PERFORMANCE EVALUATION OF A COMMERCIAL WILD BLUEBERRY HARVESTER USING PRECISION AGRICULTURE TECHNOLOGIES AND MATHEMATICAL MODELING

by

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DEDICATION

I am delighted to dedicate my PhD dissertation to my uncle Ch. Sabir Hussain Sabir (Late) for his initiative to educate me. His initiative was well supported by my father Ch. Manzoor Hussain and family members. He would have been extremely proud of my accomplishment if he was alive today. A special feeling of gratitude to my family members for their encouragement, inspiration and push to achieve my goals. They taught me to love and value education and have continually supported all my dreams with patience. Without their loving support and longsuffering I would not be where I am today.

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ABSTRACT

The wild blueberry industry is currently facing increased harvesting losses due to changes in crop conditions caused by improved management practices. The objectives of this study were to sense the variations in fruit yield, plant height and topographic features to quantify overall fruit losses, evaluate the blueberry harvester for picking efficiency in relation to spatial variability, and to develop a mathematical model for prediction of fruit losses. An integrated automated sensing and control system was developed and incorporated onto a commercial blueberry harvester to sense plant height, fruit yield, slope and elevation in real-time. Four wild blueberry fields were selected and performance of the commercial blueberry harvester with developed integrated system was evaluated. Yield plots were randomly selected and the harvester was operated at different combinations of ground speed and head revolutions to mechanically harvest these plots. Total fruit yield, berry losses, plant height, fruit zone and slope were recorded manually from each plot.

Results reported that the developed system performed rapidly and reliably to estimate pre-harvest fruit losses, plant height, fruit yield, slope and elevation in real-time. Significant relationship between fruit yield and total fruit losses suggested that losses during harvesting were proportional to fruit yield. Results of means comparison showed that a combination of 1.2 km h^{-1} and 26 rpm resulted in significantly lower losses in high yielding fields. Spatial variability in fruit losses corresponding with the variations in crop characteristics, fruit yield and slope suggested that these parameters had a significant effect on fruit losses during mechanical harvesting. Results of modeling suggested that the predictive capabilities of the artificial neural network model to estimate fruit losses were significantly better than the multiple regression model for training and validation datasets. Overall, the results suggested a suitable combination of ground speed and header revolutions based on proper characterization and quantification of spatial variability in fruit yield, plant characteristics, and topographic features can minimize fruit losses during harvesting. This study can help to identify the factors responsible for fruit losses and to suggest optimal harvesting scenarios to improve berry picking efficiency and recovery to increase harvestable yield, which will improve farm profitability with no additional cost.

LIST OF ABBREVIATIONS AND SYMBOLS USED

ABBREVIATIONS

ANOVA – Analysis of Variance

ANN – Artificial Neural Network

BOG – Berries on the Ground

BP-ANN – Back-propagated Artificial Neural Network

C.V. – Coefficient of Variation

CVs – Coefficient of Variations

CE – Coefficient of Efficiency

CSV – Comma Separated Value

DGPS – Differential Global Positioning System

DBE – Doug Bragg Enterprises

F – Function Layer

GIS – Geographical Information System

GLM – General Linear Model

ha – Hectare

IDW – Inverse Distance Weighting

LS – Least Squares

LTB – Losses through the Blower

Max – Maximum

Min – Minimum

n – Number of Samples

MR – Multiple Regression

NS – Non-significant

n/a – Not Applicable

PHL – Pre-harvest Fruit Losses

r – Coefficient of Correlation

R^2 – Coefficient of Determination

RMSE – Root Mean Square Error

RTK-GPS – Real-time Kinematics Global Positioning System

S.D – Standard Deviation

TFY – Total Fruit Yield

TFL – Total Fruit Losses

UHBP – Un-harvested Berries on the Plants

W – Weight Layer

YC – Yield Collected by the Harvester from the Harvested Plot.

%E – Percent Variation

GREEK LETTERS

β_0 – Intercept

β_i – Regression Coefficients

ε – Error Term

f – Non-linear Function

u_i – Normalized Value of Input

γ – Semivariance

MATHEMATICAL VARIABLES

H – Output of Artificial Neural Network Model

h – Lag Distance

i – Number of Inputs

I – Inputs Parameters for Artificial Neural Network Model

Min_i – Minimum Value of Input

Max_i – Maximum Value of Input

$N(h)$ – Number of Sample Pairs

R_i – Actual Value of Input

x – Input Variables

x_i – Spatial Location

Y – Output

$Z(x_i)$ – Regionalized Variable at Spatial Location

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CHAPTER 1 INTRODUCTION

Northeastern North America is the world's leading producer of wild blueberry *(Vaccinium angustifolium* Ait.) with over 86,000 ha under management and producing 112 million kg of fruit, valued at $470 million annually (Yarborough, 2013). The wild blueberry industry is rapidly growing with over 7,700 ha of new area of production over the past 20 years in Canada (Yarborough, 2009). Blueberry fields are developed by clearing woodlands and removing competing vegetation (Eaton, 1988). Newly established blueberry fields contain 30 to 50% bare spots/weed patches (Zaman et al., 2008). Blueberry 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 harvest. Selective herbicides, fungicides and fertilizers are applied for optimizing plant growth to encourage improved berry production (Esau et al., 2014). Harvesting of wild blueberries does not take place until approximately 90% of the berries are blue (Dale et al., 1994; Mehra et al., 2012).

Wild blueberries have been hand raked for the past 100 years. The substantial increase in fruit yields with improved management practices over last few decades, shortage and quality of labor, and increase of wages have consequently demanded for mechanical harvesting (Yarbrough, 2001). Research on the development of a mechanical harvester started in early 1950s, but a viable harvester was not commercialized until 1980s due to technical difficulties including rough terrain, poor harvesting efficiency and fruit damage (Hall et al., 1983; Richard, 1982). Currently, the mechanically harvested blueberry area is more than 80% of the total area in Canada (PMRA, 2005). The wild blueberry industry is facing increased harvesting losses with the existing commercial harvester due to changes in crop conditions caused by the improved management practices (Farooque et al., 2014; Yarborough, 2009). This situation emphasizes the need to evaluate the performance of harvester using precision agriculture (PA) technologies and mathematical modeling to suggest optimal scenarios for effective berry recovery and quality.

Innovative PA technologies comprised of sensors, controllers, hardware, software, differential global positioning system (DGPS) and geographical information system (GIS) can provide the tools that allow us to identify the factors affecting harvesting efficiency in spatially variable fields (Bausch and Delgado 2003). Coupled with a DGPS, sensors are capable of acquiring high spatial resolution data which can aid in decision making (Holland et al., 2006). An ultrasonic sensor, a digital color camera, a slope sensor and a real-time kinematics global positioning system (RTK-GPS), coupled with custom developed hardware and software, have been used to estimate plant height, fruit yield and topographic features for wild blueberry cropping system (Swain et al., 2009; Zaman et al., 2010b; Zaman et al., 2011; Chang et al., 2012a; Saleem, 2012). However, integration of these sensors, newly developed custom software and a ruggedized computer on a commercial blueberry harvester to sense plant height, fruit yield, slope and elevation on-the-go has never been tested and evaluated. Real-time mapping of fruit yield, plant characteristics and topographic features can be used to assess overall fruit losses and to develop relationships, which can be helpful to adjust the harvester operational settings to enhance berry picking efficiency.

Non-destructive yield mapping to quantify overall fruit losses during harvesting emphasizes the need for physical evaluation of the commercial blueberry harvester (Farooque et al., 2013) to suggest optimal operational parameters for effective berry recovery. Many researchers have attempted to evaluate the wild blueberry harvesters for fruit losses up to the early 1990s (Rhodes, 1961; Abdalla, 1963; Hayden and Soule, 1969; Hall et al., 1983; Sibley, 1992; Yarborough, 1992), but no work has been done in last 20 years to study the performance of harvester corresponding to the changes in crop conditions. Detailed evaluations of the harvester in relation to spatial variations in fruit yield, plant characteristics and topographic features will suggest optimal operational settings for the grower's community to increase harvestable yield.

With the installation of sensors and control systems on mechanical harvesters, it has been evident that the fruit yield, plant parameters and topographic features exhibits significant spatial variability (Bramley and Hamilton, 2004; Zaman et al., 2010 a; Farooque et al., 2012a) which can have an impact on fruit losses during mechanical harvesting. Spatial variations in fruit yield are mainly caused by heterogeneity in crop characteristics, soil physical and chemical properties, and weather conditions (Wong and Asseng, 2006; Rogerio et al., 2006; Kaleita et al., 2007; Cemek et al., 2007, Mann et al., 2010). Heterogeneity may occur at small scale or large scale, even in the same variable of interest or in the same community (Du Feng et al., 2008). Knowledge of spatial variability is critical for planning and implementing the operational recommendations for mechanical harvesting of wild blueberries. Harvesting of spatially variable fields at standard operational settings without characterizing the spatial variability can result in increased fruit losses during harvesting. Variability in fruit losses corresponding with the spatial variations in crop characteristics, fruit yield and slope of the ground can be helpful in identifying the factors responsible for fruit losses.

Fruit losses during harvesting are consequence of complex interactions between mechanical parameters, crop characteristics, weather conditions, soil structure, operator skills and field topography (Adams et al., 1998; Bryant et al., 2000; Farooque et al., 2013; Salter et al., 1980). Owing to the dynamicity of these relationships, determination of ideal settings to optimize yield and quality has always remained a challenge (Fritz and Weichmann, 1979). Inherently, the nature of the harvesting processes that govern the picking efficiency are complicated and non-linear (Chen et al., 2001). Modeling network of relationships requires an approach that is robust, scalable and flexible with a choice of various learning algorithms. In the case where inputs and outputs are intrinsically variable, a system that is intended to be predictive is more appropriate (McCarthy et al., 2001; Reidsma et al., 2009). Therefore, a model which can 'learn' from successive field trials is ideal because it will certainly become more reliable through time and will be able to adapt to unforeseen changes in the data (Huang and Foo, 2002). The data-driven modeling approach of connecting one set of data (output) with another corresponding set (input) is more appropriate to find relationships. Understanding and predicting the relationships between the machine operating parameters, fruit losses, topographic features and crop characteristics can aid in better berry recovery during mechanical harvesting.

Wild blueberry growers are facing increased harvesting losses with their existing harvesters due to changes in crop conditions (healthy and tall plants, high plant density, tall weeds and significant increase in fruit yield) caused by improved management practices (herbicides, fertilizers, pesticides, pollination, *etc.*) emphasizing the need to evaluate the harvester using PA technologies and mathematical modeling approaches. This study can help to identify the factors responsible for fruit losses and to suggest best operating conditions to improve berry picking efficiency and recovery. Improved berry picking efficiency based on proper characterization and quantification of spatial variability has the potential to increase profit margins for the farmer's community to justify the ever increasing cost of production.

