment combinations of ground speed and header RPM were allocated to each category of the plant characteristics. The joint effect of plant characteristics and machine operating parameters on harvesting losses was examined by harvesting selected plots mechanically. Stem thickness was used as a covariate for data analysis in each category of plant characteristics. The year of data collection was treated as a block in data analysis.

The randomly selected plots in each field were harvested using a commercially available single head wild blueberry harvester. The harvester was operated at selected levels of ground speed and header RPM within each plot to collect fruit yield (FY) and berry losses. Pre-harvest losses were collected and recorded to distinguish any loss other than the combination of machine and plant characteristics. Just before harvesting the selected plots, the picker bars were cleaned of any foreign debris and previously harvested fruit was transported to the storage bin. The post-harvest berry losses, *i.e.,* ground loss (GL), shoot loss (SL) and blower loss (BL) were collected after harvesting the selected plots. Total loss (TL) was obtained by adding the GL, SL and BL for each plot within selected fields. Detailed procedure about the collection of berry losses can be seen in

Chapter 3. Five readings of plant height (PH), plant density (PD) and stem thickness (ST) were recorded manually for each plot within selected fields. The picking performance of the blueberry harvested was tested and evaluated in relation to different categories of plant characteristics and machine operating parameters.

### 4.3 Statistical Analysis

Minitab 17 (Minitab Inc. NY, USA) and SAS 9.3 (SAS Institute Inc., NC, USA) statistical software were used to perform the statistical analysis. Minimum, maximum, mean, standard deviation, coefficient of variation and skewness of the collected data were determined using descriptive statistics. Normality of the collected data was checked at the 5% level of significance using Anderson-Darling (AD) test. Residual versus fitted plots were developed to verify the constant variance of the error terms. The violation of model assumptions led to suitable transformation of original data to induce normality and constant variance of the error terms. Independence of the error terms was achieved through randomization of treatments within each selected field. Factorial analysis of covariance (ANCOVA) using general linear model (GLM) procedure was performed to study the joint effect of plant characteristics and machines operating parameters on berry losses during mechanical harvesting of the wild blueberries. Least square (LS) method was applied to perform the multiple means comparison (MMC) of significantly different treatments.

### 4.4 Results and Discussion

#### 4.4.1 Summary Statistics

Summary statistics of FY, SL, GL, BL, TL, PH, ST and PD for selected fields is presented in Table 4-1. The coefficient of variation (CV) is a first approximation of the field heterogeneity and according to Wilding (1985), the selected parameters are least variable if the CV < 15%, moderate with CV ranging from 15 to 35% and most with CV > 35%. In field "A" FY, SL, GL, BL and TL were highly variable with the CV > 35%, while PH, ST and PD were moderately variable (Table 4-1). Results of field “B” revealed that the SL and GL were highly variable with the CV > 35%, and rest of the parameters were least to moderately variable (Table 4-1). Summary statistics of field “C” indicated that the higher variability in SL, GL, BL and TL as compare to FY, PH, PD and ST. The SL was found to be highly variable for field D. All other parameters were observed to be least to moderately variable within field D (Table 4-1).The variability in berry losses could be due to the intrinsic or/and extrinsic sources. Intrinsic sources may include natural soil variations and yielding nature of different clones within selected fields, whereas, extrinsic sources include harvester operation, operator skills, field topography and crop management practices (Hepler and Yarborough, 1991).

The SL was found to be significantly higher (242.40 kg $ha^{-1}$) for field D when compared with other fields (< 100 kg $ha^{-1}$), indicating the inadequate performance of the harvester in berry picking for this field (Table 4-1). This might be due to exceptionally higher yield at this field. The SL were 1.52%, 1.66%, 1.36% and 3.06% in fields A, B, C and D, respectively. The GL were observed to be higher for fields B, C and D as compare to filed A. The possible reason for the higher ground losses could be the improper relative motion of the machine operating parameters. The inadequate ground speed and head revolutions of the harvester can induce impact and centrifugal forces, which can enhance the GL due to shattering losses and can lower the berry recovery in the storage bin. The GL were found to be 6.32%, 11.29%, 10.46% and 11.97% for fields A, B, C and D, respectively. Farooque et al. (2014) reported that the picked berries were dropped off over the harvested strip due to the impact force of the harvester head and the centrifugal force developed by the higher level of header RPM, pushing the berries away from center and contributing towards the ground losses.

**Table 4-1:** Summary statistics of fruit yield, berry losses, plant height, stem thickness and plant density for selected wild blueberry fields.

**Field A**

| Parameters | Min | Max | Mean | Mean (%) | SD | CV (%) | Skewness |
|---|---|---|---|---|---|---|---|
| FY (kg $h^{-1}$) | 253 | 7635 | 2618 | - | 1570 | 59.98 | 0.89 |
| SL (kg $h^{-1}$) | 0 | 299.37 | 39.68 | 1.52 | 62.47 | 157.95 | 3.12 |
| GL (kg $h^{-1}$) | 3.38 | 708.4 | 165.4 | 6.32 | 127.3 | 76.99 | 1.44 |
| BL (kg $h^{-1}$) | 0 | 220.23 | 22.16 | 0.80 | 33.01 | 148.94 | 3.50 |
| TL (kg $h^{-1}$) | 5.1 | 833.7 | 227.2 | - | 167.3 | 73.60 | 1.51 |
| TL (%) | 0.99 | 26.85 | 8.68 | 8.68 | 5.07 | 56.02 | 1.45 |
| PH (cm) | 13 | 34 | 22.99 | - | 3.63 | 15.80 | 0.06 |
| ST (cm) | 0.17 | 0.36 | 0.23 | - | 0.04 | 16.97 | 0.85 |
| PD * | 350 | 840 | 590 | - | 127 | 21.61 | 0.10 |

**Field B**

| Parameters | Min | Max | Mean | Mean (%) | SD | CV (%) | Skewness |
|---|---|---|---|---|---|---|---|
| FY (kg $h^{-1}$) | 1690 | 10445 | 5556 | - | 1942 | 34.96 | 0.11 |
| SL (kg $h^{-1}$) | 23.77 | 319.54 | 92.23 | 1.66 | 38.34 | 41.57 | 2.77 |
| GL (kg $h^{-1}$) | 147.9 | 1056.3 | 627.5 | 11.29 | 234.12 | 39.17 | 0.10 |
| BL (kg $h^{-1}$) | 21.13 | 110.92 | 63.67 | 1.14 | 18.62 | 29.25 | 0.22 |
| TL (kg $h^{-1}$) | 192.8 | 1228 | 783.5 | - | 256.7 | 34.07 | -0.01 |
| TL (%) | 7.99 | 22.34 | 14.10 | 14.10 | 3.09 | 22.20 | -0.02 |
| PH (cm) | 19 | 39 | 26.95 | - | 3.96 | 14.70 | 0.44 |
| ST (cm) | 0.22 | 0.39 | 0.31 | - | 0.04 | 12.38 | 0.07 |
| PD * | 290 | 755 | 470 | - | 106.22 | 22.59 | 0.53 |

**Field C**

| Parameters | Min | Max | Mean | Mean (%) | SD | CV (%) | Skewness |
|---|---|---|---|---|---|---|---|
| FY (kg $h^{-1}$) | 1574 | 8419 | 5290 | - | 1372 | 25.94 | -0.02 |
| SL (kg $h^{-1}$) | 10.56 | 302.82 | 72.18 | 1.36 | 42.38 | 58.71 | 2.78 |
| GL (kg $h^{-1}$) | 137.3 | 799.3 | 381.3 | 10.46 | 158.0 | 41.43 | 0.53 |
| BL (kg $h^{-1}$) | 24.65 | 130.28 | 56.73 | 1.07 | 21.50 | 37.89 | 1.10 |
| TL (kg $h^{-1}$) | 302.8 | 1464.8 | 682.4 | - | 251.6 | 36.88 | 0.66 |
| TL (%) | 4.47 | 24.53 | 12.89 | 12.89 | 4.377 | 32.90 | 0.38 |
| PH (cm) | 14.33 | 31.66 | 24.06 | - | 4.02 | 16.71 | -0.31 |
| ST (cm) | 0.14 | 0.28 | 0.21 | - | 0.03 | 15.38 | 0.17 |
| PD * | 245 | 820 | 550 | - | 121.74 | 22.14 | 0.05 |

**Field D**

| Parameters | Min | Max | Mean | Mean (%) | SD | CV (%) | Skewness |
|---|---|---|---|---|---|---|---|
| FY (kg $h^{-1}$) | 4134 | 13884 | 7934 | - | 1978 | 24.93 | 0.70 |
| SL (kg $h^{-1}$) | 56.3 | 507.0 | 242.4 | 3.06 | 102.2 | 42.17 | 0.62 |
| GL (kg $h^{-1}$) | 345.1 | 1200.7 | 772.4 | 11.97 | 218.0 | 28.23 | -0.35 |
| BL (kg $h^{-1}$) | 10.56 | 158.45 | 92.53 | 1.16 | 29.84 | 32.25 | -0.16 |
| TL (kg $h^{-1}$) | 616.2 | 2035.2 | 1342.9 | - | 329.6 | 24.54 | -0.01 |
| TL (%) | 7.86 | 32.45 | 16.93 | 16.93 | 5.548 | 31.32 | 0.65 |
| PH (cm) | 9.80 | 27.00 | 18.19 | - | 3.75 | 20.65 | 0.40 |
| ST (cm) | 0.13 | 0.28 | 0.19 | - | 0.04 | 19.01 | 0.80 |
| PD * | 370 | 930 | 630 | - | 112 | 17.77 | 0.16 |

**Note:** FY (fruit yield), SL (shoot loss), GL (ground loss), BL (blower loss) and TL (total loss) were recorded in kg $ha^{-1}$, PH (plant height) and ST (stem thickness) in cm, and *PD (plant density) was recorded in 530 stems per square meter.

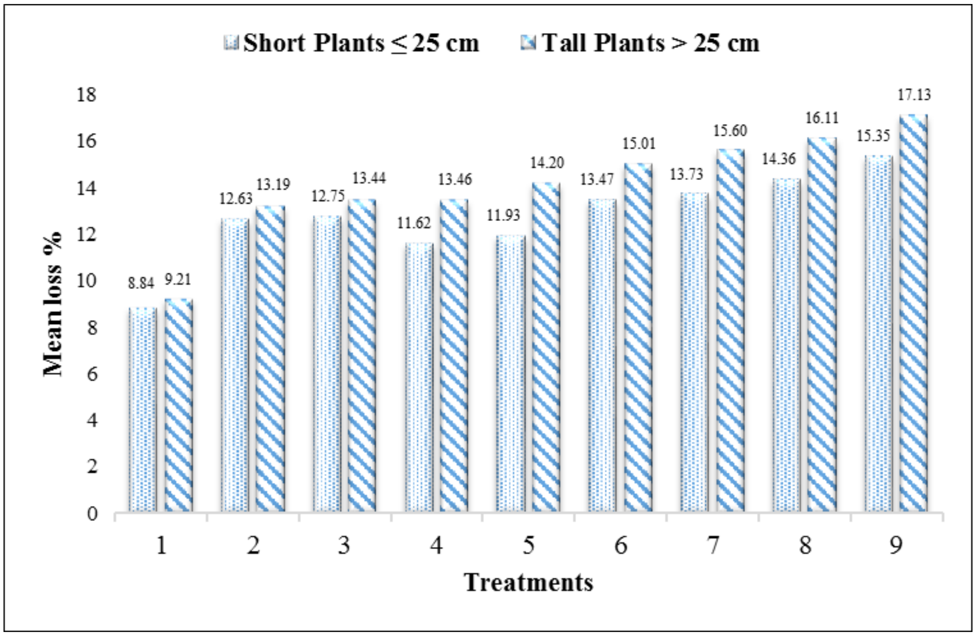
The BL for fields A, B, C and D were observed to be 0.8%, 1.14%, 1.11% and 1.16%, respectively. Results indicated higher total losses in field D (16.93%), when compared with fields A (8.68%), B (14.10%) and C (12.89%). Results of total losses within selected fields suggested that the berry losses during mechanical harvesting were proportional to the fruit yield. These results were in agreement with the finding of Farooque et al. (2014).

The total FY was found to be variable within selected fields (Table 4-1). The total FY was found to be 2618 kg ha$^{-1}$, 5556 kg ha$^{-1}$, 5290 kg ha$^{-1}$ and 7934 kg ha$^{-1}$ for fields A, B, C and D, respectively (Table 4-1). The FY was significantly higher for field D, when compared with other monitoring fields, which might be due to better management practices and more effective pollination at this field. The FY was observed to be lowest at field A, which might be due to high proportion of bare spots and weed patches present in this fields. Fields B and C were produced similar fruit yield that can be seen with their mean values (Table 4-1). Results revealed that the mean ST was similar for selected fields, except field B, where the mean ST was higher (0.31 cm). The possible reason for higher ST at field B might be due to tall plants. The visual inspections also reported that the plants were tall with less number of branches and higher ST for field B. The PH was found to be consistent within selected fields, except for field B, where plants were observed to be taller (Table 4-1). Mean values of the PH were 22.99, 26.95, 24.06 and 18.19 cm for fields A, B, C and D, respectively. The mean PD ranged from 470 to 630 plants/m$^2$ within selected fields (Table 4-1). Field A was found to have the lowest PD, while the PD was the highest for field D (630 plants/m$^2$). Higher PD with more branches at field D might also be contributing to the higher fruit yield at this site (Table 4-1).

### 4.4.2 Effect of Plant Height and Plant Density on Berry Losses

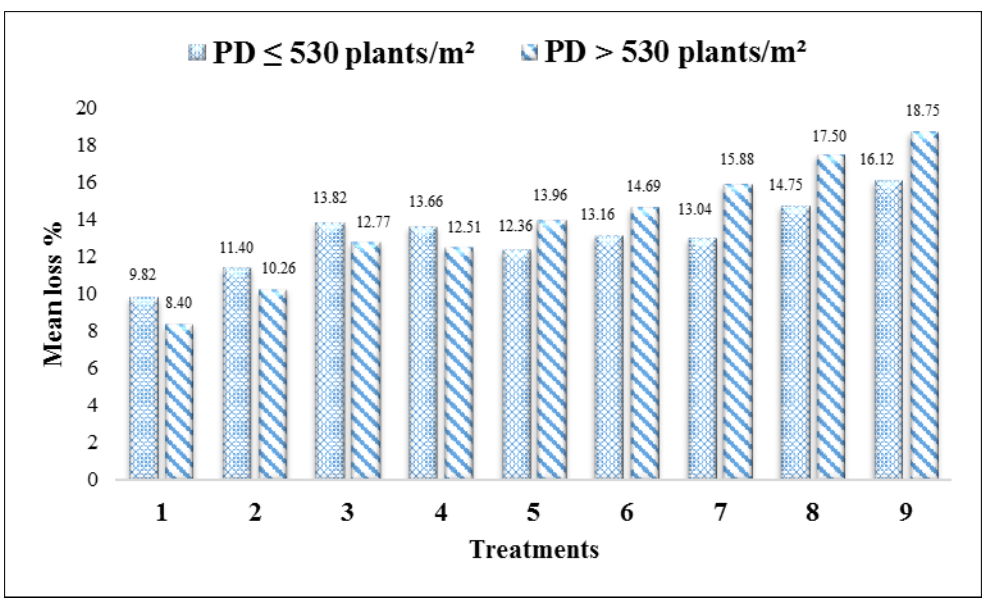
Wild blueberry crop characteristics have changed significantly due to improved management practices over the last two decades. Summary statistics confirmed the existence of moderate to high variability in FY, and plant characteristics (Table 4-1), which can have an impact on berry losses during mechanical harvesting. In order to examine the effect of PH and PD on berry losses, the collected data were divided into two groups, *i.e.,* short and tall plants, and low and high plant density. Mean berry losses were compared for all selected treatment combinations of ground speed and header RPM of the harvester (Figs. 4-1 and 4-2). Results of mean comparison suggested that the berry losses were similar for short (PH ≤ 25 cm) and tall (PH > 25 cm) plants (Fig. 4-1). Treatment 1 (1.2 km $h^{-1}$ and 26 RPM) was found to have minimum berry losses (8.84% and 9.21%) in short and tall plants, respectively (Fig. 4-1). Visual observation revealed that harvester was not easily picked the berries in those areas where the PH was less than 10 cm irrespective of PD and FY. These areas brought up more berry losses and cause of soil digging during harvesting operation. Berry losses in tall plants increased gradually with an increase in ground speed and header RPM. Higher berry losses (> 15%) in the tall plants at higher ground speed (2 km $h^{-1}$) and header RPM might be due to clogging of teeth bars. Results indicated that the operator has to adjust the picking head accordance to PH within the field for effective berry recovery. However, the picking performance of the harvester was better at 1.2 $kmh^{-1}$ ground speed and header 26 RPM. It might have provided a better opportunity for the harvester to pick efficiently in both short and tall plants within selected fields.

The berry losses were found to have ranging from 8.40 to 18.75% in high PD plots (PD > 530 plants/$m^2$) and ranged from 9.82 to 16.12% in low PD plots (PD ≤ 530 plants/$m^2$) within selected fields (Fig. 4-2). Higher PD plots showed the minimum berry losses (8.40%) at 1.2 $kmh^{-1}$ and 26 RPM (Treatment 1) as compared to all other treatment combinations. Higher berry losses in high PD class could be due to more vegetative growth and more berry yield. Moreover, minimum berry losses (9.82%) were obtained in the low PD plots at Treatment 1. Berry losses were also increased gradually in low PD class with increase in ground speed and header RPM (Fig. 4-2). Lower PD can decrease the support required by the plants for effective picking. When harvester moves the low dense plant areas, the plants tend to incline due to impact force of picker bars that may cause of more shattering loss.




**Treatment 1:** 1.2 km h$^{-1}$ and 26 RPM
**Treatment 2:** 1.2 km h$^{-1}$ and 28 RPM
**Treatment 3:** 1.2 km h$^{-1}$ and 30 RPM
**Treatment 4:** 1.6 km h$^{-1}$ and 26 RPM
**Treatment 5:** 1.6 km h$^{-1}$ and 28 RPM
**Treatment 6:** 1.6 km h$^{-1}$ and 30 RPM
**Treatment 7:** 2.0 km h$^{-1}$ and 26 RPM
**Treatment 8:** 2.0 km h$^{-1}$ and 28 RPM
**Treatment 9:** 2.0 km h$^{-1}$ and 30 RPM

**Figure 4-1:** Effect of plant height on berry losses during mechanical harvesting at different combinations of ground speed and header RPM.