Objective and Goals

Therefore the objectives of this study were to:

- **(i)** Perform evaluation of multiple ground based sensors mounted on a commercial wild blueberry harvester to sense plant height, fruit yield and topographic features on-the-go during harvesting,
- **(ii)** Effect of ground speed and header revolutions on the picking efficiency of commercial wild blueberry harvester,
- **(iii)** Response of wild blueberry fruit losses to spatial variability in fruit yield, crop characteristics and ground slope, and
- **(iv)** Develop a predictive model for wild blueberry fruit losses during harvesting using an artificial neural network (ANN).

CHAPTER 2 PERFORM EVALUATION OF MULTIPLE GROUND BASED SENSORS MOUNTED ON A COMMERCIAL WILD BLUEBERRY HARVESTER TO SENSE PLANT HEIGHT, FRUIT YIELD AND TOPOGRAPHIC FEATURES ON-THE-GO DURING HARVESTING

Non-destructive mapping of fruit yield, plant height and topographic features can aid in developing strategies for effective berry recovery during mechanical harvesting. An integrated automated system comprising of an ultrasonic sensor, a digital color camera, a slope sensor, a RTK-GPS, custom software and ruggedized computer was developed. The system was incorporated onto a commercial wild blueberry harvester to measure plant height, fruit yield, slope and elevation simultaneously while harvesting. Four wild blueberry fields were selected to evaluate the performance of the developed system. Field boundaries, bare spots, weeds and grass patches were mapped with a RTK-GPS prior to start the experiment.

Linear regression was used to calibrate the actual fruit yield with the percentage of blue pixels (R^2 = 0.79 to 0.92; $P < 0.001$; $n = 40$) using a 0.91 × 0.70 m quadrat at selected points from all fields. The output voltage of an ultrasonic sensor was significantly correlated with manually measured plant height (R^2 = 0.94; $P < 0.001$; $n = 13$). Comprehensive surveys were conducted in selected fields to sense plant height, fruit yield, slope and elevation rapidly in real-time during harvesting. Maps developed in ArcGIS 10 showed substantial variability in measured parameters across the fields, suggesting higher fruit yield and lower plant height in low lying areas (mild slope) and vice versa. Results of zonal statistics also supported the results identified by the maps. Overall, the results of calibration, validation and mapping indicated that the developed system was an accurate, reliable and efficient to map plant height, fruit yield, slope and elevation in real-time. Results also revealed that the hardware and software of the developed system performed rapidly and reliably to estimate pre-harvest wild blueberry fruit yield, which can be used to quantify overall fruit loss during mechanical harvesting. This information can also be used to develop site-specific fertilization strategies to optimize crop productivity while minimizing environmental risks.

The work presented in this chapter has been published in *Computers and Electronics in Agriculture Journal* 91:135-144, entitled "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".

2.1 INTRODUCTION

The wild blueberry industry may significantly benefit from PA technologies that allow measurement and mapping of soil, crop and fruit parameters in real-time. Fruit yield and quality of blueberries is influenced by the spatial variation in soil properties, plant characteristics and topographic features (Farooque et al., 2012a). Wild blueberry growers are facing increased harvesting losses due to changes in crop conditions caused by improved management (selective herbicides, fungicides, pollination, fertilizer, *etc.*) (Esau et al., 2014). This situation emphasizes the need for the development of an integrated sensing system comprising of low-cost sensors and controllers for accurate estimation of pre-harvest fruit losses, plant height and topographic features in real-time during mechanical harvesting. Mapping these parameters can aid in increased berry picking efficiency of the blueberry harvester (Farooque et al., 2014; Boydell and McBratney, 2002).

Multiple sensors are widely adopted in PA systems to measure and map soil and plant characteristics in real-time to make management decisions. The PA systems involves a wide spectrum of sensors, hardware and software for data acquisition, automated recording, analogue and digital processing of data, up to symbolic analysis all within framework to assess spatial variations within the field. Mobile ground or proximal sensors are an emerging technology designed to overcome many of the limitations associated with the current instrumentation of satellite or aircraft-based sensing systems (Bausch and Delgado, 2003). Satellite or airborne platforms deliver spectral information; however, they may not be available in time for critical management decisions to be implemented. Also, remote sensing data is constrained by weather conditions, obtaining up-to-date aerial photography is very expensive, the quality is variable and data processing is also intensive and complicated (Malay, 2000). Ground sensing technologies are able to get around the problem of weather conditions and their close proximity to the canopy reduces or eliminates soil reflectance interference. Coupled with a DGPS, these ground sensors are able to deliver data of high spatial resolution that can be integrated with material delivery systems to facilitate real-time applications of agrochemicals (Holland et al., 2006).

Many researchers have studied the spatial variation in soil properties, plant characteristics and fruit yield for different cropping systems using ground based sensing and control systems. Lan et al. (2009) developed a ground-based, multi-source information collecting system and tested the feasibility of the system on cotton; it consisted of normalized difference vegetation index (NDVI) sensor, crop canopy analyzer for leaf area index (LAI), hyperspectral radiometer, multi-spectral camera and crop height sensors. Rosell et al. (2009) used a low-cost tractor mounted scanning light detection and ranging

(LIDAR) system capable of making non-destructive recording of tree-row structure in orchards and vineyard. Moshou et al. (2006) investigated proximal optical sensing to diagnose disease infestations on wheat and to discriminate between pathological and nutritional stresses. Zaman and Schumann (2003) developed a ground-based ultrasonic sensor system for tree volume measurement in citrus groves to implement variable rate nitrogen application (Zaman et al., 2005), and estimate citrus fruit yield (Zaman et al., 2006). Gil et al. (2007) developed a multi-nozzle air-blast sprayer fitted with ultrasonic sensors and electro-valves in order to modify flow rate from the nozzles in real-time, in relation to the variability of vine canopy width. Johnson et al. (2003) have shown a significant correlation (R^2 = 0.74) between NDVI and LAI values in vines suggesting that NDVI map can be used to interpret spatial patterns in infestation and disease, water status, fruit characteristics and wine quality. Mazzetto et al. (2010) integrated optical and analogue sensors for monitoring canopy health and vigor for vineyard. Malay (2000) developed an optical sensor based yield monitoring system to estimate wild blueberry fruit yield. The accuracy of the CERES II yield monitoring system (R.D.S Technology, Gloucester, U.K.) was influenced by the debris common to blueberry harvest (grass, rocks and sticks), which caused an overestimation of the yield. The inclined elevator and uneven topography were also responsible for these overestimations.

An accurate yield mapping system may be possible with the addition of a digital color camera on the blueberry harvesters to estimate yield prior to harvesting. Many researchers worked on fruit yield estimation in a non-destructive fashion (Annamalai et al., 2004; Chinchuluun and Lee, 2006; Mac-Arthur et al., 2006; Schumann et al., 2007; Zaman et al., 2010b) for various cropping system. Schumann et al. (2007) developed a ground based digital photography and ultrasonic ranging system for mapping tree characteristics and fruit yield in real-time for citrus orchards. Zaman et al. (2008) evaluated the performance of a cost-effective 10 mega pixel digital color camera for wild blueberry fruit yield estimation. Results of their study suggested that the digital photography technique can be implemented for estimation of fruit yield by calculating the blue pixel ratio using image processing algorithms. Zaman et al. (2010b) developed an automated yield monitoring system (AYMS) consisting of a digital color camera, ruggedized laptop computer, custom software and a RTK-GPS. They successfully estimated and mapped fruit yield in wild blueberry fields. However, ordinary digital color cameras are not viable for commercial yield monitoring system to incorporate into the harvesters for yield mapping. Chang et al. (2012a) developed an automated yield monitoring system II (AYMS II) consisting of two μEye color cameras, a RTK-GPS, a custom software and a ruggedized laptop computer, mounted on a Specialized Farm Motorized Vehicle for real-time fruit yield mapping.

Ultrasonic sensors are widely used for non-destructive estimation of plant heights (Sui et al., 1989; Schumann and Zaman, 2003). Vansichen and De Baerdemaeker (1992) measured the distance between crop divider of the harvester and the un-harvested crop by using an ultrasonic sensor. Wild et al. (1998) tested and evaluated three methods, *i.e.* mechanical, image processing and ultrasonic sensing to measure the width of cut in a combine harvester. Results of their study indicated that the ultrasonic sensor estimates were very accurate when compared with image processing and mechanical device. Kataoka et al. (2002) suggested that the ultrasonic sensor had an advantage over the laser beam sensor for plant height estimation of soybean and corn crops. Shrestha et al. (2002) mounted an ultrasonic sensor above and perpendicular to plant canopy to sense corn plant height in a lab environment. Swain et al. (2009) developed and tested low-cost ultrasonic system for tall weed and bare spot mapping in wild blueberry fields. They reported that the ultrasonic sensor was capable of detecting the tall weed and bare spots within the blueberry fields. Dionisio et al. (2012) developed an ultrasonic system for weed detection in cereal crops. Results of their study indicated that the ultrasonic sensors were capable of differentiating the weed and non-weed infested areas with up to 93% success.

Zaman et al. (2011) developed and evaluated a prototype variable rate sprayer for tall weed detection and spraying in real-time using ultrasonic sensors. Zaman et al. (2010a) developed a cost-effective system using reliable and inexpensive sensors for real-time measurement and mapping of slope in wild blueberry fields. Saleem et al. (2014) used RTK-GPS and GIS to derive topographic features and relate them with hydrologic attributes in wild blueberry fields. Fruit yield, plant height, slope, and elevation were mapped using individual sensors by different researchers (Zaman et al., 2008, Zaman et al., 2010a; Zaman et al., 2011; Chang et al., 2012a) for wild blueberry cropping system. However, the integration of a digital color camera, an ultrasonic sensor, a slope sensor, a RTK-GPS, newly developed custom software and a ruggedized computer was performed in this study. The integrated system was mounted on a commercial harvester to map fruit yield, plant height, slope and elevation real-time in one go.

Many researchers have attempted to characterize and quantify spatial variation in soil properties, plant characteristics and fruit yield for different cropping systems using multiple sensor and control systems (Moshou et al., 2006; Lan et al., 2009; Rosell Polo et al., 2009; Mazzetto et al., 2010; Zaman et al., 2010b; Zaman et al., 2011; Chang et al., 2012a; Chang et al., 2012b). However, to date little attention has been paid to wild blueberry production system. In the present study, a ground based multiple sensors system (software and hardware) comprised of an ultrasonic sensor, a digital color camera, a slope sensor, and a RTK-GPS was developed and incorporated into a blueberry harvester to propose practical ground sensing solutions and match crop monitoring needs by means of tools that could be directly used at farm level. The performance of developed system was tested and evaluated with regard to estimate plant height, fruit yield, slope, and elevation in real-time for selected wild blueberry fields. The potential and capability of the developed system to estimate pre-harvest fruit losses during mechanical harvesting was also examined.

2.2 MATERIALS AND METHODS

2.2.1 Development of Multiple Sensors System

2.2.1.1 Hardware Components

The developed system consisted of an ultrasonic sensor (Q45U; Banner Engineering Corp., Minneapolis, MN, USA), a μEye 1220SE/C digital color camera (IDS Imaging Development System Inc., Woburn MA, USA), a tilt sensor (Memsic 2125; Parallax Inc., Rocklin, CA, USA) sensing the tilt of a vehicle in any orientation on a slope, a HiPer® lite+ RTK-GPS (Topcon positioning systems Inc., Livermore, CA, USA) for geo-referencing and a ruggedized computer Latitude E6400 XFR (Dell Inc., Round Rock, TX, USA). The developed system was incorporated into a commercial wild blueberry harvester for mapping plant height, fruit yield, slope and elevation (Fig. 2-1).

The camera and RTK-GPS were mounted at the front of the harvester at a height of 0.95 m with a clear view of ground. An ultrasonic sensor was mounted 0.8 m above the ground surface on the steel pivot arm (Fig. 2-1). A bicycle wheel was used at the end of the steel pivot arm to keep the height of the sensor constant during operation of the system. The National Marine Electronics Association (NMEA-0183) standard code sentences of RTK-GPS was used for calculation of coordinates of the ultrasonic sensor, the center of camera images, and the slope sensor simultaneously. The camera comprised of a 1/3 inch CMOS sensor, a C-mount for lens (LM4NCL, Kowa Optimed Inc., Torrance, CA, USA) and a global shutter to reduce blurring of images. The camera lense had 3.5 mm focal length and was set up with fixed aperture (f/4.0) and infinity focus for clear image acquisition. The images from the camera were acquired according to the speed of harvester and processed data were stored with calculated coordinates in a ruggedized computer. The calculated coordinates and elevation data were continuously stored in a ruggedized computer through the serial port at 5 Hz. Slope sensor was mounted inside the cabin of tractor to measure the slope of the tractor in any orientation. In this study, a pre-calibrated slope sensor was used. Details about the configuration of the slope sensor can be adopted from Zaman et al. (2010a).

2.2.1.2 Software Development

Custom image processing software was developed in C++ using Visual Studio 2010 (Microsoft, Redmond, WA, USA) for a 32-bit Windows operating system to estimate the percentage of blue pixels representing ripe fruit in the field of view of images taken by the camera. The software interface was capable of capturing a 24-bit RGB 720 × 480 image (total covered field area of 0.91 m × 0.70 m) and processing the percentage of blue pixels, an ultrasonic sensor recording for plant height estimation, elevation reading from RTK-GPS along with geo-referenced coordinates and pre-calibrated tilt sensor recordings for measurement of slope simultaneously in a ruggedized computer through a serial communication cable in real-time. Exposure time and digital gain for camera were automatically controlled to adjust for variable outdoor light conditions (> 500 lux). The acquired images were saved in BMP file format. Coordinates from previous and current RTK-GPS output were converted to decimal degrees and used to automatically estimate the timing for the next image and ultrasonic sensor data acquisition. Detailed working principle of the custom developed software is explained in Figure 2-2.

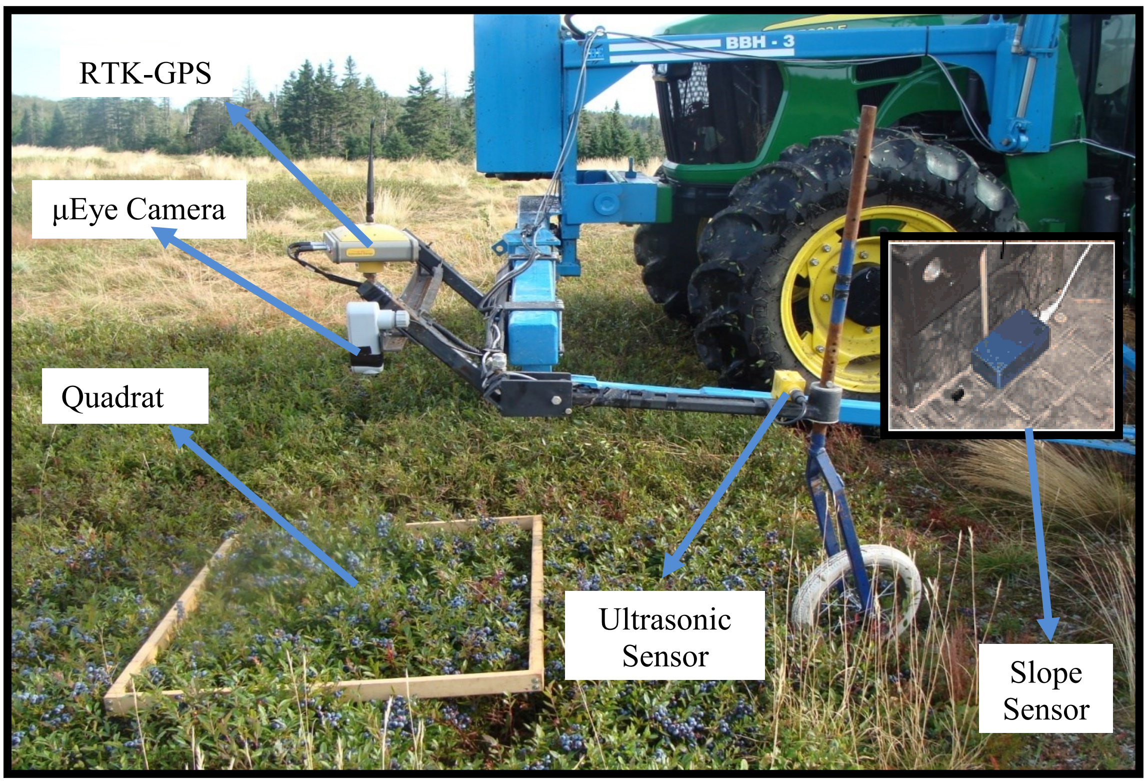


Figure 2-1: Configuration of multiple sensors mounted on a commercial wild blueberry harvester.

The custom software was used to enhance and count the blue pixels in the quadrat region of each image, using red-green-blue (RGB) pixel ratio and expressing the result as a percentage of total quadrat pixels. The ratio used was (B*255)/(R+G+B), and a manually obtained threshold (> 80) adequately discriminated the apparent blueberry fruit pixels from the remaining pixels in an image. Overestimated tendency due to the reflection and dark shadow was corrected by removing over and under intensity pixels ((R+G+B) > 500 or < 40). Small noisy clusters of pixels in the image which were incorrectly identified as fruit were removed by applying one pass of 2×2 erosion filter. Result of percentage blue pixels in the quadrat region of each image was calculated automatically by running the software in real-time. The geo-referenced final results of plant height, blue pixels, slope and elevation were saved as comma separated value (CSV) files (Fig. 2-2). The data collected by multiple sensors were imported into ArcGIS 10 (ESRI, Redlands, CA, USA) for further processing.

2.2.2 Calibration of Multiple Sensors

2.2.2.1 The Experimental Sites

Four wild blueberry fields were selected in the Nova Scotia and New Brunswick provinces of Canada to evaluate the performance of multiple sensors mounted on a commercial wild blueberry harvester. The selected fields were the Cooper site (45.480573°N, 63.573471°W; 3.2 ha), Small Scott site (45.600641°N, 63.086512°W; 1.9 ha), Tracadie site (47.2824117°N, 65.1440212°W; 2.9 ha) and Frankweb site (45.241900°N, 63.401143°W; 4.6 ha) (Fig. 2-3). The Cooper and Small Scott fields were in their vegetative sprout year of the biennial crop production cycle in 2010 and crop year in 2011, while the Tracadie and Frankweb fields were in sprout year in 2011 and crop year in 2012. The selected fields had been under commercial management over the past decade and received biennial pruning by mowing for the past several years along with conventional fertilizer, pollination, weed and disease management practices. The soils at the experimental fields were classified as sandy loam (Orthic Humo-Ferric Podzols), which is a well-drained acidic soil (Webb and Langille, 1996).

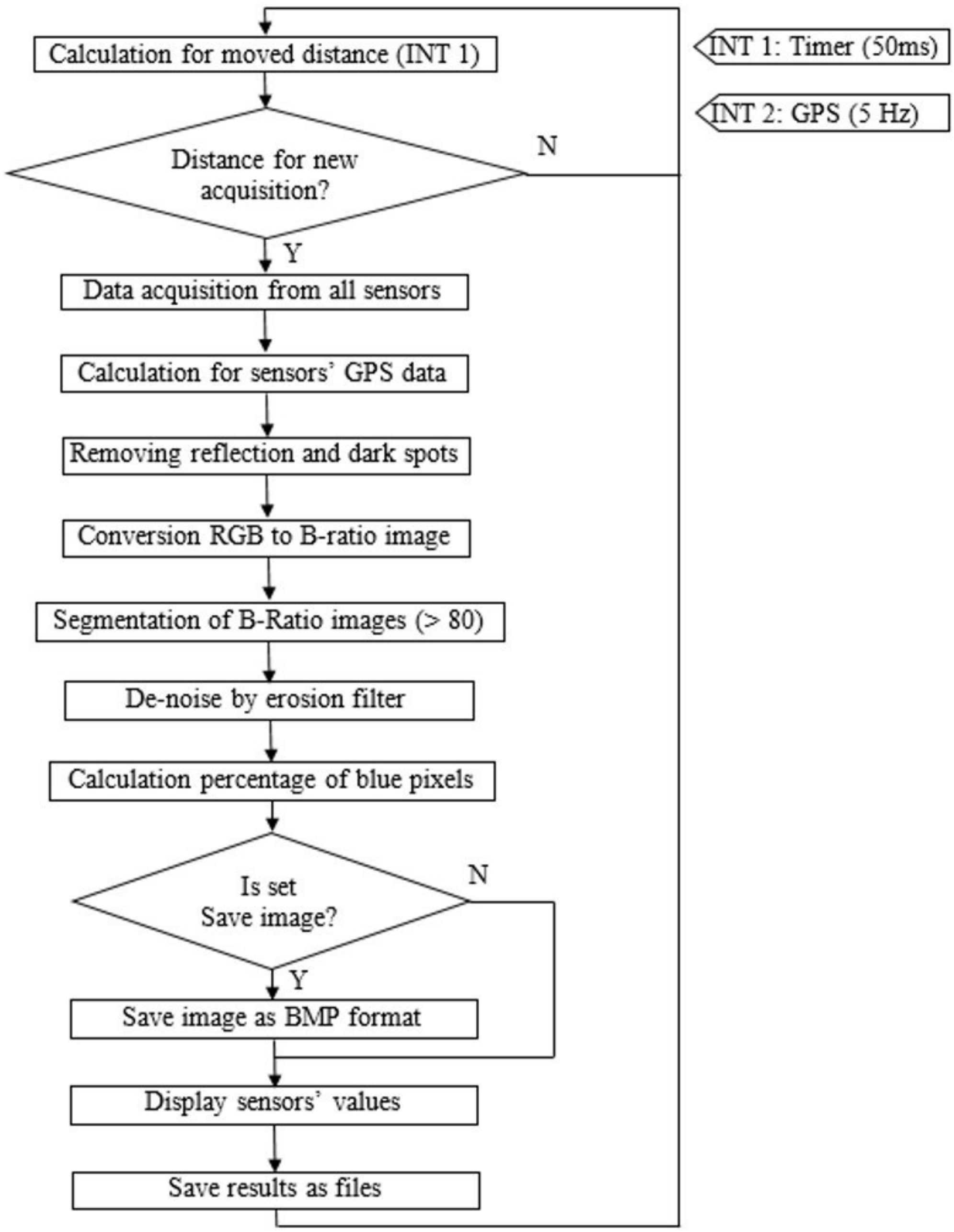


Figure 2-2: Flow chart showing the working principle of custom developed computer program for multiple sensors mounted on a commercial blueberry harvester.