**Treatment 1:** 1.2 km h$^{-1}$ and 26 RPM
**Treatment 2:** 1.2 km h$^{-1}$ and 28 RPM
**Treatment 3:** 1.2 km h$^{-1}$ and 30 RPM
**Treatment 4:** 1.6 km h$^{-1}$ and 26 RPM
**Treatment 5:** 1.6 km h$^{-1}$ and 28 RPM
**Treatment 6:** 1.6 km h$^{-1}$ and 30 RPM
**Treatment 7:** 2.0 km h$^{-1}$ and 26 RPM
**Treatment 8:** 2.0 km h$^{-1}$ and 28 RPM
**Treatment 9:** 2.0 km h$^{-1}$ and 30 RPM

**Figure 4-2:** Effect of plant density on berry losses during mechanical harvesting at different combinations of ground speed and header RPM.

Berry losses in both categories of PD suggested that the lower ground speed in conjunction with lower header RPM provided a gentle lift of teeth through the plants resulting in an increased berry recovery during mechanical harvesting. Berry losses were observed to be almost double at Treatment 9 in both categories of PD within selected fields (Fig. 4-2). Treatments 5, 6 and 7 showed slight variation in berry losses in the plots contained with lower PD, which might be due to improper relative velocity. Overall, the berry losses were lower at lower ground speed and header RPM (1.2 km $h^{-1}$ and 26 RPM) in both PD categories.

### 4.4.3 Effect of Tall Plants-Low Plant Density on Berry Losses

The ANCOVA and MMC were performed in order to examine and quantify the role played by the different categories of plant characteristics on picking performance of the harvester. The selected yield plots within the fields were harvested at selected treatment combinations of machine operating parameters. Results of ANCOVA suggested that the berry losses during mechanical harvesting in tall plants - low plant density category were significantly affected by the levels of the treatments as shown by the p-value ($< 0.05$) (Table 4-2). Results reported that the main effects of ground speed and header RPM, and their interactions were having an impact of berry losses (Table 4-2). This might be due to greater impact force of the picker bars at higher ground speed and header RPM that might result in increased shattering losses during harvesting in tall plants with low PD plots. When harvester teeth moves through less dense plants, the plants tend to incline due to impact force of picker bars. The inclination results in away movement of plants from picker bars and subsequently result in increased berry losses. The ST was also found to have a significant effect on berry losses in tall plant - low plant density category within selected fields. Significant role of ST on berry losses as indicated that might be due to sticking of thick stems in teeth bars of the head causing eradication of plants, resulting in an increased berry losses during mechanical harvesting. Since, the main and interaction effects of the treatments were found to have significant impact on berry losses. Therefore, MMC were performed to find a suitable combination with minimum berry losses during harvesting.

**Table 4-2:** Results of ANCOVA and LS means comparison of tall plants-low PD category.

| **ANCOVA** | | | |
|---|---|---|---|
| **Effects** | **DF** | **F-value** | **P-value** |
| Stem thickness | 1 | 45.87 | 0.0199 |
| Speed | 2 | 2.76 | <0.0001 |
| RPM | 2 | 3.65 | <0.0001 |
| Speed*RPM | 4 | 4.91 | <0.0001 |

| **LS means comparison** | | | |
|---|---|---|---|
| **Treatments** | **Speed (km $h^{-1}$)** | **RPM** | **Mean Loss (%)** |
| 1 | 1.20 | 26 | 11.06 c |
| 2 | 1.20 | 28 | 12.24 c |
| 3 | 1.20 | 30 | 14.16 bc |
| 4 | 1.60 | 26 | 8.06 d |
| 5 | 1.60 | 28 | 9.04 cd |
| 6 | 1.60 | 30 | 10.68 cd |
| 7 | 2.00 | 26 | 16.36 ab |
| 8 | 2.00 | 28 | 18.21 a |
| 9 | 2.00 | 30 | 19.06 a |

Means with no letter shared are significantly different at p = 0.05.

Results of MMC for tall plant - low plant density category showed the mixed trend for mean loss (%) at different treatment combinations of ground speed and header RPM (Table 4-2). The reason could be the inconsistent/spatially variable berry yield of the selected fields. Results of LS means comparison revealed that the Treatment 4 (1.6 km $h^{-1}$ and 26 RPM) was the best combination in tall and less dense plant plots with minimum (8.06%) berry losses (Table 4-2), when compared with other treatment combinations. The performance of the harvester at Treatment 4 was adequate with minimum losses in tall plants with lower density, which might be due to appropriate relative velocity at this combination, providing the teeth bars enough time for berry recovery. Non-significant differences were found between Treatments 1 and 2, and similar results were observed for Treatments 8 and 9 (Table 4-2). However, the Treatments 8 and 9 were found to have the highest berry losses during mechanical harvesting (Table 4-2). Higher losses at

Treatments 8 and 9 might be due to the higher ground speed and header RPM, causing more impact and centrifugal forces resulting in an increased berry losses during harvesting. Treatments 3, 5, 6 and 7 shared same letters indicating non-significant difference among each other. The visual inspections also supported the results identified by the ANCOVA and MMC (Fig. 4-3).

**Figure 4-3:** Berry losses in tall plants and low plant density plot after mechanical harvesting.

### 4.4.4 Effect of Tall Plants-High Plant Density on Berry Losses

Results of ANCOVA suggested that the main effect of ground speed and interaction effect (Speed × RPM) were significant for berry losses during harvesting. The main effect of header RPM on berry losses were found to be non-significant ($p$-value $< 0.05$) (Table 4-3). In tall plants and high plant density category, the stem thickness was found to have significant effect on berry losses during harvesting (Table 4-3). The plants in this category had more stem thickness and high density within selected fields. Thicker stemmed plants might stick between the picker bars, causing decreased picker bar capacity, resulting in an increased berry losses during harvesting. Higher stem thickness can also enhance the plant pulling during mechanical harvesting of wild blueberries.

**Table 4-3:** Results of ANCOVA and LS means comparison for tall plants-high PD category.

| ANCOVA | | | |
|---|---|---|---|
| **Effects** | **DF** | **F-value** | **P-value** |
| Stem thickness | 1 | 65.30 | 0.0021 |
| Speed | 2 | 2.50 | <0.0001 |
| RPM | 2 | 3.98 | 0.1645 |
| Speed*RPM | 4 | 6.16 | <0.0001 |

| LS means comparison | | | |
|---|---|---|---|
| **Treatments** | **Speed (km $h^{-1}$)** | **RPM** | **Mean Loss (%)** |
| 1 | 1.20 | 26 | 9.06 d |
| 2 | 1.20 | 28 | 10.64 d |
| 3 | 1.20 | 30 | 13.67 cd |
| 4 | 1.60 | 26 | 15.74 cd |
| 5 | 1.60 | 28 | 17.22 cd |
| 6 | 1.60 | 30 | 17.67 bc |
| 7 | 2.00 | 26 | 18.29 b |
| 8 | 2.00 | 28 | 20.10 a |
| 9 | 2.00 | 30 | 20.45 a |

Means with no letter shared are significantly different at p = 0.05.

Results of LS means comparison indicated that the lower ground speed and header RPM (Treatment 1) showed minimum berry losses (9.06%) during harvesting in the plots where the plants were tall and dense (Table 4-3). Non-significant difference in mean losses was observed at 26 and 28 RPM for the harvester's ground speed of 1.2 km $h^{-1}$ (Table 4-3). Lower losses at Treatment 1 might be due to the gentle lift provided by the teeth bars to improve berry picking efficiency. Additionally, the Treatment 1 provided more time for the picker bars to pick more effectively and convey the berries to the storage bin. Treatments 3, 4 and 5 were non-significantly different from each other in relation to berry losses with selected wild blueberry fields (Table 4-3). Treatments 8 and 9 were found to be non-significantly different from each other, however, the berry losses were the highest at these treatments. Higher losses for Treatments 8 and 9 in tall plants - high plant density category might be due to the higher radial and tangential forces caused by the higher ground speed and header RPM during mechanical harvesting (Farooque et al., 2014). Higher radial and tangential forces might result in spilling of berries away from the center causing increased losses during harvesting. Treatments 8 and 9 can also cause an impact force and aggressive action of picker bar resulting in fruit damage during mechanical harvesting. The berry losses in this category of the plant characteristics is also illustrated in Figure 4-4.

**Figure 4-4:** Berry losses in tall plants and high plant density plot after mechanical harvesting.

### 4.4.5 Effect of Short Plants-Low Plant Density on Berry Losses

Results of ANCOVA indicated that the berry losses during mechanical harvesting were significantly (p-value < 0.05) affected by main and interaction effects of the ground speed and header RPM (Table 4-4). The lower picking efficiency of the harvester could be reason for the significance of the main and interaction. The ST was found to have non-significant effect on berry losses in the plots with short and less dense plants during mechanical harvesting. These results revealed that the ST was not a contributing factor in berry picking efficiency for this category of the plants. Results of ANCOVA reported that the ground speed and header RPM were the influential factors causing fluctuation in berry losses for short plants - less plant density category during mechanical harvesting.

**Table 4-4:** Results of ANCOVA and LS means comparison for short plants-low PD category.

| **ANCOVA** | | | |
|---|---|---|---|
| **Effects** | **DF** | **F-value** | **P-value** |
| Stem thickness | 1 | 31.57 | 0.1382 |
| Speed | 2 | 2.99 | <0.0001 |
| RPM | 2 | 3.89 | <0.0001 |
| Speed*RPM | 4 | 5.45 | <0.0001 |
| **LS means Comparison** | | | |
| **Treatments** | **Speed (km $h^{-1}$)** | **RPM** | **Mean Loss (%)** |
| 1 | 1.20 | 26 | 13.41 bc |
| 2 | 1.20 | 28 | 12.62 c |
| 3 | 1.20 | 30 | 9.56 d |
| 4 | 1.60 | 26 | 8.18 e |
| 5 | 1.60 | 28 | 8.63 de |
| 6 | 1.60 | 30 | 10.26 d |
| 7 | 2.00 | 26 | 15.15 b |
| 8 | 2.00 | 28 | 17.42 ab |
| 9 | 2.00 | 30 | 18.67 a |

Means with no letter shared are significantly different at p = 0.05.

Results of MMC indicated that the Treatment 4 was the best treatment combination with minimum berry losses (8.18%) within selected fields (Table 4-4). The lower losses for treatment 4 might be due to proper relative motion of the head required for efficient picking in low PH with less PD. Results revealed that the Treatment 3 to Treatment 6 were non-significantly different from each other. Similarly, the Treatments 1 (13.41%) and 2 (12.62%) were non-significantly from each other within selected fields. These results reported that operating mechanical harvester at lower ground speed in conjunction with lower RPM in not a good option in short plants with less density. Lower PD can decrease the support required by the plants for effective picking. Treatment 9 resulted in significantly higher losses as compared to other treatment combinations (Table 4-4). Overall, higher ground speed and header RPM treatments produced more berry losses as compared to lower ground speed and header RPM treatments in short and less dense plants within selected fields (Table 4-4). The possible reason for higher losses at Treatments 8 and 9 might be due to the higher radial and impact forces applied by the teeth bars on short and less dense plants. The lower plant-to-plant support in less dense plots could be problematic while the header combs through the bushes at higher RPM. Higher losses at Treatments 8 and 9 were also evident visually (Fig. 4-5).

**Figure 4-5:** Berry losses in short plants and low plant density after mechanical harvesting.

### 4.4.6 Effect of Short Plants-High Plant Density on Berry Losses

Results of ANCOVA indicated that the berry losses during mechanical harvesting were significantly affected by the main effect of ground speed and interaction effect (Speed × RPM) within selected fields (Table 4-5). Stem thickness and the main effect of RPM were found to be non-significant for berry losses in short and dense plants within selected fields (Table 4-5). In factorial experiments, if the higher order interactions is significant, their main effects can be ignored. These results emphasized the need for MMC to determine which treatment differ significantly from each other within selected fields.

The Results of LS means comparison revealed that the mean berry losses ranged from 9.74% to 19.78% in short pants and high dense plants plots within selected fields (Table 4-5). Treatment 2 was the best combination with minimum berry losses (9.74%) for short and dense plants within selected fields (Table 4-5). Treatments 1, 3 and 4 were non-significantly different from each other in selected wild blueberry fields (Table 4-5). Results suggested an increase in berry losses with an increased in ground speed and header RPM (Table 4-5). These results were in agreement with the findings of Farooque et al. (2014). Treatments 8 and 9 were found to the worst with significantly higher berry losses when compared with other treatment combinations.

**Table 4-5:** Results of ANCOVA and LS means comparison for short plants-high PD category.

| **ANCOVA** | | | |
|---|---|---|---|
| **Effects** | **DF** | **F-value** | **P-value** |
| Stem thickness | 1 | 38.12 | 0.2635 |
| Speed | 2 | 2.36 | <0.0001 |
| RPM | 2 | 4.16 | 0.2378 |
| Speed*RPM | 4 | 6.22 | <0.0001 |
| **LS Means Comparison** | | | |
| **Treatments** | **Speed (km $h^{-1}$)** | **RPM** | **Mean (%)** |
| 1 | 1.20 | 26 | 10.96 d |
| 2 | 1.20 | 28 | 9.74 e |
| 3 | 1.20 | 30 | 10.56 de |
| 4 | 1.60 | 26 | 12.48 d |
| 5 | 1.60 | 28 | 14.71 cd |
| 6 | 1.60 | 30 | 15.33 c |
| 7 | 2.00 | 26 | 17.88 b |
| 8 | 2.00 | 28 | 18.22 ab |
| 9 | 2.00 | 30 | 19.78 a |

Means with no letter shared are significantly different at p = 0.05.

Higher impact force of the picker bars on the plants at high ground speed and header RPM could be the reason for higher losses at Treatments 8 and 9. Visual observation indicated that the wild blueberry plants were lodged in the plots having short plants and high PD. Short plants were unable to hold the plants upright due to the weight of the fruit in densely populated plots. The picker bars were less efficient in harvesting the fruit from lodged plants resulting in an increased losses during harvesting. Moreover, the results revealed that the GL and SL in the plots having short plants and high density were more. This could be due to higher unpicked berries because of lodging after harvesting the plots. Overall, the results of ANCOVA and MMC reported that the ground speed and header RPM were responsible for berry losses in variable plant characteristics. Results revealed that the selection of the ground speed and header RPM in accordance with the plant height and density can enhance the berry recovery during mechanical harvesting of wild blueberries.

### 4.5 Conclusions

Results of this study revealed that the PH and PD were substantially variable within selected fields. The wild blueberry harvester performance for berry picking was better in short plants areas (PH ≤ 25 cm) as compared to tall plants areas (PH > 25 cm) of the field. In the areas having less PH (< 10 cm) resulted in more loss and reduce the berry picking efficiency of the harvester. Based on the results it is proposed that operator should adjust harvester head height according to the variation in plant height within wild blueberry field to reduce berry losses. Higher dense plants (PD > 530 plants/m$^2$) showed minimum berry losses (< 10%) at 1.2 km h$^{-1}$ ground speed with variable combinations of header RPM as compared to less dense plants. An increase in ground speed of the harvester resulted in higher berry losses in both PH and PD categories. Results of ANCOVA concluded that the ground speed alone and the interaction effect (Speed × RPM) were significant for berry losses during mechanical harvesting in all categories of plant characteristics within selected fields. The stem thickness (ST) was found to be significantly affecting the berry losses in tall plants but the role of ST was non-significant in short plants plots. The significant role of ST in the tall plants indicates the berry losses might be possible due to thicker plants which may cause of picker bar teeth clogging and plant eradication. Results of multiple mean comparison for selected categories of plant characteristics showed the significant results of berry losses at all nine treatment combinations of machine parameters. The best treatment combination with minimum berry losses in plant characteristics during mechanical harvesting, *i.e.,* Treatment 1 (1.2 km h$^{-1}$ with 26 RPM) for tall plants - high PD category, Treatment 2 (1.2 km h$^{-1}$

with 28 RPM) for short plants - low PD category, and Treatment 4 (1.6 km $h^{-1}$ with 26 RPM) for short plants - low PD and tall plants - low PD categories. All other treatment combinations resulted in higher losses within selected fields. Base on the results of this study it is concluded that the selection of an optimum combination of ground speed and header RPM in relation to plant characteristics can minimize berry losses in order to improve farm profitability.

# CHAPTER 5: IMPACT OF THE FRUIT CHARACTERISTICS ON BERRY LOSSES DURING HARVESTING

## 5.1 Introduction

Canada produced approximately 100 million kilograms of wild blueberry fruit yield in 2014 which was 1.5% higher than previous year's crop and also more than the five year average of 57 million kilograms (Yarborough, 2015). Wild blueberry fruit production differs in many ways from other fruit crops as it is not planted, have native existence in the fields and developed from deforested farmlands (Trevett, 1962). These fields are managed on two-year production cycle, first year is vegetative and second year is fruit year (Hall, 1955). Wild blueberry fields are pruned by burning or flail mowing to encourage vegetative growth of the plants at the start or in the spring of vegetative year. In the fruit or crop year, plants start flowering and fruits are developed, which leads to harvesting in the August of fruit year (Barker et al., 1964).

Wild blueberry harvesting is not carried out until almost 90 percent of the berries turn into blue color (Kinsman, 1993). Over the past century hand-held metal rakes were used to harvest the wild blueberry and these are still being used on approximately 20% of the crops harvested (PMRA, 2005). Wild blueberry harvesting losses by hand-raking is different among the crews with an overall average of 20% of fruit yield (Kinsman, 1993). Shorter harvesting season and shortage in quality labor have also increased the demand for a reliable mechanical harvester (Kinsman, 1993). Hall et al. (1983) reported that many mechanical harvesting systems were developed in last few decades to improve berry recovery and reduce harvesting losses. But a viable commercial machine was not adopted until 1980s due to low stature of the plants, uneven field topography, and competition of crop with weed species which present formidable obstacles during mechanical harvesting in wild blueberry fields (Yarborough, 2002). Darlington cranberry harvester was modified for wild blueberry harvesting (Dale et al., 1994). Due to the limitations of unresolved difficulties in field terrain, the developed harvester could only pick 56% of berries (Yarborough, 1992). Dale et al. (1994) indicated that a successful harvester was developed by DBE in Collingwood, NS in 1979. The DBE harvester picked 68% berries in weedy fields and revealed 75% picking performance in well managed fields (Hall et al., 1983). Improved management practices, since then, have resulted in changed crop parameters and significant increase in wild blueberry fruit yield (Yarborough and Ismail, 1985; Litten et al., 1997; Yarborough and Bhowmik, 1988). Yarborough (1992) reported that harvesting is the largest cost of production with significant increase in fruit yield, the use of mechanical harvesters can be reduced production costs.

Farooque et al. (2014) reported that the fruit zone ranges from 10 cm to 31 cm in different wild blueberry fields. Fruit size was recorded from ranged from 0.48 cm to 1.27 cm (Soule, 1969). Fruit yield has also increased two to three fold by application of selected fertilizer, herbicides and pruning methods in wild blueberry fields (Yarborough, 2004). Metzger and Ismail, (1976) reported that average fruit yield was 960 kg $ha^{-1}$ from 1969 to 1974. However, from 1985 to 1989 the average yield of 1580 kg $ha^{-1}$ was recorded in selected wild blueberry fields (DeGomez and Smagula, 1990). Litten et al. (1997) reported that the use of DAP fertilizer increased the plant growth, floral buds and wild blueberry fruit yield in Maine, USA. Farooque et al. (2014) reported average fruit yield of 8000 kg $ha^{-1}$ in well managed wild blueberry field located in central Nova Scotia and observed more than 10% of fruit losses during mechanical harvesting. They also suggested that the harvesting losses were proportional to harvestable fruit yield. Holshouser (2011) reported that the harvest losses can vary from 3 to 10% due to lodging in soybean fields. Lodging can result in decreased picking efficiency and increased harvesting losses (Woods and Searingin, 1977). The picker bars should make contact with the top one-third of the plant to achieve better soybean yield (Huitink, 2013). Lodging of wild blueberry plants at the edges of bare spots lowers the fruit zone which might result in increased fruit loss (Farooque et al., 2014). Therefore, a detailed insight is required to identify optimum combination of fruit and machine characteristics for improved harvestable berry yield.

Over the past 20 years, improved management practices including pruning, pollination and extensive use of agrochemicals and fertilizers have resulted in healthy fruit and tall plants with deep fruit zone (Farooque, 2015). Farooque et al. (2014) evaluated the performance efficiency of a commercial wild blueberry harvester for berry losses during harvesting and suggested an optimum combination of ground speed and header revolutions which can minimize berry losses during mechanical harvesting. However the importance of fruit characteristics on the picking efficiency of wild blueberry has not been investigated. There is a need to conduct research on quantifying the berry losses as a function of machine and fruit parameters (fruit zone and fruit size), which emphasize the need to study the harvesting dynamics in spatially variable fruit characteristics. Therefore, the objective of this study was to determine the impact of the fruit characteristics on berry losses during harvesting.

## 5.2 Materials and Methods

Four wild blueberry fields E, F, G and H were selected in 2011, 2012, 2013 and 2014, respectively, to examine the effect of fruit characteristics on picking efficiency of the (DBE) wild blueberry harvester. The selected fields were in the Londonderry (Field E) (45.48°N, 63.57°W; 3.20 ha), Highland Village (Field F) (45.24°N, 63.40°W; 2.57 ha), Hardwood Hill (Field G) (45.43°N, 63.51°W; 2.05 ha,) and Debert-II (Field H) (45.45°N, 63.45°W; 1.01). Over the past decade, these fields had been under commercial management and received biennial pruning by mowing along with weed, and disease management practices.

A real-time kinematics global positioning system (RTK-GPS) was used to map the boundaries of the fields, bare spots and yield plots within the fields. Thirty six yield plots (0.91 x 3.0 m; same as the width of harvester) were randomly selected using a measuring tape in the path of the operating harvester at each experimental field. A 3 × 3 factorial design was used with three levels of harvester's ground speed (1.2, 1.6 and 2.0 km $h^{-1}$) and header revolutions (26, 28 and 30 RPM). In order to examine the effect of fruit zone (FZ) and fruit yield (FY) on berry losses, the collected data for FZ and FY at all combinations of ground speed and head RPM were divided into two groups, *i.e.,* low (FZ ≤ 17 cm) and high (FZ > 17 cm) fruit zone, and low (FY ≤ 3000 kg $ha^{-1}$) and high (FY > 3000 kg $ha^{-1}$) fruit yield. The randomly selected plots were constructed at each site in a way to establish four categories of the fruit characteristics, *i.e.,* low fruit yield - low fruit zone, low fruit yield - high fruit zone, high fruit yield - low fruit zone, and high fruit yield - high fruit zone. Fruit diameter was used as a covariate for all four experiments. Each year was used as a block (replication), making 4 blocks for each fruit characteristics. All nine treatment combinations of ground speed and head RPM of the harvester were allocated to each category of the of the fruit characteristics. The picking performance of the blueberry harvester was examined in relation to different categories of fruit characteristics and machine operating parameters.

DBE Commercially available mechanical wild blueberry harvester was used to collect the yield data from randomly selected plots in each field. Five readings of fruit zone (FZ) were taken with simple ruler and similarly five readings for fruit diameter (FD) were recorded manually with Vernier caliper from each plot within selected fields. The harvester was operated at selected levels of ground speed and header RPM within each plot to collect fruit yield and berry losses. In each plot, fruit yield was collected by attaching a bucket to the harvester conveyer belt at storage bin during harvesting. Pre harvest losses were collected manually prior to harvest an each plot in selected wild blueberry fields. Just before harvesting the selected plots, the picker bars were cleaned of any foreign debris and previously harvested fruit was transported to the storage bin.

The post-harvest berry losses, *i.e.,* ground loss (GL), shoot loss (SL) and blower loss (BL) were collected after harvesting the selected plots. Detailed procedure can be seen in Chapter 3.

**5.3 Statistical Analysis**

Descriptive statistics (minimum, maximum, mean, standard deviation, coefficient of variation and skewness) of collected data was performed in Minitab 17 (Minitab Inc. NY, USA). SAS 9.3 (SAS Institute Inc., NC, USA) statistical software was used to perform statistical analysis. Anderson-Darling (AD) normality test was performed to check the normality at the 5% level of significance and residual versus fitted values plot indicated whether the variance of the error terms was constant. Independence was achieved through randomization of treatments within the field. Analysis of covariance (ANCOVA) using general linear model (GLM) procedure was performed to study the effect of the selected factors on berry losses. Least significant (LS) means was used as the multiple means comparison (MMC) for comparing significantly different treatments in statistical analysis.

**5.4 Results and Discussion**

Montgomery (2009) reported that coefficient of variation (CV) is a first approximation of field heterogeneity. The selected parameters are least variable if the CV < 15%, moderate with CV ranging from 15 to 35% and most with CV > 35%. Table 5-1 revealed the summary statistics of Fields E, F, G and H for fruit yield (FY), shoot loss (SL), ground loss (GL), blower loss (BL), total loss (TL), fruit zone (FZ) and fruit diameter (FD). The variability in berry losses could be due to the intrinsic or/and extrinsic sources. According to Hepler and Yarborough (1991), intrinsic sources may include natural soil variations and yielding nature of different clones, whereas, extrinsic sources include harvester operation, operator skills, field topography and crop management practices.

### 5.4.1 Summary Statistics

In Fields “E” and “F” FY, SL, GL, BL and TL were highly variable with the CV > 35%, while FZ was moderately variable and FD was less variable (Table 5-1). Results of Field “G” revealed that the SL was highly variable with the CV > 35%, and rest of the parameters were moderately variable. Summary statistics of Field “H” indicated higher variability in SL, GL, BL and TL as compared to FY, FZ and FD (Table 5-1). The total FY was found to be variable within selected fields (Table 5-1). The total mean FY was found to be 3705 kg $ha^{-1}$, 8136 kg $ha^{-1}$, 7948 kg $ha^{-1}$ and 3342 kg $ha^{-1}$ for Fields E, F, G and H, respectively (Table 5-1). The FY was found to be higher at Field F and G that could be due to effective use of agrochemicals and pollination in these fields. The FY was observed to be lowest at Fields E and H, which might be due to high proportion of bare spots and weed patches present in these fields. The SL was found to be significantly higher for Fields F and G when compared with other fields (< 100 kg $ha^{-1}$), indicating the lack of picking performance of the harvester in these field (Table 5-1). This might be due to especially higher yield at this site. The mean SL was 2.26%, 3.0%, 3.02% and 2.10% in Fields E, F, G and H, respectively. The GL was observed to be higher for field F as compared to Fields E, G and H. The GL were found to be 7.85%, 13.49%, 11.11% and 8.42% for Fields E, F, G and H, respectively (Table 5-1). The possible reason for the higher GL could be the improper relative motion of the machine operating parameters. Farooque et al. (2014) reported that the picked berries were dropped off over the harvested strip due to the impact force of the harvester head and the centrifugal force developed by the higher level of header RPM, pushing the berries away from center and contributing towards the ground losses. The berry losses through the blower for Fields E, F, G and H were found to be 1.17%, 1.74%, 1.11% and 0.97%, respectively. Overall, higher total mean loss in Field F (18.24%) was recorded as compared to the Fields E (11.28%), G (15.24%) and H (11.49%) (Table 5-1).

**Table 5-1:** Summary statistics of fruit yield, berry losses, fruit zone and fruit diameter for selected fields.

**Field E**

| Parameters | Min | Max | Mean | Mean (%) | SD | CV (%) | Skewness |
|---|---|---|---|---|---|---|---|
| FY (kg ha$^{-1}$) | 305 | 9914 | 3705 | - | 2014 | 54.35 | 0.82 |
| SL (kg ha$^{-1}$) | 4.90 | 342.70 | 83.58 | 2.26 | 77.41 | 92.61 | 1.50 |
| GL (kg ha$^{-1}$) | 19.60 | 891 | 291 | 7.85 | 186 | 63.94 | 1.15 |
| BL (kg ha$^{-1}$) | 4.92 | 225.21 | 43.47 | 1.17 | 39.05 | 89.83 | 1.99 |
| TL (kg ha$^{-1}$) | 58.70 | 1096.70 | 418 | - | 225.6 | 53.96 | 0.79 |
| TL (%) | 3.73 | 25.50 | 11.28 | 11.28 | 5.86 | 46.38 | 0.62 |
| FZ (cm) | 7.80 | 25.30 | 19.35 | - | 3.56 | 18.42 | -0.45 |
| FD (cm) | 0.70 | 1.08 | 0.90 | - | 0.07 | 7.86 | -0.19 |

**Field F**

| Parameters | Min | Max | Mean | Mean (%) | SD | CV (%) | Skewness |
|---|---|---|---|---|---|---|---|
| FY (kg ha$^{-1}$) | 2218 | 17968 | 8136 | - | 2915 | 35.81 | 0.83 |
| SL (kg ha$^{-1}$) | 42.90 | 574.71 | 244.30 | 3.0 | 115.7 | 47.37 | 0.67 |
| GL (kg ha$^{-1}$) | 131.50 | 1847 | 1098.12 | 13.49 | 385.3 | 35.97 | -0.34 |
| BL (kg ha$^{-1}$) | 31.60 | 528.90 | 142.21 | 1.74 | 90.6 | 63.78 | 2.16 |
| TL (kg ha$^{-1}$) | 240.20 | 2616.10 | 1484.6 | - | 545.9 | 37.42 | 0.0 |
| TL (%) | 4.70 | 29.47 | 18.24 | 18.24 | 4.68 | 25.69 | -0.25 |
| FZ (cm) | 11 | 24.80 | 17.55 | - | 3.28 | 18.70 | 0.06 |
| FD (cm) | 0.69 | 1.05 | 0.90 | - | 0.07 | 7.92 | -0.23 |

**Field G**

| Parameters | Min | Max | Mean | Mean (%) | SD | CV (%) | Skewness |
|---|---|---|---|---|---|---|---|
| FY (kg ha$^{-1}$) | 4972 | 13070 | 7948 | - | 1528 | 19.22 | 0.87 |
| SL (kg ha$^{-1}$) | 91.50 | 461.30 | 240.40 | 3.02 | 92.7 | 38.57 | 0.54 |
| GL (kg ha$^{-1}$) | 419 | 1566.90 | 883.30 | 11.11 | 266.8 | 30.21 | 0.53 |
| BL (kg ha$^{-1}$) | 35.21 | 154.93 | 88.29 | 1.11 | 26.50 | 30.01 | 0.43 |
| TL (kg ha$^{-1}$) | 672.50 | 2063.40 | 1212.0 | - | 325.7 | 26.87 | 0.36 |
| TL (%) | 6.76 | 25.78 | 15.24 | 15.24 | 4.84 | 30.77 | 0.17 |
| FZ (cm) | 8.83 | 33.66 | 15.66 | - | 4.08 | 26.05 | 1.37 |
| FD (cm) | 0.69 | 2.03 | 0.91 | - | 0.18 | 20.09 | 4.50 |

**Field H**

| Parameters | Min | Max | Mean | Mean (%) | SD | CV (%) | Skewness |
|---|---|---|---|---|---|---|---|
| FY (kg ha$^{-1}$) | 1081 | 6866 | 3342 | - | 1163 | 34.80 | 0.79 |
| SL (kg ha$^{-1}$) | 17.61 | 179.58 | 70.23 | 2.10 | 41.54 | 59.14 | 0.74 |
| GL (kg ha$^{-1}$) | 105.60 | 535.20 | 281.60 | 8.42 | 127.10 | 45.13 | 0.60 |
| BL (kg ha$^{-1}$) | 10.56 | 63.38 | 32.60 | 0.97 | 11.55 | 35.42 | 0.43 |
| TL (kg ha$^{-1}$) | 179.60 | 743 | 384.50 | - | 155.2 | 40.36 | 0.57 |
| TL (%) | 3.59 | 25.15 | 11.49 | 11.49 | 5.288 | 42.48 | 0.47 |
| FZ (cm) | 10.40 | 23.90 | 16.07 | - | 2.45 | 15.26 | 0.32 |
| FD (cm) | 0.71 | 1.22 | 0.89 | - | 0.08 | 9.43 | 1.21 |

**Note:** FY (fruit yield), SL (shoot loss), GL (ground loss), BL (blower loss) and TL (total loss) were recorded in kg ha$^{-1}$, FZ (fruit zone) and FD (fruit diameter) in cm.

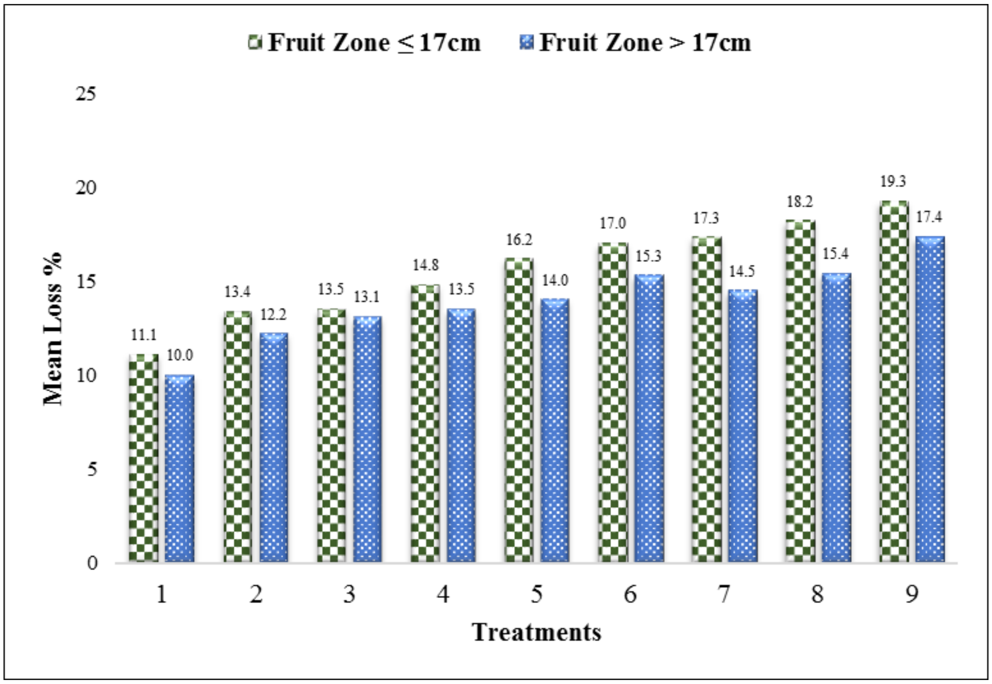
Results suggested that the berry losses during mechanical harvesting were proportional to the fruit yield within selected fields. The FZ was found to be consistent within selected fields.

Mean values of the FZ were 19.35, 17.55, 15.66 and 16.07 cm for Fields E, F, G and H, respectively. Results revealed that the mean FD was similar for all selected fields (~0.9 cm) (Table 5-1).