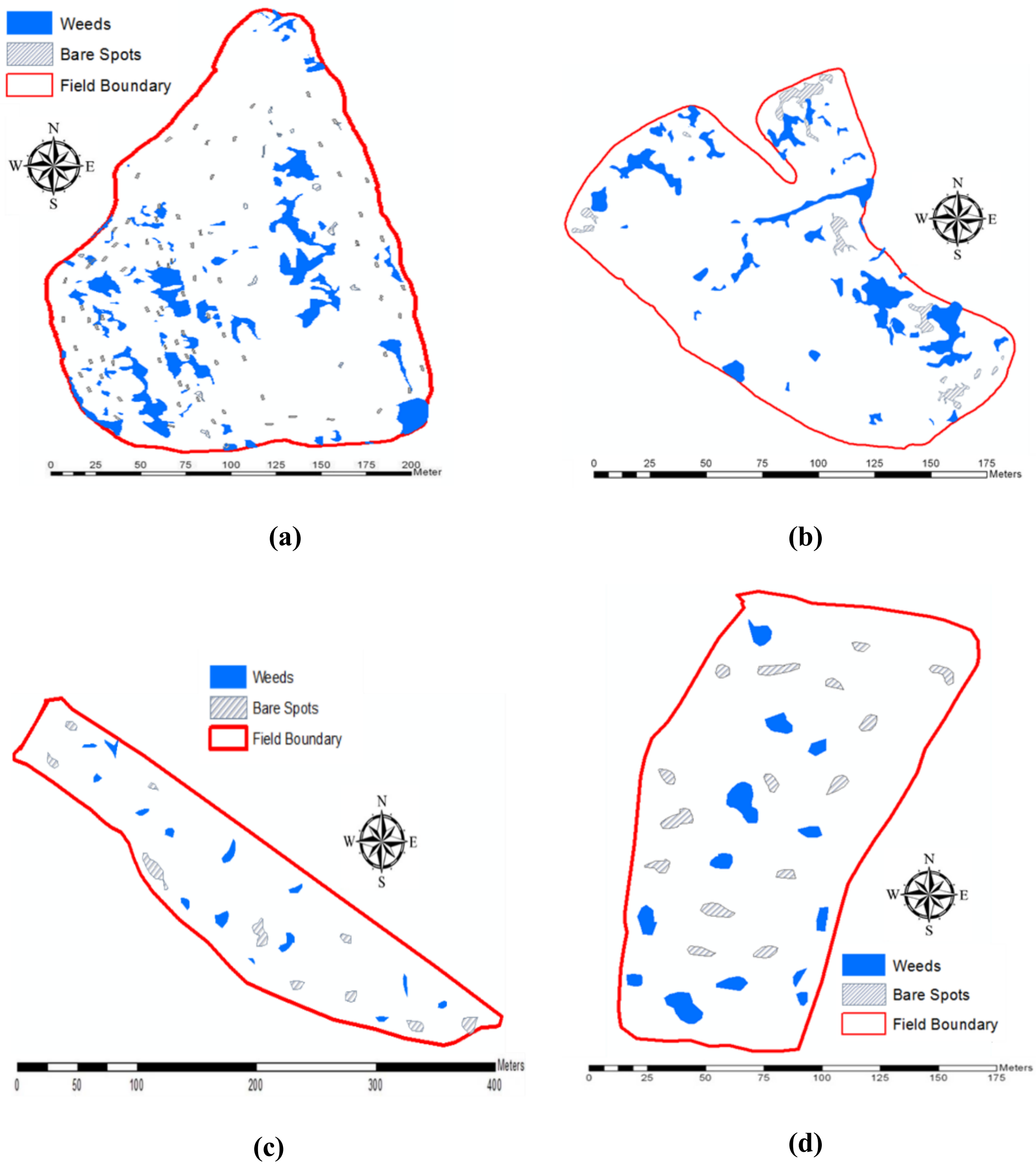


Figure 2-3: Layouts of selected wild blueberry fields, (a) Cooper site, (b) Small Scott site, (c) Tracadie site and (d) Frankweb site.

2.2.2.2 Digital Color Image Acquisition

A 0.91 × 0.70 m wooden quadrat was constructed and placed at randomly selected points in all fields to define the area of interest and to acquire images. The images were taken from the selected points using a μEye digital color camera. The quadrat portion of the images was masked out and the percentage of blue pixels was estimated using the custom software developed in C++ programing language. Calibration a μEye digital color camera was carried out at 80 randomly selected data points (20 points in each field) within the selected fields.

2.2.2.3 Manual Fruit Yield Measurement

Manual harvesting was performed using a hand rake (Fig. 2-4) from the same 80 randomly selected data points (20 points in each field), where the images were collected. Wild blueberries were separated from debris including leaves, grass and weeds for each sample and weighed at the time of harvest.

Figure 2-4: A hand rake for manual harvesting of wild blueberries.

2.2.2.4 Ultrasonic Sensor Calibration for Plant Height Estimation

An ultrasonic sensor was calibrated prior to estimate the plant height in real-time. The corresponding sensor voltages were recorded using a U3-HV (LabJack Corp., Lakewood, CO, USA) I/O unit for calibration purposes. In order to accomplish the calibration of ultrasonic sensor, points were randomly selected within the selected fields and manual plant height readings were recorded using a ruler. The ultrasonic sensor output voltage were also recorded from same selected points. Measured plant height (from ground to canopy) and sensor's voltage were compared by linear regression to examine the performance accuracy of the ultrasonic height measurements. Calibration was carried out at 13 randomly selected data points.

2.2.3 Statistical Analysis

Linear regression was used to calibrate the actual fruit yield and plant height with the percentage of blue pixels and sensor's output voltage, respectively in each field. The calibration equation of the Cooper site was used to predict fruit yield in the Small Scott site and the Small Scott site's was used to predict fruit yield in the Cooper site for validation. Similar validations were performed for the Tracadie and Frankweb sites. Calibration and validation of regression equations/models, coefficient of determination (R^2) and root mean square (*RMSE*) were calculated with SAS 9.1 (SAS Institute, Cary, NC, USA) statistical software. Geostatistical analysis was performed using GS+ Geostatistics for the Environmental Sciences Version 9 software (Gamma Design Software, LLC, Woodhams St, Plainwell, MI, USA) to characterize spatial variability in measured parameters. The semivariograms were produced and sill, nugget, range and sill to nugget ratio were calculated, as a result of corresponding semivariogram analysis. Geostatistical parameters

(Partial sill and range of influence) combined with ordinary kriging were applied to generate detailed maps in ArcGIS 10 software to analyze spatial variability in fruit yield, plant height, slope and elevation visually. Maps were produced at the same scale and equal number of classes in order to allow for an easy comparison. For the Tracadie and Frankweb sites during 2012, the slope data were not recorded in real-time, but retrieved from the rasterized elevation data using the Spatial Analyst extension of the ArcGIS 10 software. Total yield predicted from µEye digital color camera was compared with the actual yield to quantify overall fruit losses during mechanical harvesting for selected fields.

2.2.4 Real-time Field Performance of the Developed System

The performance of the software and hardware of the developed system was assessed by surveying the four fields (Fig. 2-3) with the sensing density of 0.91 × 0.70 m. The ranges of target ground speed, monitored on the main software screen during the surveys (Fig. 2-5), were 1.5 ~ 1.7 km h^{-1}. Real-time yield, plant height and topographic feature mapping was carried out by acquiring images, ultrasonic sensor voltages, slope sensor signals and elevation readings from multiple sensors mounted onto a blueberry harvester, which was operated by a 62.5 kW John Deere tractor. The software was able to process the images to estimate the percentage of blue pixels, ultrasonic sensor voltage to predict plant height, slope sensor signals to calculate slope and RTK-GPS for elevation in real-time during mechanical harvesting. In order to assess the accuracy of the multiple sensors, the percentage of blue pixels of each image were correlated with manually harvested fruit yield. Ultrasonic sensor output voltages were also calibrated with plant heights. For slope sensor, the calibration equation developed by Zaman et al. (2010a) to estimate the slope in real-time was used. The camera was set to 10 ms for maximum exposure and 30 for maximum gain during the surveying to reduce image blurring and noise, respectively. Variations in the natural sky illumination (sunny or cloudy) did not affect the quality of the image processing result and consequently the correlation of blue pixels with fruit yield (Zaman et al., 2008). The ordinary kriging technique in combination with geo-statistical parameters was used to interpolate and map the estimated fruit yield, plant height, slope and elevation data in each field using ArcGIS10 software. The bare spots/weeds in the selected fields were manually mapped with a RTK-GPS (Fig. 2-3). Maps were placed side-side by for comparison. The interface of a custom developed software for data acquisition from multiple sensors and storage into a laptop computer is presented in Figure 2-5.