### 5.4.2 Effect of Fruit Zone and Fruit Yield on Berry Losses

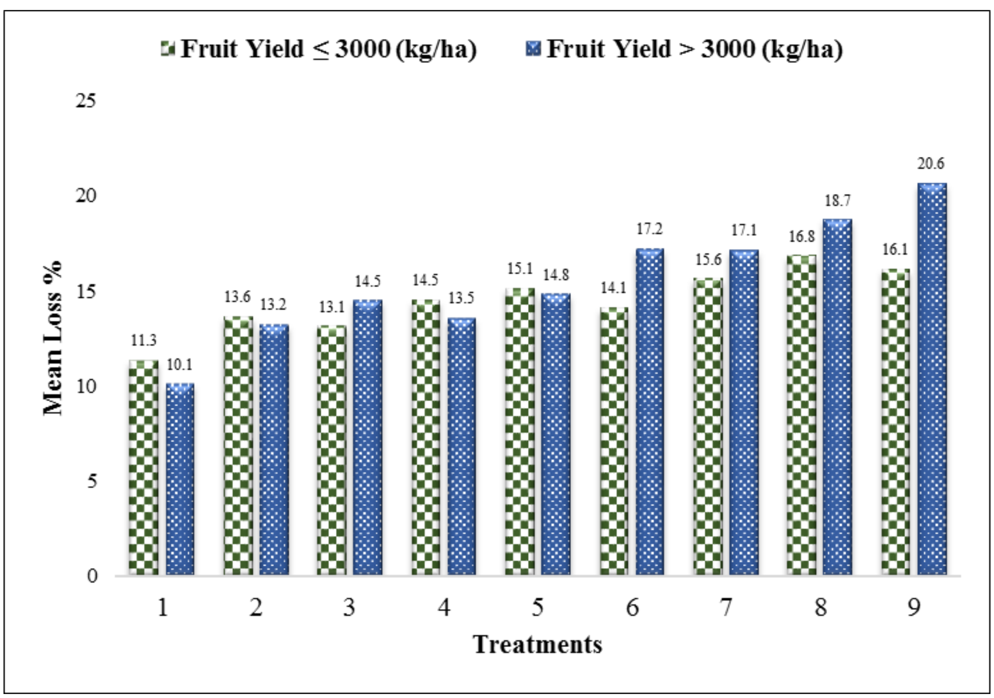
Results of summary statistics revealed the existence of moderate to high variability in fruit characteristics (Table 5-1), which indicated that losses are influenced by fruit characteristics during mechanical harvesting. Mean berry losses were compared in both FZ and FY classes at nine treatment combinations of ground speed and header RPM of the wild blueberry harvester (Figs. 5-1 and 5-2). Berry losses in low FZ (FZ ≤ 17 cm) plants ranged from 11.1% to 19.3%, whereas in high FZ plants (FZ > 17 cm) ranged from 10.0% to 17. 4% (Fig. 5-1). Visual observations revealed that the FZ has direct relationship with PH. Therefore, in the high FZ plots harvester picked the berries more effectively as compared to low FZ plots at all treatment combinations (Fig. 5-1). Treatment 1 was found to have minimum berry losses (10.0%) at 1.2 km $h^{-1}$ and 26 header RPM in high FZ plots. Which indicated that combining action was adequate in high FZ plots and harvester has better chance to pick the berries efficiently during harvesting. Berry losses were more in the plants having lower FZ (≤ 17 cm) (Fig. 5-1), these plants mostly on the edge of bare spots and slop of the field. Harvester was not able to harvest the low FZ plants due to short PH and lodging which may cause of soil digging during harvest operation. Reel should make contact with the top one-third of the plant for effective picking performance during mechanical harvesting (Huitink, 2013). Moreover, Treatments 4, 5 and 6 indicated better picking performance in high FZ as compared to low FZ plants. Berry losses were increased gradually with an increase in ground speed and header RPM in both low FZ plants (Fig. 5-1). Higher treatment combination (Treatments 7, 8 and 9) indicated that more berry losses at high FZ plants, which might be due to shattering loss by impact force of head rotation or clogging of teeth bars due to more vegetative growth.

Results suggested that the head adjustment is needed in considering the FZ to reduce the berry losses during harvesting.




**Treatment 1:** 1.2 km h$^{-1}$ and 26 RPM
**Treatment 2:** 1.2 km h$^{-1}$ and 28 RPM
**Treatment 3:** 1.2 km h$^{-1}$ and 30 RPM
**Treatment 4:** 1.6 km h$^{-1}$ and 26 RPM
**Treatment 5:** 1.6 km h$^{-1}$ and 28 RPM
**Treatment 6:** 1.6 km h$^{-1}$ and 30 RPM
**Treatment 7:** 2.0 km h$^{-1}$ and 26 RPM
**Treatment 8:** 2.0 km h$^{-1}$ and 28 RPM
**Treatment 9:** 2.0 km h$^{-1}$ and 30 RPM

**Figure 5-1:** Effect of fruit zone on berry losses during mechanical harvesting at different combinations of ground speed and header RPM.




**Treatment 1:** 1.2 km h$^{-1}$ and 26 RPM
**Treatment 2:** 1.2 km h$^{-1}$ and 28 RPM
**Treatment 3:** 1.2 km h$^{-1}$ and 30 RPM
**Treatment 4:** 1.6 km h$^{-1}$ and 26 RPM
**Treatment 5:** 1.6 km h$^{-1}$ and 28 RPM
**Treatment 6:** 1.6 km h$^{-1}$ and 30 RPM
**Treatment 7:** 2.0 km h$^{-1}$ and 26 RPM
**Treatment 8:** 2.0 km h$^{-1}$ and 28 RPM
**Treatment 9:** 2.0 km h$^{-1}$ and 30 RPM

**Figure 5-2:** Effect of fruit yield on berry losses during mechanical harvesting at different combinations of ground speed and header RPM.

In order to find the berry losses during harvesting according to fruit yield (FY), plots were categorized into two different classes of FY such as low FY (FY $\leq$ 3000 kg $ha^{-1}$) and high FY (FY > 3000 kg $ha^{-1}$). Berry losses were ranged from 10.1 to 20.6% in high FY plots and losses in the low FY plots were found to have ranged from 11.3 to 16.1% within selected fields (Fig. 5-2). High FY plots revealed the more berry losses as compared to low FY plots. It might be possible due to low FZ or machine aggression during harvesting. Berry losses in both categories of FY suggested that the lower ground speed (1.2 km $h^{-1}$) in combination with lower header RPM (26) of the harvester provided a better opportunity to the picker bars through the plants resulting in an increased berry recovery during mechanical harvesting. Treatment 1 indicated minimum berry losses (10.1%) in the high FY plots. All other treatments showed slight variation in berry losses in the plots contained with high and low FY, which might be due to improper relative velocity of picker bars to the ground speed of the harvester. In low FY plots indicated that no treatment combination is proper to reduce berry losses during harvesting. These results agreement with Farooque et al. (2014). Berry losses were found to have almost double at Treatment 9 in high FY category within selected fields (Fig. 5-2). Results suggested that higher levels of ground speed and header RPM were inadequate for berry picking efficiency during harvesting.

### 5.4.3 Effect of High FZ-Low FY on Berry Losses

The wild blueberry harvester was operated at selected treatment combinations of ground speed and header RPM at selected yield plots within the fields. The ANCOVA and MMC were performed to analyze the different categories of fruit characteristics on picking performance of the harvester. Results of ANCOVA suggested that the main effect of ground speed and interaction effect (Speed × RPM) were significant in high FZ and low FY category as shown by p-value ($p < 0.05$) (Table 5-2). The main effect of header RPM and FD were found to be non-significant on berry losses during mechanical harvesting. Results reported that the significance of main effect of ground speed and interaction effect of (Speed × RPM) might be due to improper relative motion between the picker bars and ground speed that might result in increased shattering losses during harvesting (Table 5-2). According to Huitink (2013) the reel should also make contact with the top one-third of the plant for effective picking performance during mechanical harvesting. However, the two way interaction effect of the treatments was found to have significant effect on berry losses. So, least significant (LS) means as the multiple means comparison were performed to find a suitable combination with minimum berry loses during harvesting.

**Table 5-2:** Results of ANCOVA and LS means comparison of high FZ-low FY category.

| ANCOVA | | | |
|---|---|---|---|
| **Effects** | **DF** | **F-value** | **P-value** |
| Fruit diameter | 1 | 31.22 | 0.1236 |
| Speed | 2 | 2.67 | <0.0001 |
| RPM | 2 | 5.12 | 0.2142 |
| Speed*RPM | 4 | 3.25 | <0.0001 |
| **LS means comparison** | | | |
| **Treatments** | **Speed (km $h^{-1}$)** | **RPM** | **Mean Loss (%)** |
| 1 | 1.20 | 26 | 8.26 c |
| 2 | 1.20 | 28 | 11.24 bc |
| 3 | 1.20 | 30 | 13.42 b |
| 4 | 1.60 | 26 | 9.08 c |
| 5 | 1.60 | 28 | 13.86 b |
| 6 | 1.60 | 30 | 16.38 ab |
| 7 | 2.00 | 26 | 14.40 b |
| 8 | 2.00 | 28 | 15.18 b |
| 9 | 2.00 | 30 | 17.32 a |

Means with no letter shared are significantly different at p = 0.05.

Wild blueberry fields are spatially variable in crop characteristics and topography. Therefore, results of LS means showed the mixed trend for mean berry losses (%) at different treatment combinations of ground speed and header RPM of the wild blueberry harvester (Table 5-2). Results of LS means comparison indicated that the Treatments 1 and 4 were non-significantly different from each other as best treatment combinations in high FZ and low FY plots with minimum berry losses of 8.26% and 9.08%, respectively (Table 5-2). At these treatment combinations, the harvester achieved the better picking performance with minimum berry losses. Result indicated that higher FZ provide better opportunity to picker bars for effective berry recovery. Treatments 2, 3, 5, 7 and 8 shared similar letters indicating non-significant difference among each other during harvesting. Moreover, the Treatments 6 and 9 were found to have the highest berry losses during mechanical harvesting (Table 5-2). Higher losses at Treatments 6 and 9 might be due to the higher ground speed and header RPM, causing more impact and centrifugal forces resulting in increased losses during harvesting.

### 5.4.4 Effect of High FZ-High FY on Berry Losses

Results of ANCOVA suggested that the berry losses during mechanical harvesting in high FZ - high FY category were significantly affected by the levels of the treatments as shown by the p-value (< 0.05) (Table 5-3). The inadequate picking efficiency of the harvester could be the reason for significance of the main and interaction effect of ground speed and header RPM.

**Table 5-3:** Results of ANCOVA and LS means comparison of high FZ-high FY category.

| **ANCOVA** | | | |
|---|---|---|---|
| **Effects** | **DF** | **F-value** | **P-value** |
| Fruit diameter | 1 | 27.44 | 0.0021 |
| Speed | 2 | 2.21 | <0.0001 |
| RPM | 2 | 4.78 | <0.0001 |
| Speed*RPM | 4 | 5.37 | <0.0001 |
| **LS means comparison** | | | |
| **Treatments** | **Speed (km $h^{-1}$)** | **RPM** | **Mean Loss (%)** |
| 1 | 1.20 | 26 | 10.65 e |
| 2 | 1.20 | 28 | 12.26 de |
| 3 | 1.20 | 30 | 14.17 d |
| 4 | 1.60 | 26 | 15.34 d |
| 5 | 1.60 | 28 | 16.81 c |
| 6 | 1.60 | 30 | 18.92 bc |
| 7 | 2.00 | 26 | 17.15 c |
| 8 | 2.00 | 28 | 19.38 b |
| 9 | 2.00 | 30 | 21.16 a |

Means with no letter shared are significantly different at p = 0.05.

The FD was also found to have significant effect on berry losses during harvesting (Table 5-3) in this category that might be possible due to the berries moved or spilled away during combing action of picker bars in high yielding plots. High FZ - high FY category, more impact force of picker bars on the plants with relative ground speed may have caused increased harvesting losses and decrease the berry quality due to bruising action. In the plots where FZ and FY were high, Treatment 1 indicated that LS means comparison result with minimum berry losses (10.65%) during harvesting (Table 5-3). Lower losses at Treatment 1 might be due to the gentle lift provided by the teeth bars to improve berry picking efficiency. Additionally, the higher FZ provided more time for the picker bars to pick more effectively. Treatments 2, 3, and 4 were non-significantly different from each other in relation to berry losses within selected wild blueberry fields (Table 5-3). Similar results were found at Treatments 5, 6, 7 and 8, which were non-significantly each other. However, Treatment 9 was found to be significant with maximum berry losses (21.6%) in this category (Table 5-3). Higher losses for Treatment 9 in high FZ-high FY category might be due to the higher radial and tangential forces caused by the higher ground speed and header RPM during mechanical harvesting. Higher radial and tangential forces might result in spilling of berries away from the center causing increased losses during harvesting (Farooque et al., 2014). Aggressive actions in picker bars can have resulting in fruit damage and reduce picking performance of wild blueberry harvester.

### 5.4.5 Effect of Low FZ-Low FY on Berry Losses

Results of ANCOVA reported that the ground speed and interaction effect (Speed × RPM) were the influential factors causing fluctuation in berry losses for low FZ - low FY category during mechanical harvesting (Table 5-4). The FD and header RPM were found to have non-significant effect on berry losses in the low FZ-low FY plants during mechanical harvesting. FD was not a contributing factor in berry picking efficiency for this category. Berry losses in this category could be due to harvester was not able to pick the berries in low FZ plants. Visual observation also revealed that the rough terrain and weeds in low FZ have resulted in more losses during harvesting.

**Table 5-4:** Results of ANCOVA and LS means comparison of low FZ-low FY category.

| ANCOVA | | | |
|---|---|---|---|
| **Effects** | **DF** | **F-value** | **P-value** |
| Fruit diameter | 1 | 31.57 | 0.1382 |
| Speed | 2 | 2.99 | <0.0001 |
| RPM | 2 | 3.89 | 0.0842 |
| Speed*RPM | 4 | 5.45 | <0.0001 |

| LS means Comparison | | | |
|---|---|---|---|
| **Treatments** | **Speed (km h$^{-1}$)** | **RPM** | **Mean Loss (%)** |
| 1 | 1.20 | 26 | 11.96 bc |
| 2 | 1.20 | 28 | 8.92 c |
| 3 | 1.20 | 30 | 12.63 b |
| 4 | 1.60 | 26 | 14.16 bc |
| 5 | 1.60 | 28 | 10.08 c |
| 6 | 1.60 | 30 | 17.35 ab |
| 7 | 2.00 | 26 | 18.75 a |
| 8 | 2.00 | 28 | 16.42 b |
| 9 | 2.00 | 30 | 19.22 a |

Means with no letter shared are significantly different at p = 0.05.

Results of MMC revealed the berry losses in low FZ-low FY category ranging from 8.92% to 19.22% during harvesting within selected fields (Table 5-4). Results indicated that the Treatments 2 and 5 were non-significantly different from each other, but Treatment 2 was the best treatment combination with minimum berry losses (8.92%). It could be due to proper relative velocity of the picker bars required for effective berry recovery in low FZ - low FY category. Results revealed that the Treatment 1 and Treatment 3 were non-significantly different from each other. Similarly, the Treatments 4 and 6 were non-significantly different from each other within selected fields. Treatment 9 resulted in significantly higher losses as compared to other treatment combinations (Table 5-4). Overall, higher treatment combinations of ground speed and header RPM produced more berry losses as compared to lower treatments in low FZ - low FY plots within selected fields (Table 5-4). The possible reason for higher losses at higher treatments might be due improper radial speed and impact forces of picker bars in conjunction to ground speed of the harvester in low FZ and less FY plants during harvesting.

### 5.4.6 Effect of Low FZ-High FY on Berry Losses

Results of ANCOVA indicated that the berry losses during mechanical harvesting were significantly affected by the main effect of ground speed, header RPM and FD, and interaction effect (Speed × RPM) within selected fields (Table 5-5). The lower picking performance of the harvester in this particular category might be due to plants were very short or due to high berry yield cause of lodging. The plants having low FZ were unable to hold the plants upright due to the weight of the berries in high FY plots. The picker bars were less efficient in harvesting the fruit from lodged plants resulting in increased losses during harvesting. Visual observation revealed that the number of berries couldn't easily pick and spilled away through picker bars during combing action of harvester head.

**Table 5-5:** Results of ANCOVA and LS means comparison of low FZ-high FY category.

| ANCOVA | | | |
|---|---|---|---|
| **Effects** | **DF** | **F-value** | **P-value** |
| Fruit diameter | 1 | 38.12 | <0.0001 |
| Speed | 2 | 2.36 | <0.0001 |
| RPM | 2 | 4.16 | <0.0001 |
| Speed*RPM | 4 | 6.22 | <0.0001 |
| **LS Means Comparison** | | | |
| **Treatments** | **Speed (km $h^{-1}$)** | **RPM** | **Mean (%)** |
| 1 | 1.20 | 26 | 11.32 e |
| 2 | 1.20 | 28 | 13.80 de |
| 3 | 1.20 | 30 | 16.41 c |
| 4 | 1.60 | 26 | 17.08 d |
| 5 | 1.60 | 28 | 18.72 cd |
| 6 | 1.60 | 30 | 20.86 b |
| 7 | 2.00 | 26 | 18.21 c |
| 8 | 2.00 | 28 | 20.12 bc |
| 9 | 2.00 | 30 | 22.65 a |

Means with no letter shared are significantly different at p = 0.05.

If the higher order interactions are significant in factorial experiments, their main effects can be ignored. These results emphasized the need for MMC to determine which treatments significantly different from each other in the experiment. The results of LS means comparison revealed that the Treatment 1 was the best combination with minimum berry losses (11.32%) for low FZ - high FY plants within selected fields (Table 5-5). Results suggested increase in berry losses with increase in ground speed and header RPM of the wild blueberry harvester (Table 5-5). Treatments 4 and 5 were non-significantly different from each other in selected wild blueberry fields (Table 5-5). Treatments 6, 8 and 9 were found to be worst with significantly higher berry losses when compared with other treatment combinations. Higher impact force of the picker bars on the plants at high ground speed and header RPM could be the reason for higher losses at these treatments. These results were in agreement with the findings of Farooque et al. (2014). Overall, the results of ANCOVA and MMC indicated that selection of an ideal combination of ground speed and header RPM in relation to fruit characteristics can minimize berry losses during harvesting and improve the farm profitability of the wild blueberry growers.

## 5.5 Conclusions

Results of this study revealed that there was substantial variation in fruit characteristics within selected fields. The wild blueberry harvester picked the berries more effectively in high FZ (> 17 cm) plants at nine all treatment combinations of ground speed and header RPM as compared to low FZ plants (≤ 17 cm). Results showed minimum berry losses in high yielding (FY > 3000 kg ha$^{-1}$) plots at 1.2 km h$^{-1}$ with 26 RPM as compared to low FY plots (FY ≤ 3000 kg ha$^{-1}$) during harvesting. Based on the results of ANCOVA, it is concluded that the ground speed alone and the interaction effect (Speed × RPM) were significant for berry losses in all categories of fruit characteristics during mechanical harvesting. Berry losses affected by FD in high FY plots indicated that berries were not easily pick or spill away during harvesting. Results of multiple mean comparison indicated 1.2 km h$^{-1}$ and 26 header RPM was the best treatment combination for selected categories of fruit characteristics. Based on the results of this study it is concluded the optimum combination of harvester operational parameters in accordance with the variability in fruit characteristics can minimize berry losses during harvesting.