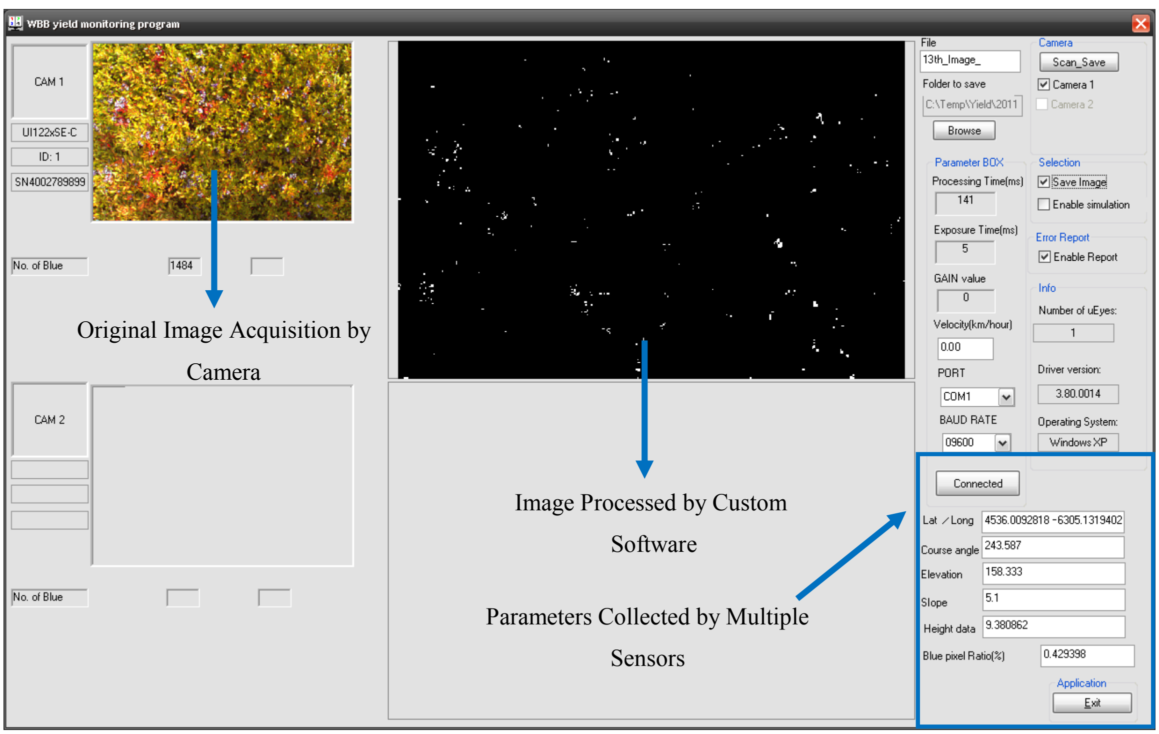
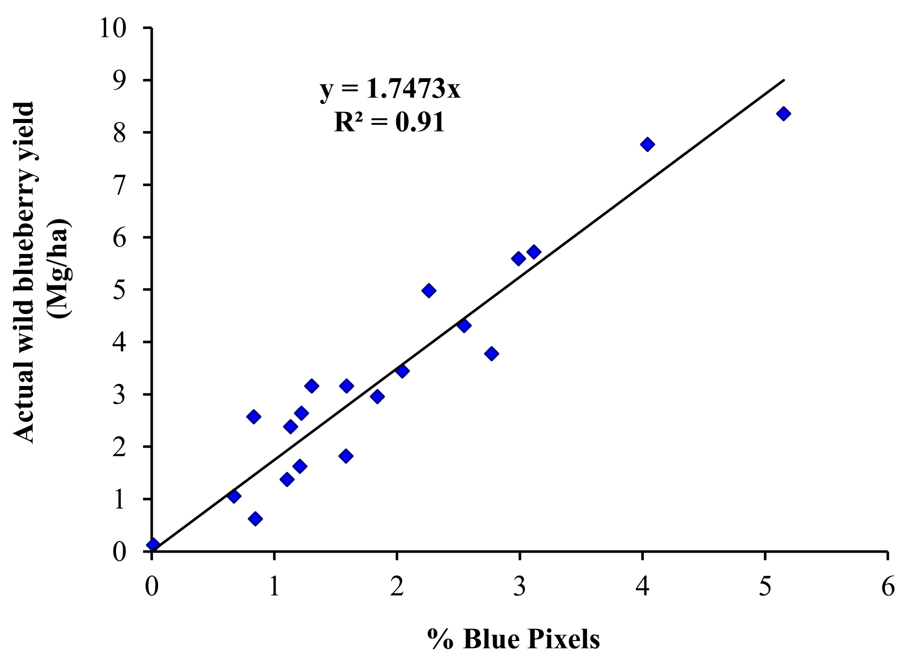


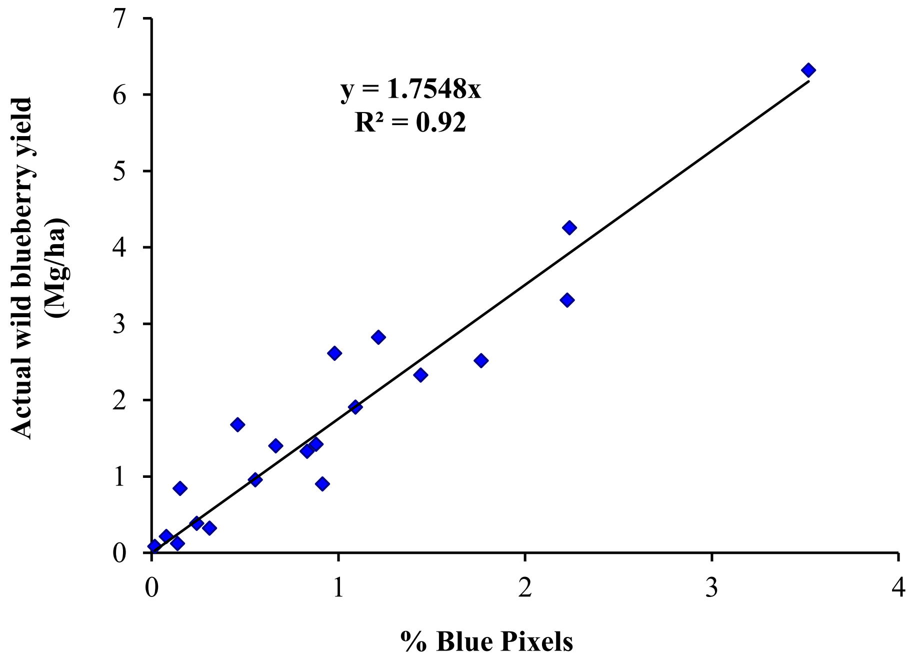
Figure 2-5: Custom software interface for multiple sensors system mounted onto a commercial wild blueberry harvester.

2.3 RESULTS AND DISCUSSION

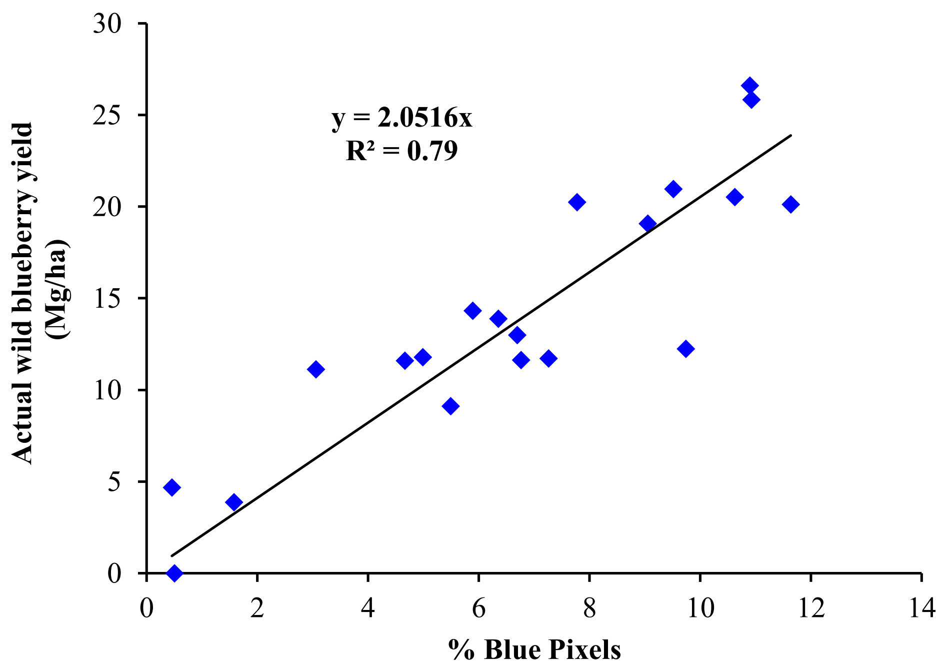
The percentage of blue pixels representing the fruit yield in the harvested quadrat region of the image was calculated with custom software. The percentage blue pixels varied from 0% (bare spots) to 5.81% in Cooper site, from 0% to 3.98% in Small Scott site, from 0% to 12.33% in Tracadie site and from 0% to 19.25% in Frankweb site (Fig. 2-6). Results of regression analysis suggested that the percentage of blue pixels was significantly correlated with manually harvested fruit yield in Cooper site ($R^2 = 0.91$; $P < 0.001$), Small Scott site ($R^2 = 0.92$; $P < 0.001$), Tracadie site ($R^2 = 0.79$; $P < 0.001$) and Frankweb site ($R^2 = 0.85$; $P < 0.001$) (Fig. 2-6). Significant correlations between actual fruit yield and percentage of blue pixels revealed that a µEye digital color camera can be used to estimate the pre-harvest fruit yield non-destructively within the wild blueberry fields.



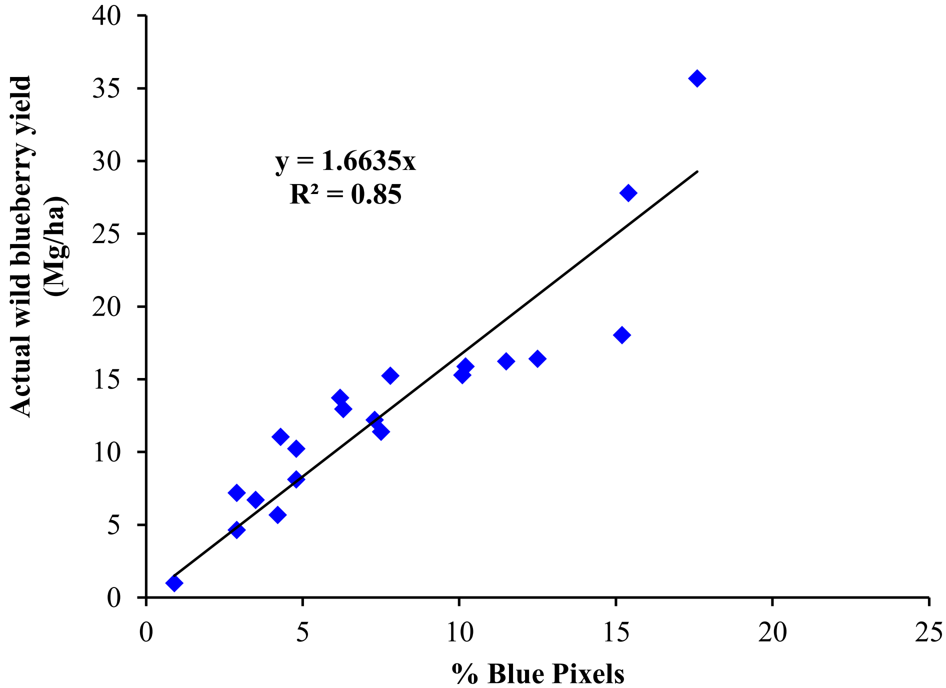
(a)


y = 1.7548x
R² = 0.92
Actual wild blueberry yield
(Mg/ha)
% Blue Pixels
0
1
2
3
4
5
6
7
0
1
2
3
4

(b)


y = 2.0516x
R² = 0.79
Actual wild blueberry yield
(Mg/ha)
% Blue Pixels
0
5
10
15
20
25
30
0
2
4
6
8
10
12
14

(c)

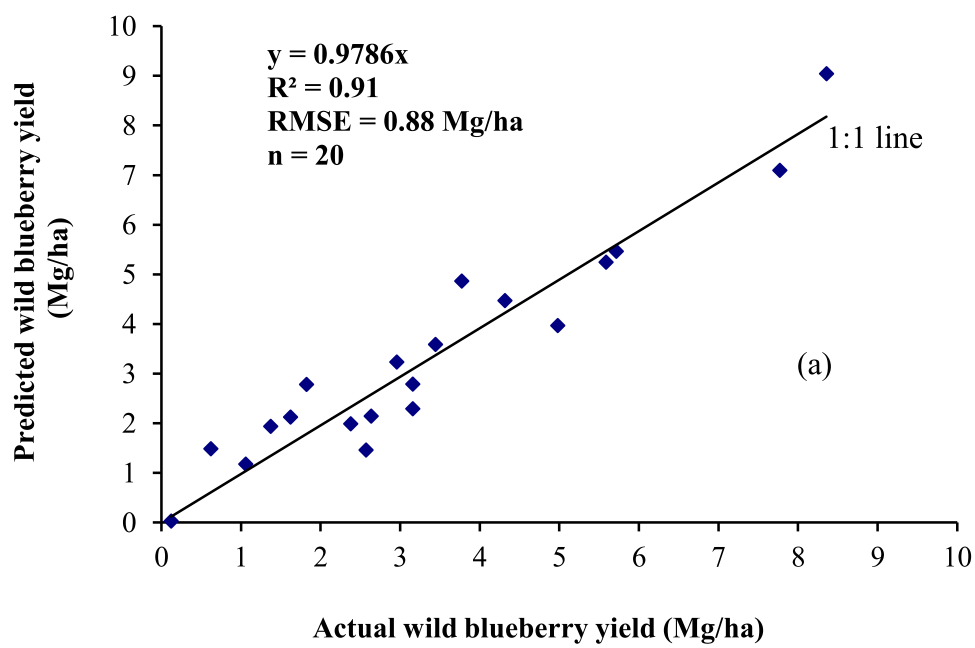


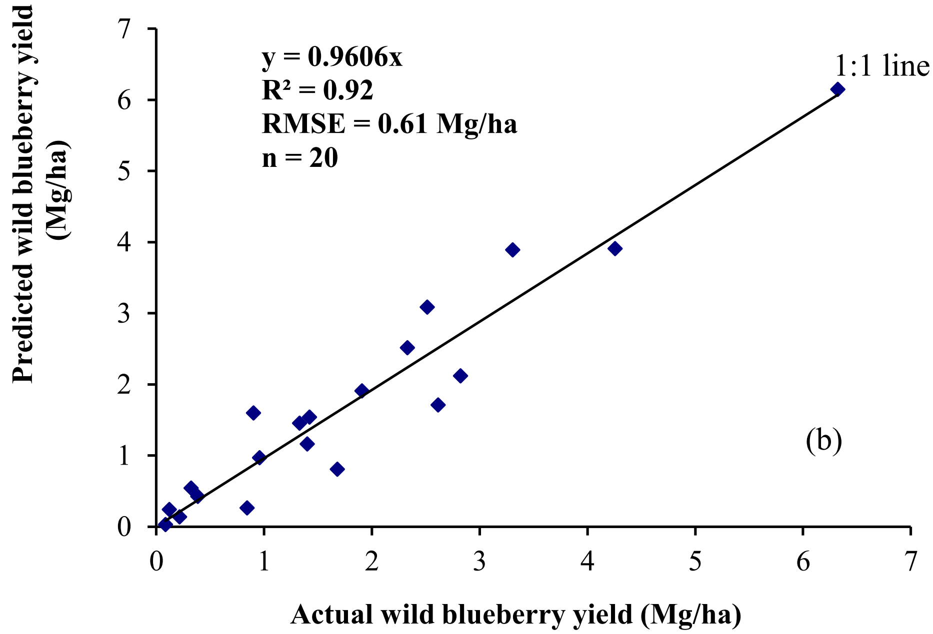
(d)

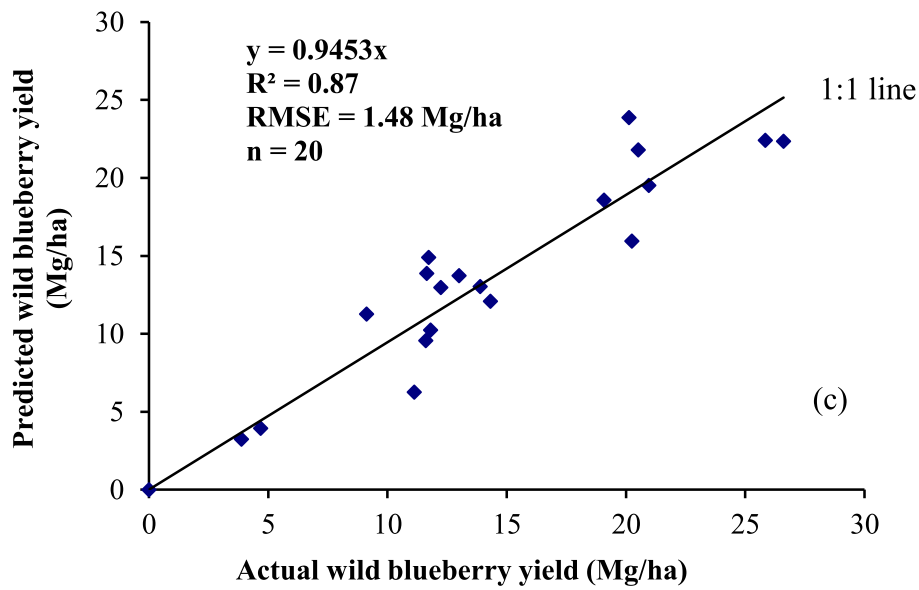
Figure 2-6: Relationship between percentage of blue pixels (%) and actual fruit yield (Mg ha^{-1}) for (a) Cooper site, (b) Small Scott site, (c) Tracadie site and (d) Frankweb site.

The correlations between actual and predicted fruit yield (using validation equation from Small Scott site) in Cooper site (R^2 = 0.91; P < 0.001; *RMSE* = 0.88 Mg ha^{-1}) and Small Scott site (using validation equation from Cooper site) (R^2 = 0.92; P < 0.001; *RMSE* = 0.61 Mg ha^{-1}) were highly significant (Fig. 2-7 a and b). Results of scatter plots revealed that the actual and predicted fruit yield were significantly correlated for Tracadie site (using validation equation from Frankweb site) (R^2 = 0.87; P < 0.001; *RMSE* = 1.48 Mg ha^{-1}) and Frankweb site (using validation equation from Tracadie site) (R^2 = 0.85; P < 0.001; *RMSE* = 1.20 Mg ha^{-1}) (Fig. 2-7 c and d). The slight bias can be seen in the scatter plots where fruit yield was over or under-estimated within the selected fields (Fig. 2-7 a-d). The over-estimation of fruit yield with digital color camera might be due to less vegetation and more exposure of berries to the camera. The dense canopy (vegetation) might be the reason for under-estimation of fruit yield, because the berries were hidden under the leaves.

The zero percentages of blue pixels were due to the presence of bare spots or weeds (no blueberry fruit) within the selected wild blueberry fields. The presence of bare spots in wild blueberry fields is due to natural colonization of plants developed from native stands on deforested farmland by removing competing vegetation (Eaton, 1988). The *RMSE* values for Tracadie and Frankweb sites were observed to be higher when compared with Cooper and Small Scott sites. Higher *RMSE* for Tracadie and Frankweb sites might be due to the high yielding nature of these fields causing over and under estimations. Overall, the results of calibration and validation reported that a digital color camera mounted on the blueberry harvester was capable of estimating pre-harvest fruit yield in real-time during mechanical harvesting. Pre-harvest fruit yield estimates can be compared with the actual yield to quantify overall fruit loss during harvesting.




y = 0.9606x
R² = 0.92
RMSE = 0.61 Mg/ha
n = 20
1:1 line
(b)
Predicted wild blueberry yield (Mg/ha)
Actual wild blueberry yield (Mg/ha)


y = 0.9453x
R² = 0.87
RMSE = 1.48 Mg/ha
n = 20
1:1 line
(c)
Predicted wild blueberry yield (Mg/ha)
Actual wild blueberry yield (Mg/ha)

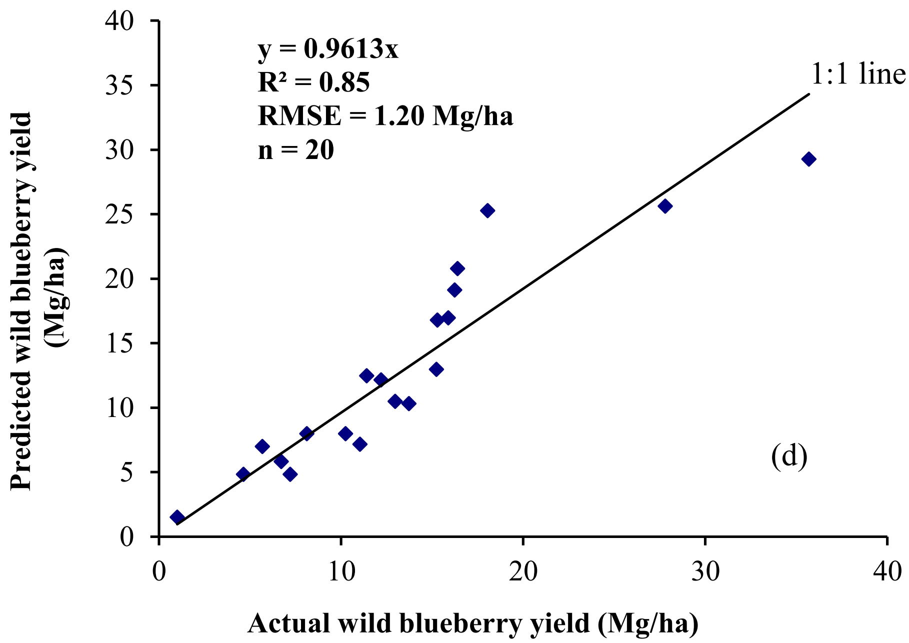


Figure 2-7: Scatter plots of measured and predicted fruit yield in (a) Cooper site, (b) Small Scott site, (c) Tracadie site and (d) Frankweb site.