# CHAPTER 6: DETERMINE THE OPTIMUM COMBINATION OF CROP CHARACTERISTICS AND MACHINE PARAMETERS FOR EFFECTIVE BERRY RECOVERY DURING MECHANICAL HARVESTING USING ARTIFICIAL NEURAL NETWORK

## 6.1 Introduction

Eastern Canada and Maine, USA are the leading producers of wild blueberry crop in all over the world (Yarbrough, 2015). Over the past 20 years, wild blueberry fruit yield and crop conditions have changed significantly due to improved management practices (Eaton, 1994; Yarborough, 2004; Farooque et al., 2014). Significant increase in berry yield has increased the demand for mechanical harvesting (Holbein, 1991; Dale et al., 1994), as hand raking is a time consuming and labor intensive process. Wild blueberry industry is facing increased harvesting losses (15 to 25%) with current commercial harvesters (PMRA, 2005; Farooque et al., 2014). Mechanical harvesting of wild blueberry involves several factors (machine settings, crop characteristics, field conditions, climatic conditions, and operator's skills), which have an impact on picking performance of the harvester (Salter et al., 1980). Interactions among these factors are complex and non-linear in nature, demanding for a robust approach to study these complex scenarios (Adams et al., 1998; Bryant et al., 2000). Proper understanding of these complicated processes can help to enhance crop productivity (Minasny and McBratney, 2002; Farooque, 2015).

Data-driven modeling to find these non-linear relationships is considered as an effective methods as it does not relies on the physical behavior of system (Solomatine and Ostfeld, 2008). Simon and Langley (1995) narrated that data-driven modeling increases the efficiency of machine using computational methods and learning algorithms, which lead to increase level of automation. Artificial Neural Network (ANN) is commonly used as a data-driven modeling, which provides accurate results than conventional statistical models, particularly in those cases where functional relationships are multiple and non-linear (Chen et al., 2001; Farooque, 2015). The application of ANN modeling technique started in 1980s, but in the last decade, it has been used extensively in several engineering disciplines for problem solving (Sablani et al., 1995; Chen et al., 1998; Pahlavan et al., 2012). Generic nature, flexibility and best approximation capabilities have resulted in increased demand for ANN models (Cybenko, 1989; Hornik et al., 1989).

The idea behind ANN modeling is natural neurons system of living organisms, which has capability to solve complex computational problems with better understandings (Bishop, 1994). Maier and Danday (2000) explained the structure of ANN modeling network, *i.e.*, artificial neurons/nodes connect or transmit information from input layer to output layer. The ANN modeling process is carried out in a "black-box", which typically receive adjusted weight inputs from input or previous hidden layer, do transformations on receiving inputs, and pass to the next adjacent layer, which can be final output (Hornik et al., 1989; Wilby et al., 2003). Each node is directly connected with corresponding nodes and associated weights until the final output is achieved (Setiono et al., 2000). The model understands receiving inputs, altering it according to data, used to calibrate the nodes by weights manipulation and adjustment, and finally process to output (Bishop, 1994). This back and forth flow of data is used to shift transfer function and learning algorithms to various layers (McCulloch and Pitts, 1943; Kaul et al., 2005). Minimum value of mean square error (MSE) or root mean square error (RMSE) indicates the well trained ANN model (Anyaeche and Ighravwe, 2013). The ANN model can reduce its efficiency because of over training (Qin, 1999). Over training can be avoided by cross validation via an independent dataset (Bishop, 1995; Braddock et al., 1998). Adequate-size of network, followed by network generalization can avoid over-fitting or under-fitting network problems (Huang and Foo, 2002).

Many researchers have used ANN modeling in various scientific fields such as, managerial problems, yield predictions, disease estimation, agrochemicals assessment, flood forecasting, rainfall-runoff predictions and stream flow estimations (Batchelor et al., 1997; Yang et al., 1997;

Wright and Dastorani, 2001; Wright et al., 2002; Clapham and Fedders, 2004; Alvarez, 2009; Hakimpoor et al., 2011; Sobri et al., 2012). The ANN is proven to be a better performing tool as compare to other traditional predictive methods in geotechnical engineering (Shahin et al., 2001). Paulo et al. (2006) developed ANN model for decision making regarding cancer studies. The ANN has also been used in industrial problems. Saanzogni and Kerr (2001) applied feed-forward ANN network in evaluating milk production. Fast and Palme (2010) investigated condition and diagnosis of a combined heat and power plant using neural network. Braga (2000) accurately predicted spatial patterns of corn yield in relation to agronomic variables, topographic features and seasonal variability using ANN model. Farooque (2015) compared ANN model with multiple regression (MR) technique to identify the factors responsible for fruit losses in wild blueberry fields. Results of their study suggested that the ANN model was capable to predict fruit losses accurately, when compared to MR predictions.

Wild blueberry harvesting constitutes the major expense in crop production (Yarborough, 1992). Changes in crop conditions (healthy and tall plants, high plant density, and tall weeds) and significant increase in fruit yield have resulted in increased harvesting losses with existing harvesters. Literature research revealed that little work has been conducted regarding the application of ANN model to estimate berry losses for wild blueberry cropping system. Therefore, the objective of this study was to determine the optimum combination of crop characteristics and machine parameters for effective berry recovery during mechanical harvesting using ANN model.

### 6.2 Materials and Methods

Eight wild blueberry fields were selected in Nova Scotia and New Brunswick to develop a predictive model. Yield plots were made randomly in selected fields to collect fruit yield, berry losses and crop characteristics. FY and losses were collected at various combinations of ground speed and header RPM. Detailed procedure about data collection are reported in Chapter 3. The complex interactions between crop characteristics, berry losses and machine operating parameters were studied by employing ANN modeling. The crop characteristic, machine parameters and berry losses were arranged and utilized to develop a model for prediction of berry losses and to suggest optimal operating parameters to enhance berry recovery. The ANN modeling approach has non-linear and multiple processing capabilities. The ANN is a powerful tool capable of performing better than conventional statistical models (Farooque, 2015). The ANN model was developed to predict berry losses as function of several input variables collected from selected wild blueberry fields. Mathematical modeling requires minimum of two datasets; first one for development (training and internal validation) and latter for external validation. Therefore, collected data were combined and utilized as 70% for training and 30% for validation during experimentation. Those points outside the range of input variables were removed from validation data to avoid the extrapolation error). However, the validation data covered all variability in collected data.

Crop characteristics including plant height, plant density, stem diameter, fruit yield, fruit zone, fruit diameter, fruit yield and machine operating parameters were chosen as input variables, to develop the ANN model. Total berry losses during harvesting were selected as an output variable. Data containing both input and output variables were normalized to improve the performance of the model. Normalized data ranged from 0 to 1. Normalized data was transferred into a commercial available Peltarion Synapse software (Peltarion Systems®, Netherlands). The computer software allowed us to predict an optimum combination of ground speed and header RPM of wild blueberry harvester to minimize berry losses during harvesting. Normalized data were mixed using the mixer function of Peltarion Synapse software. The 70% (n = 468) of normalized data were utilized for training and 30% (n = 198) for external validation during model development. A small portion of training data (~15%; n = 72) was reserved for verification or internal validation of the developed model. A back-propagated artificial neural network (BP-ANN) was used to improve the accuracy of developed model by adjusting the weights in hidden and input layers. The BP-ANN process repeats until all given inputs nodes resulted into final output layer. Five mathematical functions were tested including tanh sigmoid, linear, exponential, morlet and logistic sigmoid. Peltarion Synapse is multi-function software and it allowed us to use desired mathematical functions, learning rate and momentum rule, which enhanced the performance of developed networks in terms of MSE, RMSE and coefficient of efficiency (CE).

To predict berry losses during mechanical harvesting, six different architectures were developed and tested to find a suitable mathematical function to process the data. All networks were run at an epoch size of 1000 with the learning rate of 0.1 and momentum rule of 0.7 for each selected mathematical functions during model development. The best mathematical function (tanh sigmoid) was chosen based on minimum MSE and RMSE. The best configured settings were included three weight layers, three function layers, 15 nodes per hidden layers at 25000 epoch size. Once completing these steps, model was configured to have optimum settings (weight layers, function layers, nodes per hidden layer, epoch etc.) for prediction of berry losses during harvesting. Optimal configuration of ANN architecture were achieved based on higher values of $R^2$, lower error rate (MSE and RMSE) and maximum CE. After achieving the proper structure and training of the network, the performance of developed ANN model was assessed for internal and external validations. Detailed procedure can be seen in Chapter 3.

## 6.3 Results and Discussion

### 6.3.1 Summary Statistics of Training and Validation Dataset

Results of summary statistics for training and validation dataset is reported in Table 6-1. Field variability in selected parameters is indicated with the coefficient of variation (CV). The parameters are least variable if CV < 15%, moderate with CV ranging from 15 to 35% and most with CV > 35% (Wilding, 1985).

**Table 6-1:** Summary statistics for the training and validation datasets.

| Parameters | Min | Max | Mean | S.D | C.V (%) | Skewness |
|---|---|---|---|---|---|---|
| **Training Dataset** | | | | | | |
| Speed (km $h^{-1}$) | 1.20 | 2.00 | 1.60 | 0.32 | 20.44 | 0.0 |
| RPM | 26.0 | 30.0 | 28.0 | 1.64 | 5.84 | 0.0 |
| FY (kg $ha^{-1}$) | 305 | 17968 | 5489 | 3007 | 54.78 | 0.63 |
| TL (%) | 5.28 | 27.47 | 14.31 | 5.33 | 37.27 | 0.30 |
| PH (cm) | 9.80 | 39.2 | 23.41 | 4.63 | 19.76 | -0.02 |
| FZ (cm) | 7.80 | 34.6 | 19.13 | 4.36 | 22.80 | 0.09 |
| ST (cm) | 1.14 | 3.96 | 2.39 | 0.31 | 12.97 | 0.52 |
| FD (cm) | 5.15 | 12.35 | 9.18 | 0.92 | 10.01 | -0.07 |
| PD (*) | 244 | 1088 | 570 | 143 | 25.08 | 0.37 |
| **Validation Dataset** | | | | | | |
| Parameters | Min | Max | Mean | S.D | C.V (%) | Skewness |
| Speed (km $h^{-1}$) | 1.2 | 2.0 | 1.60 | 0.32 | 20.44 | 0.0 |
| RPM | 26.0 | 30.0 | 28.0 | 1.64 | 5.84 | 0.0 |
| FY (kg $ha^{-1}$) | 1081 | 15383 | 5537 | 2665 | 48.14 | 0.66 |
| TL (%) | 5.32 | 26.97 | 14.37 | 5.2 | 36.18 | 0.42 |
| PH (cm) | 11.8 | 31.67 | 20.91 | 4.35 | 20.82 | 0.34 |
| FZ (cm) | 9.8 | 28.67 | 17.09 | 3.51 | 20.55 | 0.82 |
| ST (cm) | 1.28 | 3.81 | 2.02 | 0.27 | 13.37 | 1.05 |
| FD (cm) | 6.66 | 11.22 | 8.83 | 0.87 | 9.85 | 0.70 |
| PD (*) | 244 | 933 | 556 | 145 | 26.07 | 0.21 |

**Note:** FY (fruit yield) and TL (total loss) were recorded in kg $ha^{-1}$, PH (plant height) and ST (stem thickness) in cm, and *PD (plant density) was recorded in number of plants per square meter, Speed (km $h^{-1}$), RPM (revolution per minute).

Results of training and validation dataset indicated that the fruit yield (FY) and total losses (TL) were highly variable with the CV > 35%. Plant height (PH), fruit zone (FZ), stem thickness (ST) and plant density (PD) were moderately variable, while the fruit diameter (FD) was least variable in both datasets (Table 6-1). Summary statistics also showed that validation dataset contained all variability, similar to training dataset, which indicates the chances of precise predictions (Farooque, 2015). Variability in fruit losses corresponding with the variability in crop characteristics revealed that the picking performance of the harvester was influenced with the variations in selected parameters.

### 6.3.2 Model Inputs Selection

Better selection of input variables based on the significant relationships can facilitate the performance of the developed networks. Correlation matrix was developed for both training and validation datasets to identify the significant variables affecting on berry losses during mechanical harvesting. Results of correlation matrix indicated that the TL have significant relationships with FY, PH, FZ and PD, while ST and FD found to have non-significant relationship during harvesting (Table 6-2). The PH and PD showed significant negative correlation with TL in both training and validation datasets. The FZ was found to have significant positive correlation with PH (training: r = 0.76 and validation: r = 0.71) in both datasets.

**Table 6-2:** Correlation matrix between berry losses and crop characteristics.

| | Fruit Yield (kg $ha^{-1}$) | Total Losses (%) | Plant Height (cm) | Fruit Zone (cm) | Stem Dia. (cm) | Fruit Dia. (cm) |
|---|---|---|---|---|---|---|
| **Training Data** | | | | | | |
| Total Losses | 0.82*** | | | | | |
| Plant Height | -0.26** | -0.17** | | | | |
| Fruit Zone | -0.21* | -0.14* | 0.76*** | | | |
| Stem Thickness | -0.11* | -0.13$^{NS}$ | 0.69*** | 0.41* | | |
| Fruit Diameter | 0.08$^{NS}$ | -0.07$^{NS}$ | 0.26$^{NS}$ | 0.27* | 0.24$^{NS}$ | |
| Plant Density | 0.43** | -0.52** | -0.24** | -0.25$^{NS}$ | -0.33* | -0.22$^{NS}$ |
| **Validation Data** | | | | | | |
| | Fruit Yield (kg $ha^{-1}$) | Total Losses (%) | Plant Height (cm) | Fruit Zone (cm) | Stem Dia. (cm) | Fruit Dia. (cm) |
| Total Losses | 0.81*** | | | | | |
| Plant Height | -0.19** | -0.14** | | | | |
| Fruit Zone | -0.23 ** | -0.12** | 0.71*** | | | |
| Stem Thickness | -0.09 $^{NS}$ | 0.11$^{NS}$ | -0.62** | -0.31$^{NS}$ | | |
| Fruit Diameter | 0.07$^{NS}$ | -0.11$^{NS}$ | 0.19$^{NS}$ | 0.22* | 0.13$^{NS}$ | |
| Plant Density † | 0.46** | -0.51** | -0.22** | -0.24$^{NS}$ | 0.35* | -0.19$^{NS}$ |

**Note:** Significance of correlations indicated by *, ** and ***, are equivalent to p = 0.05, p = 0.01 and p = 0.001. Where NS, non-significant at p = 0.05. († Plant density = plants/$m^2$)

Visual observation also supported this finding. Since, the PH and FZ were significantly correlated with each other, therefore, only PH was selected as an input. Significant positive correlation of TL with FY was in agreement with the finding of Farooque et al. (2014). Overall, results suggested that the PH, PD and FY were mainly responsible for berry losses during harvesting. Berry losses during harvesting were also influenced by the ground speed and header

RPM either alone or their interaction. Farooque et al. (2014) suggested that a suitable combination of ground speed and header RPM is required to improve berry picking performance of blueberry harvester. Based on results of correlation matrix and findings of previous studies, the FY, PH, PD, ground speed and header RPM were chosen as input variables. Total berry losses during harvesting were selected as an output variable. That would be model output in both training and validation dataset. Results of correlation analysis by Peltarion Synapse software were in agreement with the correlation matrix.

### 6.3.3 Selection of a Mathematical Function

In order to find the best mathematical function, normalized data were imported to Peltarion Synapse software and as inputs and output were defined by using the software interface. The ANN model was trained with six different architectures and mathematical functions to find the best model network for prediction of TL during harvesting (Table 6-3). Minimum value of MSE and RMSE indicated the effectiveness of different mathematical functions (Table 6-3). All selected models were run at an epoch of 5000 with the learning rate of 0.1 and momentum rule of 0.7 in order to have a fair comparison.

**Table 6-3:** Tested mathematical functions to process the normalized data at an epoch size of 5000.

| Sr. No | Model Structure | Mathematical Functions | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Tanh Sigmoid | | Exponential | | Sine | | Logistic Sigmoid | | Morlet | |
| | | MSE | RMSE | MSE | RMSE | MSE | RMSE | MSE | RMSE | MSE | RMSE |
| 1 | 1 W (9/9) and<br>1 F (9/9) layers<br>9 inputs to 1 output | 0.016 | 0.13 | 0.021 | 0.15 | 0.019 | 0.14 | 0.028 | 0.17 | 0.029 | 0.17 |
| 2 | 1 W (9/9) and<br>1 F (9/9) layers<br>5 inputs to 1 output | 0.023 | 0.15 | 0.025 | 0.16 | 0.025 | 0.16 | 0.035 | 0.18 | 0.033 | 0.18 |
| 3 | 2 W (9/12 and 12/7) and<br>2 F (9/12 and 12/7) layers<br>9 inputs to 1 output | 0.019 | 0.14 | 0.034 | 0.18 | 0.022 | 0.15 | 0.048 | 0.22 | 0.042 | 0.21 |
| 4 | 2 W (9/12 and 12/8) and<br>2 F (9/12 and 12/8)<br>5 inputs to 1 output | 0.011 | 0.11 | ∞ | ∞ | 0.017 | 0.13 | ∞ | ∞ | 0.039 | 0.20 |
| 5 | 3 W (9/15, 15/11 and 11/9) and<br>3 F (9/15, 15/11 and 11/9) layers<br>5 inputs to 1 output | 0.0023 | 0.048 | 0.024 | 0.15 | 0.021 | 0.15 | 0.038 | 0.19 | 0.041 | 0.22 |
| 6 | 3 W (9/16, 16/12 and 12/9) and<br>3 F (9/16, 16/12 and 12/9) layers<br>5 inputs to 1 output | 0.009 | 0.094 | 0.022 | 0.15 | 0.031 | 0.18 | 0.032 | 0.18 | ∞ | ∞ |

Where W = Weight layer; F = Function layer and ∞ = Infinity

Tanh sigmoid was the best mathematical function with minimum MSE and RMSE values as compared to all other applied mathematical functions. Results revealed that the tanh sigmoid has better processing capabilities for selected inputs and output data and can best approximate the berry losses during mechanical harvesting (Table 6-3). Results also confirmed the findings of Farooque (2015). Logistic sigmoid function showed deprived performance with higher MSE and RMSE results, which indicated poor architecture performance to predict berry losses. Exponential, morlet and logistic sigmoid functions revealed infinity error for selected architectures, reporting their inability to handle non-linear relationships to predict fruit losses (Table 6-3). These infinity results suggested that the selected model setting was not able to process collected data for better prediction. Overall, the results reported that the tanh sigmoid function with minimum MSE (0.0023) and RMSE (0.048) was able to process this data with higher level of accuracy when compared with other mathematical functions for all developed networks.