Ultrasonic sensor was calibrated prior to estimate wild blueberry plant height in real-time. Linear calibration model showed that the plant height was significantly correlated with the sensor output voltage (R^2 = 0.94; P < 0.001) (Fig. 2-8). Result of calibration showed that the ultrasonically estimated plant height was very close to the actual values, suggesting that an ultrasonic sensor can be used to sense plant height in real-time within the wild blueberry fields. The calibration equation developed by Zaman et al. (2010a) for slope sensor was used to estimate slope of the ground on the go within the selected fields. Significant correlations between ultrasonic sensor output voltage and actual plant height, the percentage of blue pixels and actual fruit yield, and pre-calibrated slope sensor suggested that an ultrasonic sensor, a µEye digital color camera, a slope sensor and RTK-GPS can be incorporated on the blueberry harvester to estimate plant height, fruit yield and topographic features in real-time. Custom software retrieved elevation along with the geo-referenced data from the RTK-GPS mounted on the blueberry harvester. The calibration equations for multiple sensors were incorporated into the software to permit estimation of plant height, fruit yield, slope and elevation in real-time. Newly developed custom software converted the ultrasonic voltage into plant height, which is depicted in Figure 2-9. Slope data were not mapped in real-time for Tracadie and Frankweb sites, but derived from elevation data for effective utilization of the technology and to explore ideas for digital conversion. Elevation data were interpolated using ordinary kriging interpolation to develop raster maps. Rasterized maps were utilized to generate the slope raster maps using Slope Protocol of Spatial Analyst extension in ArcGIS 10 software. The conversion of elevation raster into slope is illustrated in Figure 2-10 (for Tracadie site) and Figure A-1; Appendix A (for Frankweb site).

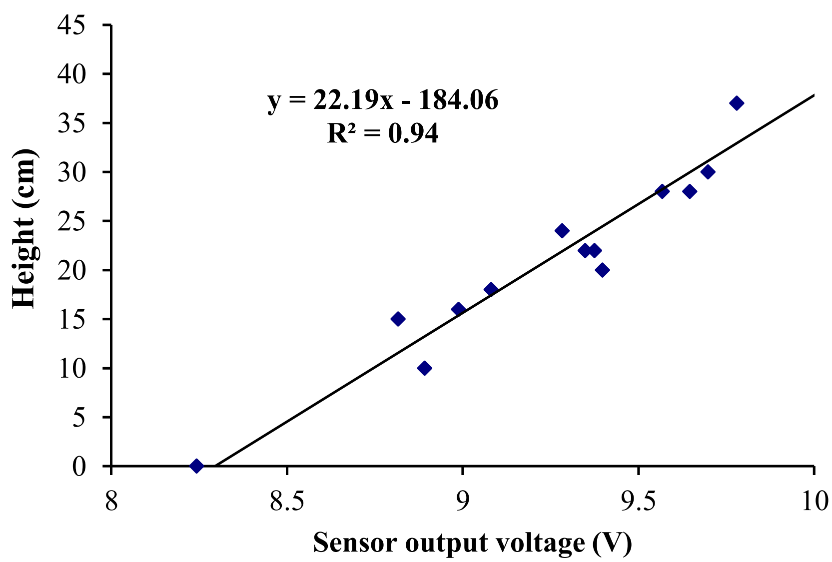


Figure 2-8: Relationship between ultrasonic sensor's output voltage and measured height of actual target plants.

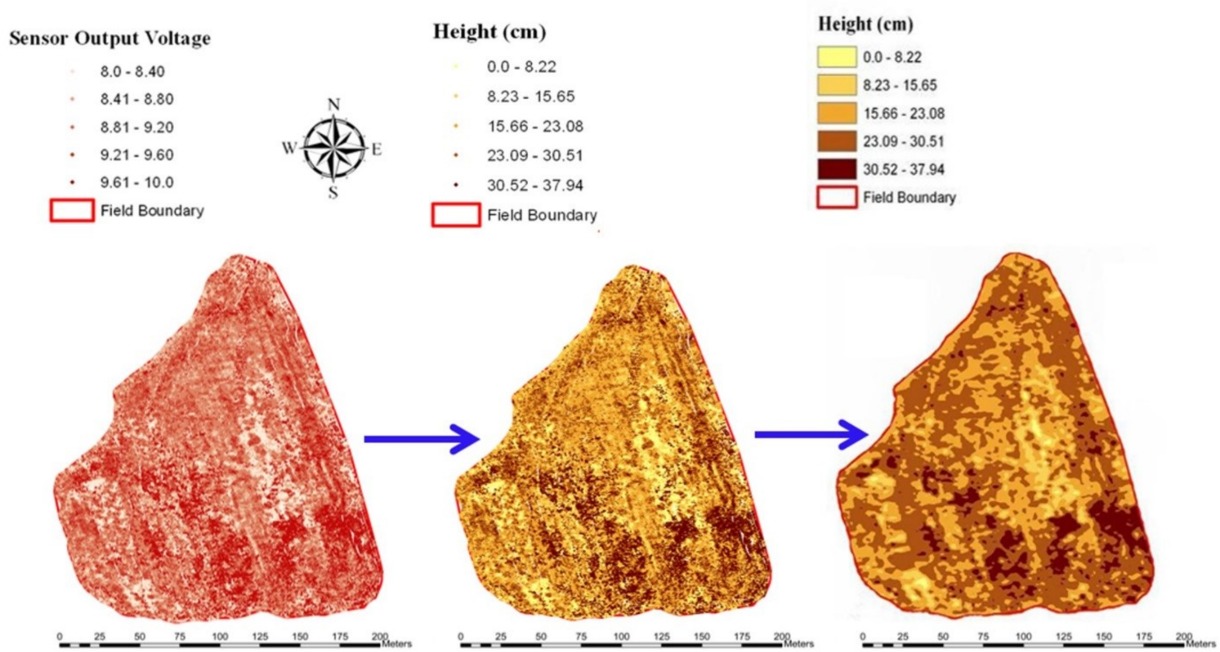


Figure 2-9: (Left) Dot map of ultrasonic sensor output voltage, (Middle) Sensor out voltage converted into plant height and (Right) Kriged map of plant height.

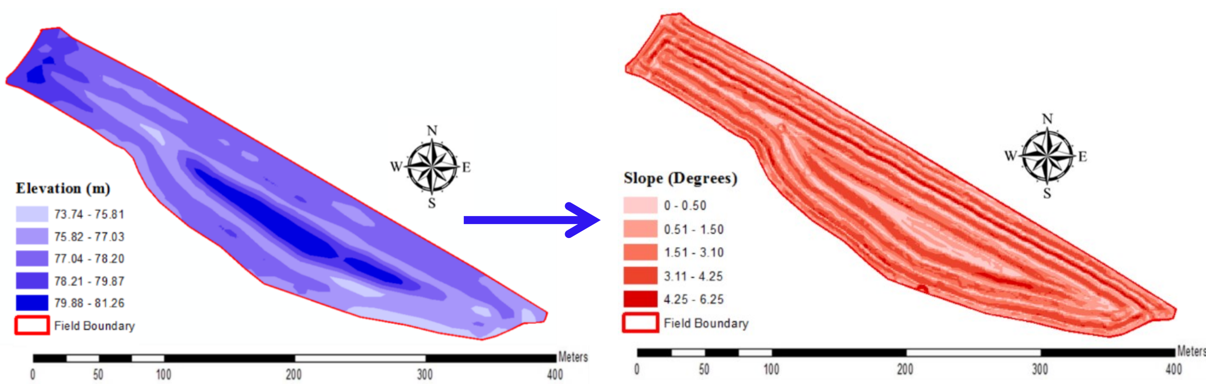


Figure 2-10: Derived slope from elevation data using Slope Protocol of Spatial Analyst extension of ArcGIS 10 software for Tracadie site.

After successful calibrations and validations of the multiple sensors, comprehensive surveys were conducted within the selected fields to sense fruit yield, plant height, slope and elevation in real-time (Figs. 2-11 and 2-12; Figs. A-2 and A-3 Appendix

A). The percentage of blue pixels were converted to fruit yield, ultrasonic sensor's voltage to plant height and slope angle to slope of the ground. Converted data were exported into ArcGIS 10 software to verify the performance of multiple sensors. Fruit yield varied from 0 (bare spots) to 34.99 Mg ha^{-1} in Cooper site (Fig. 2-11), from 0 to 10.51 Mg ha^{-1} in Small Scott site (Fig. 2-12), from 0 to 30.54 Mg ha^{-1} in Tracadie site (Fig. A-2; Appendix A) and from 0 to 39.33 Mg ha^{-1} in Frankweb site (Fig. A-3; Appendix A). Variation in ultrasonically sensed plant height ranged from 0 to 38 cm in Cooper site (Fig. 2-11), from 0 to 34 cm in Small Scott site (Fig. 2-12), from 0 to 39 cm in Tracadie site (Fig. A-2; Appendix A) and from 0 to 37 cm in Frankweb site (Fig. A-3; Appendix A). Dot maps showed that the fruit yield and plant height were highly variable within the selected fields (Figs. 2-11 and 2-12; Figs. A-2 and A-3; Appendix A).

Elevation data retrieved from RTK-GPS varied from 144 to 162 m in Cooper site (Fig. 2-11), from 297 to 303 m in Small Scott site (Fig. 2-12), from 73 to 81 m in Tracadie site (Fig. A-2; Appendix A) and from 19 to 39 m in Frankweb site (Fig. A-3; Appendix A). Variation in slope of the ground estimated from slope sensor ranged from 0 to 19.95 degrees and 0 to 20.10 degrees for Cooper and Small Scott sites, respectively (Figs. 2-11 and 2-12). Variation in slope for Tracadie and Frankweb sites were not estimated by means of a slope sensor, but derived from elevation data. These variations in slope were discussed later in this chapter. Overall, results of survey using multiple sensors indicated large variability in mapped parameter within the selected fields (Figs. 2-11 and 2-12; Figs. A-2 and A-3; Appendix A), which can have an impact on fruit losses during mechanical harvesting.