### 6.3.4 Development of predictive ANN Model

The selected ANN structure was a multilayer feed-forward neural network. The complexity of proposed model was minimized by choosing appropriate hidden layer, which control convergence of model. The ANN network's prediction capabilities was tested by additional hidden layers (2) but the results did not significantly improve. However, the model was fixed by incorporating three hidden layers, nodes per hidden layer, transfer function (tanh sigmoid) and adjusted weight with function layers (Fig. 6-1). The output layer was fixed in association with transfer function. Several trials were attempted at an epoch interval of 1000 and the errors were recorded. Initially model showed inconsistent results and finally model revealed minimum MSE (0.0023) at an epoch interval of 25,000 (Fig. 6-2). There was no improvement in MSE after epoch size of 25,000, which could be enough for network but model was trained more than 35,000 epochs.

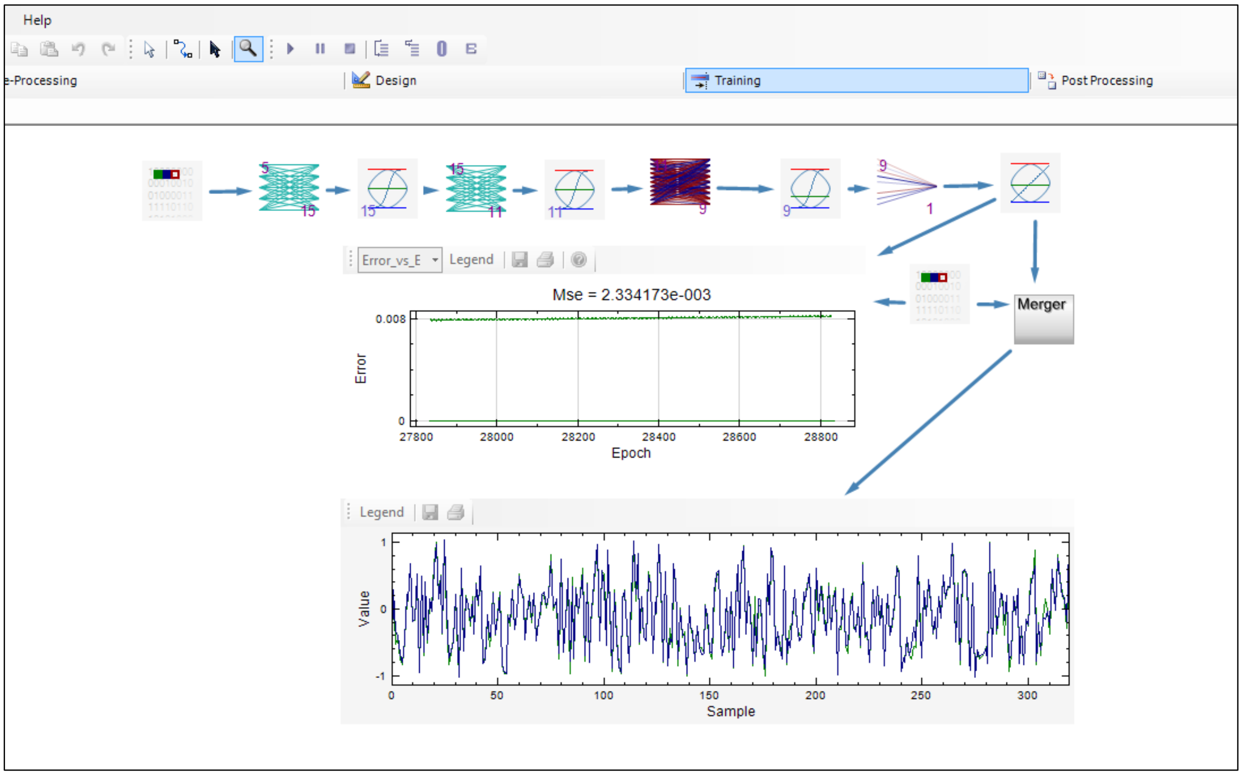



**Figure 6-1:** Optimal configurations of the proposed ANN model parameter settings.

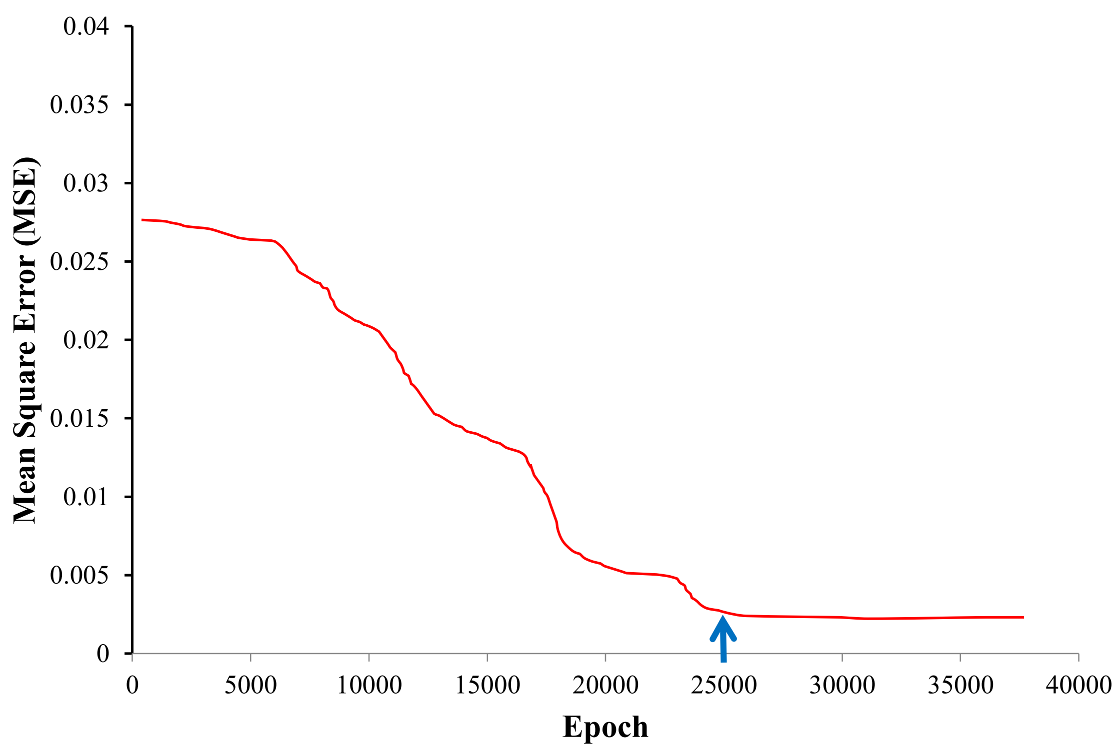



**Figure 6-2:** Relationship between mean square error (MSE) versus Epoch.

Results suggested that the fifth reported model (Table 6-4) was capable of predicting berry losses accurately as compare to other selected networks. This architecture contained 3 W and 3 F layers and revealed significant R2 (0.88), lower MSE (0.0023) and RMSE (0.048) and higher CE (0.83), when compared with other network structures (Table 6-4). Better predictions of ANN model are achieved, when error rate is close to zero (Anyaeche and Ighravwe, 2013). These results were in agreement with Farooque (2015). Results revealed that the actual losses were very close to predicted in all cases, however, model structure 5 was selected for further processing. The selected networks 1, 2, 3,4 and 6 resulted in minimum value of $R^2$ and CE, and higher MSE and RMSE, when compared with structure 5 (Table 6-4). These architectures were not able to predict berry losses accurately during mechanical harvesting. Variability in performance of different models might be due to the differences in the architectural settings of the developed networks.

**Table 6-4:** Developed networks using Tanh Sigmoid function at the epoch size of 35, 000.

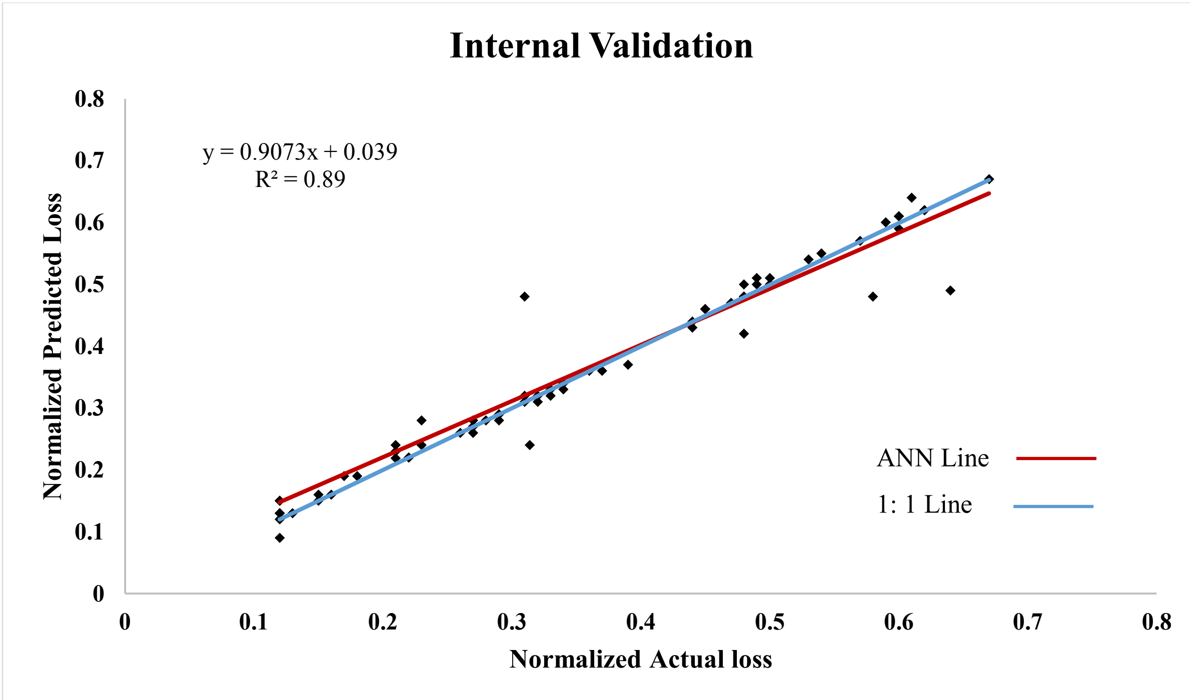
| Sr. No | Model Structure | Actual Losses | Predicted Losses | $R^2$ | MSE | RMSE | CE |
|---|---|---|---|---|---|---|---|
| 1 | 1 W (9/9) and<br>1 F (9/9) layers<br>9 inputs to 1 output | 0.34 | 0.329 | 0.42 | 0.016 | 0.13 | 0.55 |
| 2 | 1 W (9/9) and<br>1 F (9/9) layers<br>5 inputs to 1 output | 0.34 | 0.332 | 0.49 | 0.023 | 0.15 | -0.34 |
| 3 | 2 W (9/12 and 12/7) and<br>2 F (9/12 and 12/7) layers<br>9 inputs to 1 output | 0.34 | 0.324 | 0.53 | 0.019 | 0.14 | 0.28 |
| 4 | 2 W (9/12 and 12/8) and<br>2 F (9/12 and 12/8)<br>5 inputs to 1 output | 0.34 | 0.331 | 0.62 | 0.011 | 0.11 | -0.43 |
| 5 | 3 W (9/15, 15/11 and 11/9) and<br>3 F (9/15, 15/11 and 11/9) layers<br>5 inputs to 1 output | 0.34 | 0.338 | 0.88 | 0.0023 | 0.048 | 0.83 |
| 6 | 3 W (9/16, 16/12 and 12/9) and<br>3 F (9/16, 16/12 and 12/9) layers<br>5 inputs to 1 output | 0.34 | 0.347 | 0.57 | 0.009 | 0.094 | 0.61 |

Where W = Weight layer; F = Function layer; MSE = Mean square error; RMSE = Root mean square error; and CE= Coefficient of efficiency.

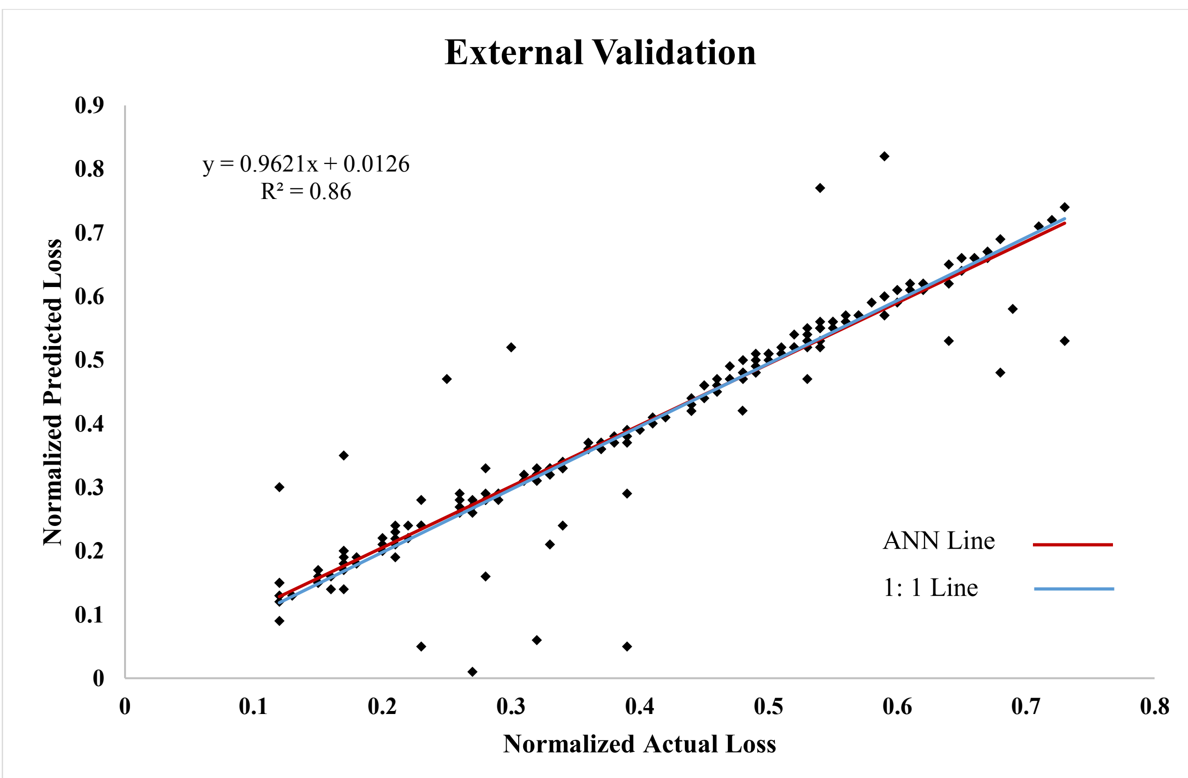
After the optimal configuration of ANN model has achieved, the developed model was validated internally and externally to verify the accuracy of selected model prior to implementation. Langman et al. (2010) reported that the ANN modeling capabilities varied with different datasets, the internal validation presumably resulted in over-and-under fitting the data and contributed to relatively poor performance when compared to training dataset. A linear regression analysis was performed between actual and predicted values to illustrate the prediction performance of the ANN model (Fig. 6-3, a & b). The model accuracy was tested by performing the internal and external validations. Higher value of regression coefficient ($R^2 = 0.89$) for internal validation dataset suggested that the model was well trained and predicted fruit losses accurately and reliably. Based on the results of this study, the proposed settings of developed ANN model are tabulated in Table (6-5). The trained model was verified with external validation dataset to examine its efficiency in predicting berry losses as function of several input variables. Results of external validation suggested that the developed model performed external validations with significantly higher accuracy ($R^2$ = 0.86). Minasny and McBratney (2002) reported that the prediction capabilities of ANN model can be improved by more input and by increasing the magnitude of the dataset. Overall, the selected ANN model (structure 5) performed accurate predictions for total losses during mechanical harvesting of wild blueberries.

**Table 6-5:** Proposed ANN model parameter settings.

| **Parameters** | **Settings** |
|---|---|
| Training pattern | 70% |
| Optimum Epoch | 25000 |
| Verification pattern | 15% |
| Number of hidden layers | 3 |
| Number of function layers | 4 |
| Learning rate | 0.1 |
| Momentum | 0.7 |
| Mathematical Function | Tanh Sigmoid |
| External validation | Independent data set (30%) |




(a)




(b)

**Figure 6-3:** Scatter plots of actual and predicted values, (a) Internal validation of training dataset and (b) External validation of independent dataset.

## 6.4 Optimum Combination of Crop Characteristics and Machine Parameters

After development and accurate predictions of ANN model for berry losses, the processed data were categorized into four classes of berry losses (< 10%, 10-15%, 15-20% and > 20%), to determine the optimum combination of crop characteristics and machine parameters for effective berry picking during mechanical harvesting.

**Table 6-6:** Summary statistics of training and validation dataset to configure optimal operating parameters for efficient harvesting.

| Class | Speed (km $h^{-1}$) | RPM | FY (kg $ha^{-1}$) | PH (cm) | PD (plants/$m^2$) | FZ (cm) | Mean Loss (%) |
|---|---|---|---|---|---|---|---|
| **Training** | | | | | | | |
| < 10% | 1.2 | 26 | 4326 | 23.46 | 600 | 21.13 | 7.8 |
| 10-15% | 1.2 | 28 | 5918 | 23.92 | 480 | 22.28 | 12.47 |
| 15-20% | 1.6 | 28 | 6546 | 29.23 | 560 | 27.81 | 17.26 |
| > 20% | 2 | 30 | 5521 | 17.24 | 440 | 15.43 | 23.13 |
| **Validation** | | | | | | | |
| Class | Speed (km $h^{-1}$) | RPM | FY (kg $ha^{-1}$) | PH (cm) | PD (plants/$m^2$) | FZ (cm) | Mean Loss (%) |
| < 10% | 1.2 | 26 | 4243 | 22.85 | 570 | 21.16 | 8.29 |
| 10-15% | 1.2 | 28 | 5879 | 21.11 | 480 | 20.27 | 12.06 |
| 15-20% | 1.6 | 28 | 6477 | 28.65 | 540 | 26.92 | 17.02 |
| > 20% | 2 | 30 | 5436 | 17.93 | 520 | 14.08 | 22.56 |

Results showed that the berry losses were lower (< 10%) in in high FY (FY > 3000 kg $ha^{-1}$), short plants (PH ≤ 25 cm), high PD (PD > 530 plants/$m^2$) and higher FZ (FZ > 17 cm) plots. The best operating combination for this category was 1.2 km $h^{-1}$ and 26 header RPM (Table 6-6). Results also revealed that berry losses were increased with increase in ground speed and RPM in higher FY, PH and FZ plots within the fields (Table 6-6). Higher berry losses (> 20%) were observed in high yielding plots with short PH (PH ≤ 25 cm) and low PD (PD ≤ 530 plants/$m^2$) at 2 km $h^{-1}$ and 30 header RPM. Higher berry losses in high yielding plots could be due to the harvester's interference with low PH and FZ plants. Another reason for this observation might be the lodging of crop resulting in poor performance of harvester. Operating a harvester at higher ground speed in combination with higher RPM of the header can increase berry losses during harvesting. These results were in agreement with the finding of Farooque (2015).

Results revealed mix trend for berry losses at selected combinations of ground speed and header RPM in relation to variable crop characteristics within selected fields (Table 6-7). Minimum berry losses were found in experimental plots with higher FY, PH, PD and FZ at 1.2 km $h^{-1}$ and 26 RPM of harvester (Table 6-7). Results indicated that the berry losses in some plots were more due to increase in FY and reduction in crop characteristics such as PH or PD (Table 6-7). Lower FY in conjunction with low PH and PD resulted in an increased fruit losses during mechanical harvesting. Possible reason for this observation could be the low plant stature with low FZ, where the harvester was not able to pick berries more effectively. Higher berry losses were obtained at 2 $kmh^{-1}$ with 30 RPM in high yielding plots (Table 6-7). Results reported that the low PD was responsible for increased losses. Results further narrated that the increase in machine operating parameters (ground speed and RPM) led to an increase berry losses during mechanical harvesting. Based on these results, it is concluded that the harvesting losses can be reduced by operating the harvester at a ground speed of 1.2 $kmh^{-1}$ in combination with 26 header RPM of the harvester in spatially variable plant characteristics within selected wild blueberry fields.

**Table 6-7:** Predictive berry losses at different combination of machine parameters and crop characteristics.

| Speed (km $h^{-1}$) | RPM | FY (kg $ha^{-1}$) | PH (cm) | PD (plants/$m^2$) | FZ (cm) | Mean Loss (%) |
|---|---|---|---|---|---|---|
| 1.2 | 26 | 4241.69 | 24.21 | 600 | 23.40 | 10.85 |
| 1.2 | 28 | 3125.30 | 28.60 | 560 | 27.75 | 13.03 |
| 1.2 | 30 | 5685.03 | 22.95 | 460 | 20.66 | 14.34 |
| 1.6 | 26 | 3795.78 | 19.31 | 650 | 18.82 | 12.49 |
| 1.6 | 28 | 2818.85 | 23.60 | 570 | 19.54 | 14.43 |
| 1.6 | 30 | 5705.32 | 24.31 | 575 | 22.86 | 15.21 |
| 2.0 | 26 | 4842.45 | 17.67 | 440 | 17.12 | 16.03 |
| 2.0 | 28 | 5430.70 | 27.73 | 620 | 25.33 | 16.84 |
| 2.0 | 30 | 6061.99 | 22.97 | 463 | 21.16 | 19.23 |

## 6.5 Conclusion

Results of this study proved that the ANN model was accurate and reliable to predict berry losses as function of crop characteristics and machine operating parameters during mechanical harvesting. Minimum value of MSE and RMSE in training process of model and higher value of $R^2$ in internal and external validation datasets, confirmed the accuracy of ANN model for better predictions. Based on the results of this study, it is suggested that berry yield can be improved to operate the harvester at 1.2 km $h^{-1}$ ground speed and 26 header RPM in conjunction with optimum crop characteristics, *i.e.,* average plant height (24 cm), average plant density (570 plants/$m^2$), average fruit yield (4300 kg $ha^{-1}$) and average fruit zone (23 cm). It is also suggested that that the developed model will help to construct an interface using C Sharpe programming language for the automation of the wild blueberry harvester. Moreover, reduction in berry losses by implementing appropriate operational settings, will generate more revenue for farmers with no additional cost to justify the ever increasing cost of production.

# CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS

The overall objective of this study was to find an optimum combination of crop characteristics and machine parameters to reduce berry losses during mechanical harvesting of wild blueberry. Crop characteristics were classified into two categories (plant characteristics and fruit characteristics), and the harvester was operated at different combinations of ground speed (1.2, 1.6 and 2.0 km $h^{-1}$) and header rpm (26, 28 and 30). Results of this study revealed that crop characteristic were substantially variable within selected fields. The wild blueberry harvester performance for berry picking was better in short plant (PH ≤ 25 cm) areas of the field. Berry losses were increased in tall plants (PH > 25 cm) areas of the field at all combination of machine parameters (speed and RPM) than short plants. Results suggested that appropriate head height adjustment based on the variation in plant characteristics can reduce berry losses during harvesting. Berry losses were observed higher on the ground in less dense plant (PD ≤ 530 plants/$m^2$) areas than high dense plant areas of the selected wild blueberry fields. The reason might be due to the more impact force of picker bar on less dense plants than high density plants. ANCOVA results of plant characteristics reported that the berry losses were significantly influenced by interaction effect (Speed × RPM) ($p < 0.05$) in all selected categories of plant characteristics. Results of multiple mean comparison suggested that wild blueberry harvester picked the berries effectively at 1.2 km $h^{-1}$ and 26 RPM with minimum berry losses (< 10%) whereas increase in the ground speed and RPM resulted in higher berry losses.

Fruit characteristics results reported that harvester revealed the poor picking performance in low FZ areas (FZ ≤ 17 cm). Harvester could not easily pick the berries in those areas where the plants were lodged due high berry yielding with low FZ plants. However, minimum berry losses were observed in high FZ areas (FZ > 17 cm) as compared to low FZ areas. Visual observations indicated that operator need to adjust the head height according to variation in FZ of the field. Berry losses were minimum in high berry yield areas (FY > 3000 kg $ha^{-1}$) at lower combination of ground speed (1.2 km $h^{-1}$) and header RPM (26) as compared to grower's combination (1.6 km $h^{-1}$ and 28 RPM). Results indicated that the berry losses were increased in high or low FY plots by increasing in ground speed and header RPM to more than 1.2 km $h^{-1}$ and 26 RPM. Significant results of ANCOVA for fruit characteristics is showed that harvesting operating parameters (Speed × RPM) were affected the berry losses during mechanical harvesting in all categories of fruit characteristics. ANCOVA results also indicated that berry losses were affected by fruit diameter in high FY plots. It might be possible due to the berries moved or spilled away during combing action of picker bars in high yielding plots. Results of multiple mean comparison for selected fruit characteristics suggested that combination of lower ground speed (1.2 km $h^{-1}$) with lower RPM (26) improved the picking performance of wild blueberry harvester.

Results of artificial neural network (ANN) modeling approach suggested that the developed model was able to predict the berry losses as function of crop characteristics and machine operating parameters during mechanical harvesting. The minimum value of MSE (0.0023) indicated that the model was well structured to estimate the berry losses during harvesting. The ANN model prediction was also confirmed with internal and external validation datasets. Summary statistics of ANN model prediction concluded that berry losses were minimum at optimum harvesting parameters, *i.e.,* 1.2 $kmh^{-1}$ ground speed and 26 header RPM and optimum crop characteristics including average plant height (24 cm), average plant density (570 plants/$m^2$), average fruit yield (4300 kg $ha^{-1}$) and average fruit zone (23 cm).

Based on the results from this study, it is suggested that picking performance of the harvester can be enhanced by using optimum machine settings based on the variations in plant and fruit characteristics within wild blueberry fields. Machine vision linked with enhanced sensing system technology in wild blueberry cropping system, can increase the level of automation of the harvester. Automation can improve real-time decision making of the harvester's controls to minimize berry losses. Operator's stress can also be reduced during harvesting by real-time adjustments of head height, ground speed, header RPM, and bin handling. Furthermore, it is also suggested that the modeling approach can be further improved in the wild blueberry harvesting. Input variables such as environmental factors, time of harvest, topographic features, and soil properties could be included to improve the accuracy of the model. The addition of these input variables aid to develop a user friendly computer interface, which will help the operator to reduce berry losses during harvesting. It will increase harvestable berry yield without additional production cost that ultimately increase farm revenue.

## REFERENCES


Abdalla, D. A. 1963. Raking and Handling of Lowbush Blueberries. Univ. Maine Coop. Ext. Bulletin No. 497. Orono, ME.

Adams, R. M., B. H. Hurd, S. Lenhart, and N. Leary. 1998. Effects of global climate change on agriculture: An interpretative review. Clim. Res. 11(1): 19-30.

Alvarez, R. 2009. Predicting average regional yield and production of wheat in the Argentine Pampas by an artificial neural network approach. Eur. J. Agron. 30: 70-77.

Ampatzidis, Y. G., Li Tan, R. Haley, R. Wortman, and M. D. Whiting. 2012. Harvest Management Information System for Specialty Crops. ASABE Paper No. 131596473.

Anyaeche, C. O. and D. E. Ighravwe. 2013. Predicting performance measures using linear regression and neural network: A comparison. Afr. J. Eng. Res. 1(3): 84-89.

Barker, W. G., I. V. Hall, and G. W. Wood. 1964. The lowbush blueberry industry in eastern Canada. Econ. Bot. 18: 357-365.

Batchelor, W., X. Yang, and A. Tschanz. 1997. Development of a neural network for soybean rust epidemics. Trans. of the ASAE. 40: 247-254.

Bell, H. P. 1950. Determinate growth in the blueberry. Can. J. Res. Com. 28: 637-644.

Bigras-Huot, F., L. Huot, and L. J. Jobin. 1972. La pollinisation du bleuet au Lac-St-Jean. I. Role de l'abeille domestique, Apis mellifera. Ann. Soc. Entomol. Que. 17: 138-169.

Bishop, M. C. 1994. Neural networks and their applications. Rev. Sci. Inst. 64: 1803-1831.

Bishop, M. C. 1995. Neural Networks for Pattern Recognition. Clarendon Press, OX.

Bourguignon, C., D. C. Percival, J. P. Privé, and R. Robinson. 2006. Spatial variation of wild blueberry N, P, and K levels using hyperspectral techniques. Can. J. Plant Sci. 86(5): 1434-1435.

Braddock, R. D., M. L. Kremmer, and L. Sanzogni. 1998. Feed-forward artificial neural network model for forecasting rainfall run-off. Environmetrics. 4: 19-32.

Braga, R. P. 2000. Predicting the Spatial Pattern of Grain Yield under Water Limiting Conditions. Ph.D. Dissertation. University of Florida, Gainesville, FL.

Bryant, C. R., B. Smit, M. Brklacich, T. R. Johnston, J. Smithers, Q. Chiotti, and B. Singh. 2000. Adaptation in Canadian Agriculture to Climatic Variability and Change. *In:* S. M. Kane and G. W. Yohe (eds.). Societal Adoption to Climate Variability and Change, pp. 181-201. Dordrecht, Kluwer Academic. The Netherlands.

Campbell, A. 2008. Valuation of Honey Bee Pollination in Canada in 2008. Market Industries and Services Branch, Agriculture and Agri Food Canada, Government of Canada. Ottawa, ON.

Chandler, F. B. and I. C. Mason. 1946. Blueberry Weeds in Maine and Their Control. Maine Agri. Exp. Sta. Bulletin No. 433. Orono, ME.

Chen, Y. R., M. Nguyen, and B. Park. 1998. Neural network with principal component analysis for poultry carcass classification. J. Food Proc. Eng. 21: 351-367.

Chen, C. R., H. S. Ramaswamy, and I. Alli. 2001. Prediction of quality changes during osmo-convective drying of blueberries using neural network models for process optimization. Drying Tech. 19(3-4): 507-523.

Chen, D., X. Du, Q. Zhang, M. Whiting, P. Scharf, and S. Wang. 2012. Performance evaluation of mechanical cherry harvesters for fresh market grade fruits. Appli. Eng. Agric. 28(4): 483-489.

Chris, J. 2008. Basic Blueberries: An Introduction to Growing Wild Blueberries on Prince Edward Island. Agdex 235/05. Department of Agriculture, Charlottetown, PEI.

Clapham, W. and J. Fedders. 2004. Modeling vegetative development of berseem clover *(Trifolium alexandrinum L.)* as a function of growing degree days using linear regression and neural networks. Can. J. Plant Sci. 84: 511-517.

Cybenko, G. 1989. Approximations by superimpositions of a Sigmoid function. Math. Cont. Signal Syst. 2: 303-314.

Dale, A. E., J. Hanson, D. E. Yarborough, R. J. McNicol, E. J. Stang, R. Brenan, J. Morris, and G. B. Hergert. 1994. Horticulture Reviews. John Wiley & Sons. NY.

Dale, M. 1999. Wild Blueberry Production and Marketing in Nova Scotia: A Situation Report. Nova Scotia Department of Agriculture and Marketing, Nappan, NS.

DeGomez, T. and J. Smagula. 1990. Mulching for Improved Plant Cover. Univ. Maine Coop. Ext. Fact Sheet No. 228. Orono, ME.

Drummond, F. 2012. Commercial bumble bee pollination of lowbush blueberry. Int. J. Fruit Sci. 12: 54-64.

Eaton, E. L. 1950. Blueberry Culture and Propagation. *In:* The Blueberry. Publ. 754. Pages 1-25. Canadian Department of Agriculture, Ottawa, ON.

Eaton, L. J. 1988. Nitrogen Cycling in Lowbush Blueberry Stands. Ph.D. Dissertation. Nova Scotia Agricultural College, Truro, NS.

Eaton, L. J. 1994. Long-term effects of herbicide and fertilizers on lowbush blueberry growth and production. Can. J. Plant Sci. 74: 341-345.

Eaton, L. J., G. W. Stratton, and K. R. Sanderson. 1997. Fertilizer phosphorus in lowbush blueberries: effects and fate. Acta. Hort. 446: 447-486.

Eaton, L. J. and K. Jensen. 1997. Protection of Lowbush Blueberry Soils from Erosion. Nova Scotia Wild Blueberry Network Info Centre. Retrieved from: www.nsac.ca/wildblue/facts/weeds/bbweed.asp. Accessed: September 15, 2014.

Eaton, L. J., R. W. Glen, and J. D. Wyllie. 2004. Efficient mowing for pruning wild blueberry fields. Small Fruits Rev. 3: 123-131.

Eaton, L. J. and V. O. Nams. 2006. Second cropping of wild blueberries: Effects of management practices. Can. J. Plant Sci. 86: 1189-1195.

Eaton, L. J. and V. O. Nams. 2012. Honey bee stocking numbers and wild blueberry production in Nova Scotia. Can. J. Plant Sci. 92: 1305-1310.

Esau, T. J., Q. U. Zaman, Y. K. Chang, A. W. Schumann, D. C. Percival, and A. A. Farooque. 2014. Prototype variable rate sprayer for spot-application of agrochemicals in wild blueberry. Appli. Eng. Agric. 30(5): 717-725.

Farooque, A. A., Y. K. Chang, Q. U. Zaman, D. Groulx, A. W. Schumann, and T. J. Esau. 2013. Performance evaluation of multiple ground based sensors mounted on a commercial wild blueberry harvester to sense plant height, fruit yield, and topographic features in real-time. Comp. Elec. Agri. (91): 135-144.

Farooque, A. A., Q. U. Zaman, D. Groulx, A. W. Schumann, D. E. Yarborough, and T. Nguyen-Quang. 2014. Effect of ground speed and header revolutions on the picking efficiency of a commercial wild blueberry harvester. Appli. Eng. Agric. 30(4): 535-546.

Farooque, A. A. 2015. Performance Evaluation of a Commercial Wild Blueberry Harvester using Precision Agriculture Technologies and Mathematical Modeling. Ph. D. Dissertation. Dalhousie University, Halifax, NS.

Fast, M. and T. Palme. 2010. Application of artificial to the condition monitoring and diagnosis of a combined heat and power plant. Energy. 35(2): 1114-1120.

Grant, D. C. and B. A. Lamson. 1972. Berry Picking Machine. U. S. Patent No. 367,692.

Gray, L. G. 1969. Development of a Hollow Reel Raking Mechanism for Harvesting Lowbush Blueberries. Master's thesis. University of Maine, Orono, ME.

Hakimpoor, H., K. Arshad, H. Tat, N. Khani, and M. Rahmandoust, 2011. Artificial neural networks applications in management. World Appl. Sci. J. 14(7): 1008-1019.

Hall, I. V. 1955. Floristic changes following the cutting and burning of a woodlot for blueberry production. Can. J. Agri. Sci. 35: 143-152.

Hall, I. V., L. E. Aalders, N. L. Nickerson, and S. V. Kloet. 1979. The biological flora of Canada. I. *Vaccinium angustifolium* Ait., sweet lowbush blueberry. Can. Field Nat. 93: 415-430.

Hall, I. V., D. L. Craig, and R. A. Lawrence. 1983. A comparison of hand raking and mechanical harvesting of lowbush blueberries. Can. J. Plant Sci. 63: 951-954.

Haykin, S. 1999. Neural Networks: A Comprehensive Foundation. 2$^{nd}$ ed. Prentice Hall PTR, Upper Saddle River, NJ.

Hepler, P. R. and A. A. Ismail. 1985. The split block design: A useful design for extension and research in lowbush blueberries. Hort. Sci. 20: 735-737.

Hepler, P. R. and D. E. Yarborough. 1991. Natural variability in yield of lowbush blueberries. Hort. Sci. 26: 245-246.

Hiregoudar, S., R. Udhaykumar, K. Ramappa, B. Shreshta, V. Meda, and M. Anantachar. 2011. Artificial neural network for assessment of grain losses for paddy combine harvester anovel approach. Comm. Comp. Inform. Sci. 140(3): 221-231.

Holbein, J. P. 1991. Mimeo Publication of North American Blueberry Council. *In:* Blueberries'91. Marmora, NJ.

Holshouser, D. 2011. Hurricane Irene May be Beneficial to Virginia Soybeans… Still Lodging Will Reduce Yield Potential. Virginia Coop. Ext. Retrieve from: http://blogs.ext.vt.edu. Accessed: April 23, 2014.

Hornik, K., M. Stinchcombe, and H. White. 1989. Multilayer feed forward networks are universal approximators. Neural Netw. 2: 359-366

Huang, W. and S. Foo. 2002. Neural network modeling of salinity variation in Apalachicola River. Water Res. 36: 356-362.

Huang, W., C. Murray, N. Kraus, and J. Rosati. 2003. Development of a regional artificial neural network prediction for coastal water level prediction. Ocean Engin. (30): 2275-2295.

Huitink, G. 2013. Harvesting Soybeans. Arkansas Soybean Handbook. Retrieved from: http://www.uaex.edu/Other_Areas/publications/PDF/MP197/MP197.pdf. Accessed: March 26, 2015.

Ismail, A. A. and D. E. Yarborough. 1979. Pruning Lowbush Blueberries Review and Update. *In:* J. N. Moore (ed.), Proc. Fourth North Amer. Blueberry Res. Workers Conf. Univ. pp. 87-95. Ark. Fayetteville, AR.

Ismail, A. A., J. M. Smagula, and D. E. Yarborough. 1981. Influence of pruning method, fertilizer, and terbacil on the growth and yield of the lowbush blueberry. Can. J. Plant Sci. 61: 61-71.

Ismail, A. A. and E. J. Hanson. 1982. Interaction of method and date of pruning on growth and productivity of the lowbush blueberry. Can. J. Plant Sci. 62: 677-682.

Ismail, A. A. 1987. Honeybees and Blueberry Pollination. Univ. Maine Coop. Ext. Bulletin No. 629. Orono, ME.

Janet, G. 2015. Personal Communication. Administrative Assistant. Wild Blueberry Producers Association of Nova Scotia, Debert, NS.

Jeliazkova, E. and D. C. Percival. 2003. Effect of drought on ericoid mycorrhizae in wild blueberry *(Vaccinium angustifolium* Ait*.)*. Can. J. Plant Sci. 83: 583-586.

Jensen, K. 1985. Weed control in lowbush blueberries in eastern Canada. Acta. Hort. 165: 259-265.

Jensen, K. and E. R. Kimball. 1985. Tolerance and residues of hexazinone in lowbush blueberries. Can. J. Plant Sci. 65: 223-227.

Jensen, K. and E. G. Specht. 2002. Response of lowbush blueberry *(Vaccinium angustifolium)* to hexazinone applied early in the fruiting year. Can. J. Plant Sci. 82: 781-783.

Karmo, E. A. 1974. Blueberry pollination-problems, possibilities. Publ. 109. Nova Scotia Department of Agriculture and Marketing. Truro, NS.

Kaul, M., R. Hill, and C. Walthall. 2005. Artificial neural networks for corn and soybean yield prediction. Agric. Syst. 85: 1-18.

Kennedy, K., N. S. Boyd, and V. O. Nams. 2010. Hexazinone and fertilizer impacts on sheep sorrel *(Rumex acetosella L.)* in wild blueberry. Weed Sci. 58: 317-322.

Kinsman, G. 1993. The History of Lowbush Blueberry Industry in Nova Scotia 1950-1990. Wild Blueberry Producers' Association, pp. 153. Debert, NS.

Langman, O., P. Hanson, S. Carpenter, and Y. Hu. 2010. Control of dissolved 316 oxygen in northern temperate lakes over scales ranging from minutes to days. Aquatic Biol. 9: 193-202.

Litten, W., J. Smagula, and S. Durham. 1997. Blueberry Surprise from Phosphorus. Maine Agri. Exp. Sta. Ann., Report 401. Orono, ME.

MacAulay, J. T. 1975. A final report on the development a mechanical harvester for lowbush blueberries. Nova Scotia Agricultural College. Truro, NS.

Madadlou, A., Z. Emam-Djomeh, M. E. Mousavi Ehsani, M. Javanmard, and D. Sheehan. 2009. Response surface optimization of an artificial neural network for predicting the size of reassembled casein micelles. Comp. Elect. in Agric. 68: 216-221.

Maier, H. R. and G. C. Dandy. 2000. Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications. Environ. Model. Softw. 15(1): 101-124.

Mainland, C. M. 1993. Blueberry production strategies. Acta. Hort. 346: 111-116.

Maurin, A. C. 2009. Perdas na Colheita Mecanizada da SOJA-Safra 2008/2009. EMATER /SEAB EMBRAPA-Soja /Londrina Curitiba. Brazil.

McCulloch, W. and W. Pitts. 1943. A logical calculus of the ideas immanent in nervous activity. Bull. Math Biophys. 5: 115-133.

McCully, K. V., M. G. Sampson, and A. K. Watson. 1991. Weed survey of Nova-Scotia lowbush blueberry *(Vaccinium angustifolium)* fields. Weed Sci. 39: 180-185.

Mckiel, C. 1958. The Design a Development of a Pneumatic Blueberry Harvester. Master's thesis. University of Maine, Orono, ME.

Melanson, M. 2015. Personal Communication. Crop Specialist, New Brunswick Department of Agriculture, Aquaculture, and Fisheries, Moncton, NB.

Metzger, H. B. and A. A. Ismail. 1976. Management practices and cash operating costs in lowbush blueberry production. Maine Agri. Exp. Sta. Ann., Report 723. Orono, ME.

Minasny, B. and A. B. McBratney. 2002. The neuro-m methods for fitting neural network parametric pedotransfer functions. Soil Sci. Soc. Am. J. 66: 352-361.

Montgomery, D. C. 2009. Design of analysis of experiments. 7th ed. John Wiley and Sons, NY.

Morse, R. A. and N. W. Calderone. 2000. The value of honey bees as pollinators of US crops in 2000. Bee Culture: 128: 1-15.

Pahlavan, R., M. Omid, and A. Akram. 2012. Energy input-output analysis and application of artificial neural networks for predicting greenhouse basil production. Energy. 37:171-176.

Patrick, A. R., W. G. Collins, P. E. Tissot, A. Drikitis, J. Stearns, P. R. Michaud, and D. T. Cox. 2002. Use of the NCEP MesoEta Data in a Water Level Predicting Artificial Neural Network. *In*: Proc. of 19th Conf. on Weather Analysis and Forecasting/15th Conf. on Numerical Weather Prediction. pp. 1-4. San Antonio, TX.

Patten, K. D. and J. Wang. 1994. Cranberry yield and fruit-quality reduction caused by weed competition. Hort. Sci. 29: 1127-1130.

Paulo, J., P. J. Lisboa, and A. G. Taktak. 2006. The use of artificial neural networks in decision support in cancer: A systematic review. Neural Netw. 19: 408-415.

Penney, B. G. and K. B. McRae. 2000. Herbicidal weed control and crop-year NPK fertilization improves lowbush blueberry *(Vaccinium angustifolium Ait.)* production. Can. J. Plant Sci. 80: 351-361.

Penney, B. G., K. B. McRae, and A. F. Rayment. 2008. Effect of long-term burn-pruning on the flora in a lowbush blueberry *(Vaccinium angustifolium Ait.)* stand. Can. J. Plant Sci. 88: 351-362.

Percival, D. C. and J. P. Privé. 2002. Nitrogen formulation influences plant nutrition and yield components of lowbush blueberry *(Vaccinium angustifolium Ait.).* Acta. Hort. 574: 347-355.

Percival, D. C. and K. R. Sanderson. 2004. Main and interactive effects of vegetative year applications of nitrogen, phosphorus and potassium fertilizer. Small Fruit Rev. 3: 105-122.

Percival, D. C. and J. Dawson. 2009. Foliar disease impact and possible control strategies in wild blueberry production. Acta. Hort. 810: 345-354.

Perron, J. M. 1985. La pollinisation du bleuet nain. Vaccinia. 10: 3-13.

Philbrook, B. D., E. S. Oplinger, and B. E. Freed. 1991. Solid-seeded soybean cultivar response in three tillage systems. J. Prod. Agric. 4: 86-91.

PMRA (Pesticide Risk Reduction Program). 2005. Crop Profile for Wild Blueberry in Canada. Annual report, Agriculture and Agri-Food Canada. Retrieved from: http://www4.agr.gc.ca/resources/prod/doc/prog/prrp/pdf/blueberry_e.pdf. Accessed: April 23, 2014.

Qin, He. 1999. Neural Network and Its Application in IR. University of Illinois at Urbana-Champaign. IL, USA.

Rabcewicz, J. and J. Danek. 2010. Evaluation of mechanical harvest quality of primocane raspberries. J. Fruit and Orna. Plant Res. 18(2): 239-248.

Richard, P. 1982. Development of a Mechanical Harvester for Lowbush Blueberries. Final Project Report. Agricultural Engineering Department, Nova Scotia Agricultural College, Truro, NS.

Rhodes, R. B. 1961. The harvesting of lowbush blueberries. ASAE Paper No. NA61-206.

Saanzogni, L. and D. Kerr. 2001. Milk production estimate using feed forward artificial neural networks. Comp. Elect. Agric. 32: 21-30.

Sablani, S. S., H. S. Ramaswamy, and S. O. Prasher. 1995, A neural network approach for thermal processing applications, J. Food Proc. Presrv. 19: 283-301.

Saleem, S. R. 2012. Variable Rate Fertilization in Wild Blueberry Fields to Improve Crop Productivity and Reduce Environmental Impacts. Master's thesis. Nova Scotia Agricultural College/ Dalhousie University, Halifax, NS.

Salter, P., I. Currah, and J. R. Fellows. 1980. Further studies on the effects of plant density, spatial arrangement and time of harvest on yield and root size in carrots. J. Agric. Sci. 94: 465-478.

Sanderson, K. R. and L. J. Eaton. 2004. Gypsum-An alternative to chemical fertilizers in lowbush blueberry production. Small Fruit Rev. 3: 57-71.

Savoie, L., P. Aras, and D. de. Oliveira. 1993. Influence d'un gradient d'abeilles domestiques sur la production du bleuet nain au Saguenay-Lac-St-Jean. Rapport d'etape (1992-93) presente a Agriculture Canada. Universite du Quebec a Montreal. QC.

Setiono, R., W. K. Leow, and J. L. Thong. 2000. Opening the Neural Network Black Box: An Algorithm for Extracting Rules from Function Approximating Artificial Neural Networks. Proc. Int. Conf. on Information Systems, pp. 176-186. BNE.

Shahin, M. A, M. B. Jaksaand, and H. R. Maier. 2001. Artificial neural network applications in geotechnical engineering. Austr. Geomech. 36(1): 49-62.

Sibley, J. K. 1992. Lowbush Blueberry Production and Marketing in Nova Scotia. A Situation Report. pp 2. Nova Scotia Department of Agriculture and Marketing. Truro, NS.

Sibley, J. K. 1994. Wild blueberry harvesting technologies: Engineering assessment. Can. Agri. Engineering. 35: 33-39.

Simon, H. A. and P. Langley. 1995. Applications of machine learning and rule induction. Comm. ACM. 38(11): 54-64.

Smagula, J. M. and A. A. Ismail. 1981. Effects of fertilizer application, preceded by terbacil, on growth, leaf nutrient concentration, and yield of the lowbush blueberry, *Vaccinium angustifolium* Ait. Can. J. Plant Sci. 61: 961-964.

Smagula, J. M. and S. Dunham. 1995. Pruning method affects lowbush blueberry yields. Hort. Sci. 784: 4-30.

Smagula, J. M. and D. E. Yarborough. 1999. Leaf and Soil Sampling Procedures. Univ. Maine Coop. Ext. Fact Sheet No. 222. Orono, ME.

Smith, D. W. and R. J. Hilton. 1971. Comparative effects of pruning by burning or clipping on lowbush blueberries in north-eastern Ontario. J. Appli. Eco. 8: 781-783.

Sobri, H., N. I. Nor, and A. H. Kassim. 2012. Artificial neural network model for rainfall–runoff relationship. J. Teknol. 37(1): 1-12.

Solomatine, D. P. and Ostfeld. 2008. A. Data-driven modelling: some past experiences and new approaches. J. Hydroinform. 10(1): 3-22.

Soule, H. M. 1969. Developing a lowbush blueberry harvester. Trans. of the ASAE. 127-129.

Soule, H. M. and G. L. Gray. 1972. Performance Tests for a Lowbush Blueberry Harvester. CSAE. pp. 72-316. Saskatoon, SK.

Stubbs, C. S. and F. A. Drummond. 2001. Bombus impatiens (Hymenoptera: Apidae): An alternative to Apis mellifera (Hymenoptera: Apidae) for lowbush blueberry pollination. J. Econ. Ento. 94: 609-616.

Takeda, F., G. Krewer, E. L. Andrews, B. Mullinix, and D. L. Peterson. 2008. Assessment of the V45 blueberry harvester on rabbiteye blueberry and southern highbush blueberry pruned to V-shaped canopy. Hort. Tech. 18: 130-138.

Torrecilla, J., L. Otero, and P. Sanz. 2004. A neural network approach for thermal/pressure food processing. J. Food Eng. 62: 89-95.

Townsend, L. R. and I. V. Hall. 1970. Trends in nutrient levels of lowbush blueberry leaves during four consecutive years of sampling. Can. Naturalist. 97: 461-466.

Trevett, M. F. 1959. Growth Studies of Lowbush Blueberry. Lowbush Blueberries. Maine Agri. Exp. Sta. Bulletin No. 581. Orono, ME.

Trevett, M. F. 1962. Nutrition and Growth of the Lowbush Blueberry. Maine, Agri. Exp. Sta. Bulletin No. 605. Orono, ME.

Trevett, M. F. and R. E. Durgin. l972. A progress report on pruning Iowbush blueberries with paraquat, dinitro herbicides and mowing. Res. Life Sci. 19(17): 1-4.

USDA, National Agricultural Statistics Service. 2015. USDA Non-Citrus Fruit and Nut. 2014 Preliminary Summary, January 2015. Retrieved from: http://www.nass.usda.gov/Publications/Todays_Reports/reports/ncit0115.pdf. Accessed: August 22, 2015.

Wild Blueberry Association of North America (WBANA). 2013. Industry Overview: New Brunswick Wild Blueberries. Fact Sheet A.1.0. NB.

Warman, P. R. 1987. The effects of pruning, fertilizers, and organic amendments on lowbush blueberry production. Plant Soil. 101: 67-72.

Weber, C. R. and W. R. Fehr. 1966. Seed yield losses from lodging and combined harvesting in soybeans. Agron. J. 58: 287-289.

Wilby, R. L., R. J. Abrahart, and C. W. Dawson. 2003. Detection of conceptual model rainfall-runoff processes inside an artificial neural network. Hydrol. Sci. J. 48: 163-181.

Wilding, L. 1985. Spatial Variability: Its Documentation, Accommodation and Implication to Soil Surveys. *In*: D. R. Nielsen and J. Bouma (eds.). pp. 166-189. Proc. of a workshop of ISSS and SSA. Wageningen, The Netherlands.

Wood, G. W. 1961. The influence of honey bee pollination on fruit set of the lowbush blueberry. Can. J. Plant Sci. 41: 332-335.

Woods, S. J. and M. L. Searingin. 1977. Influence of simulated early lodging upon soybean seed yield and its component. Agron. J. 69: 239-242.

Wright, N. G. and M. T. Dastorani. 2001. Effects of River Basin Classification on Artificial Neural Networks Based Ungauged Catchment Flood Prediction. Floodplain Management Association Conference, San Diego, CA.

Wright, N. G., M. T. Dastorani, P. Goodwin, and C. W. Slaughter. 2002. A Combination of Artificial Neural Networks and Hydrodynamic Models for River Flow Prediction. *In*: Proceedings of the Fifth International Conference on Hydro-informatics, Cardiff, U.K.

Yang, C., S. Prasher, S. Sreekanth, N. Patni, and L. Masse. 1997. An artificial neural network model for simulating pesticide concentrations in soil. Trans. of the ASAE.: 40: 1285-1294.

Yarborough, D. E. and A. A. Ismail. 1985. Hexazinone on weeds on lowbush blueberry growth and yield. Hort. Sci. 20: 406-407.

Yarborough, D. E., J. J. Hanchar, S. P. Skinner, and A. A. Ismail. 1986. Weed response, yield and economics of hexazinone and nitrogen use in lowbush blueberry production. Weed Sci. 34: 723-729.

Yarborough, D. E. and P. C. Bhowmik. 1988. Effect of hexazinone on weed populations and on lowbush blueberries in Maine. Acta. Hort. 241: 344-349.

Yarborough, D. E. 1992. Progress Towards the Development of a Mechanical Harvester for Wild Blueberries. Univ. Maine Coop. Ext. Fact Sheet No. 226. Orono, ME.

Yarborough, D. E. and J. M. Smagula. 1993. Fertilizing with Nitrogen and Phosphorus. Univ. Maine Coop. Ext. Fact Sheet No. 225. Orono, ME.

Yarborough, D. E. 1997. Production trends in the wild blueberry industry in North America. Acta. Hort. 446: 33-36.

Yarborough, D. E. and M. C. Marra. 1997. Economic Thresholds for Weeds in Wild Blueberry Fields, pp. 293-301, 6th International Symposium on Vaccinium Culture. Orono, ME.

Yarborough, D. E. and F. A. Drummond 2001. Integrated Crop Management Field Scouting Guide for Lowbush Blueberries. Univ. Maine Coop. Ext. Fact Sheet No. 204. Orono, ME.

Yarborough, D. E. 2002. Progress towards the development of a mechanical harvester for wild blueberries. Acta. Hort. 574: 329-334.

Yarborough, D. E. 2004. Factors contributing to the increase in productivity in the wild blueberry industry. Small Fruits Rev. 3: 33-43.

Yarborough, D. E. 2007. Wild Blueberry. Univ. Maine Coop. Ext. Orono, ME. Retrieved from: http://www.wildblueberries.maine.edu/Newsletters/2007/January07.html. Accessed: February 21, 2015.

Yarborough, D. E. 2009. Wild blueberry. Univ. Maine Coop. Ext. Orono, ME. Retrieved from: http://www.wildblueberries.maine.edu/Newsletters/2009/January09.html. Accessed: January 26, 2015.

Yarborough, D. E. 2013. Wild Blueberry. Univ. Maine Coop. Ext. Orono, ME. Retrieved from: http://umaine.edu/blueberries/newsletters/wild-blueberry-newsletter january-2013/. Accessed: April 04, 2014.

Yarborough, D. E. 2015. Wild Blueberry. Univ. Maine Coop. Ext. Orono, ME. Retrieved from: http://umaine.edu/blueberries/newsletters/wild-blueberry-newsletter january-2015/. Accessed: March 21, 2015.

Zaman, Q. U., A. W. Schumann, D. C. Percival, and R. J. Gordon. 2008. Estimation of wild blueberry fruit yield using digital color photography. Trans. of the ASABE. 51(5): 1539-1544.

Zaman, Q. U., A. W. Schumann, and D. C. Percival. 2010. An automated cost-effective system for real-time slope mapping in commercial wild blueberry fields. Hort. Tech. 20(2): 431-437.