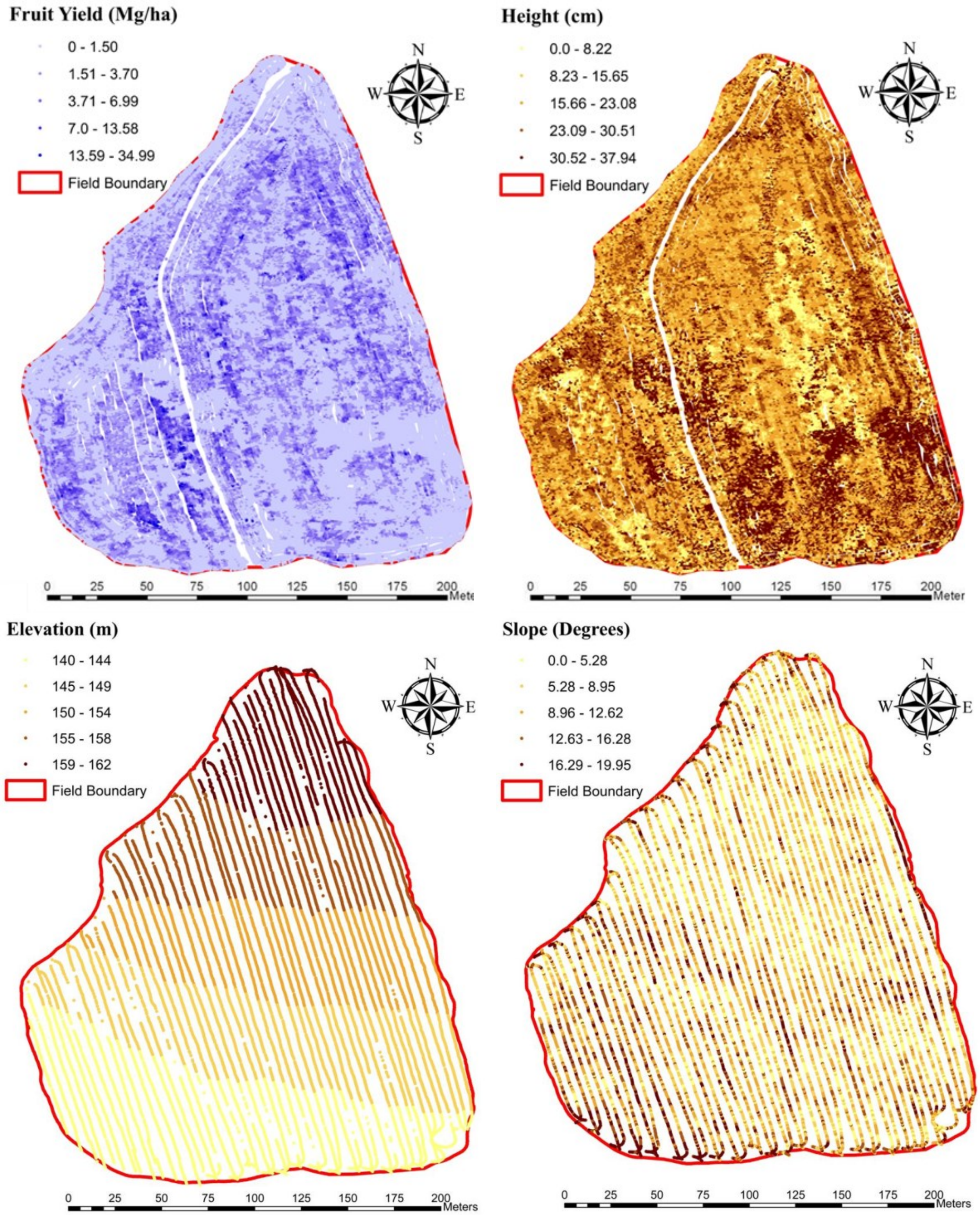


Figure 2-11: Survey dot maps of fruit yield, plant height, elevation and slope for Cooper site using multiple sensors.

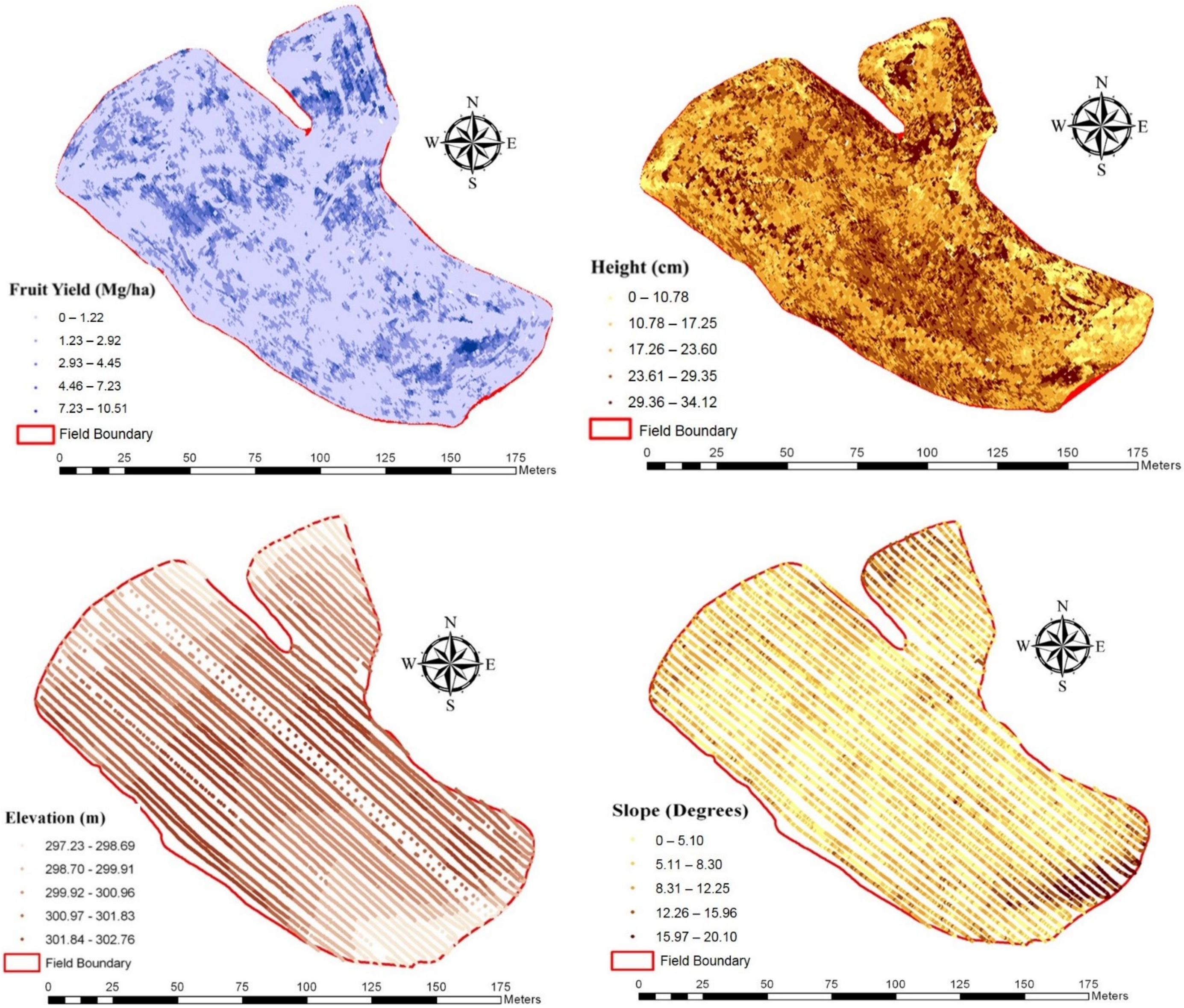


Figure 2-12: Survey dot maps of fruit yield, plant height, elevation and slope for Small Scott site using multiple sensors.

In order to quantify spatial variation of the survey data within the selected fields, geostatistical analysis was performed using GS+ software. Geostatistical analysis suggested large spatial variability in fruit yield, plant height and slope of the ground (range of influence < 33 m) within the selected blueberry fields (Table 2-1 and Table A-1; Appendix A). Fruit yield and plant height were found to be strongly spatial dependent (<

25%) indicating that the variability in these parameters is controlled by management practices (weed and disease control, fertilizer, pollination etc.) for all sites (Table 2-1 and Table A-1; Appendix A). Variations in fruit yield and plant height provided strong evidence that it can have an impact on the picking performance of harvester, since the harvesting operational recommendations are implemented uniformly by ignoring these spatial variations. Harvester adjustments in accordance with the spatial variations can result in greater berry recovery during mechanical harvesting.

The range of influence from semivariogram indicated that the elevation was less variable (29 to 100.34 m) as compare to fruit yield, plant height and slope within the selected wild blueberry fields (Table 2-1 and Table A-1; Appendix A). Results of survey dot maps (Figs. 2-11 and 2-12; Figs. A-2 and A-3; Appendix A) were in agreement with the results of geo-statistical analysis, indicating moderate variation of elevation within the selected fields. Overall, the results of geostatistical analysis narrated that the sensed parameters were moderate to highly variable within the selected fields. Substantial variation in mapped parameters and presence of bare spots/weeds within the blueberry fields emphasize the need to automate the blueberry harvester for compensation of these spatial variations, which can enhance the berry picking efficiency of commercial blueberry harvester. Increased harvesting efficiency can contribute millions of dollars to provincial and federal economies. Moreover, the data acquired from multiple sensors during mechanical harvesting can be helpful in implementing site-specific management strategies to increase fruit yield, farm profitability and mitigate environmental risks. Chang et al. (2012a) also suggested that the intensive digital photographic mapping of wild blueberry fruit yield can be used to develop management zones for site-specific fertilization.

Table 2-1. Semivarigram parameters of fruit yield, plant height, slope and elevation for Cooper and Small Scott sites.

Parameters	Nugget	Sill	Range (m)	Nugget Sill ratio (%)	R^2	Model
Cooper Site						
Fruit Yield (Mg ha^{-1})	0.29	15.16	12.70	1.91	0.56	Exponential
Plant Height (cm)	3.70	72.33	10.20	5.11	0.59	Exponential
Slope (Degrees)	4.51	16.81	21.85	26.82	0.97	Exponential
Elevation (m)	0.10	41.20	100.34	0.24	0.96	Gaussian
Small Scott Site						
Parameters	Nugget	Sill	Range (m)	Nugget Sill ratio (%)	R^2	Model
Fruit Yield (Mg ha^{-1})	2.37	21.92	32.45	10.81	0.61	Exponential
Plant Height (cm)	9.81	77.66	15.43	12.63	0.79	Gaussian
Slope (Degrees)	11.63	46.57	31.85	24.97	0.91	Spherical
Elevation (m)	4.53	52.33	36.42	8.65	0.87	Exponential

Results of kriging interpolation (Figs. 2-13 and 2-14; Figs. A-4 and A-5; Appendix A) and geostatistical analysis (Table 2-1 and Table A-1; Appendix A) confirmed the substantial variation in fruit yield, plant height, slope, and elevation within the selected fields. Detailed maps were generated in ArcGIS 10 software to visualize spatial variations in mapped parameters (Figs. 2-13 and 2-14; Figs. A-4 and A-5; Appendix A). Partial sill and ranges of influence from semivariogram were incorporated in kriging interpolation to produce maps of fruit yield, plant height, slope and elevation (Figs. 2-13 and 2-14; Figs. A-4 and A-5; Appendix A). Kriged maps showed gradual and non-random spatial variability in fruit yield, plant height and slope with significantly different values across selected fields (Figs. 2-13 and 2-14; Figs. A-4 and A-5; Appendix A).

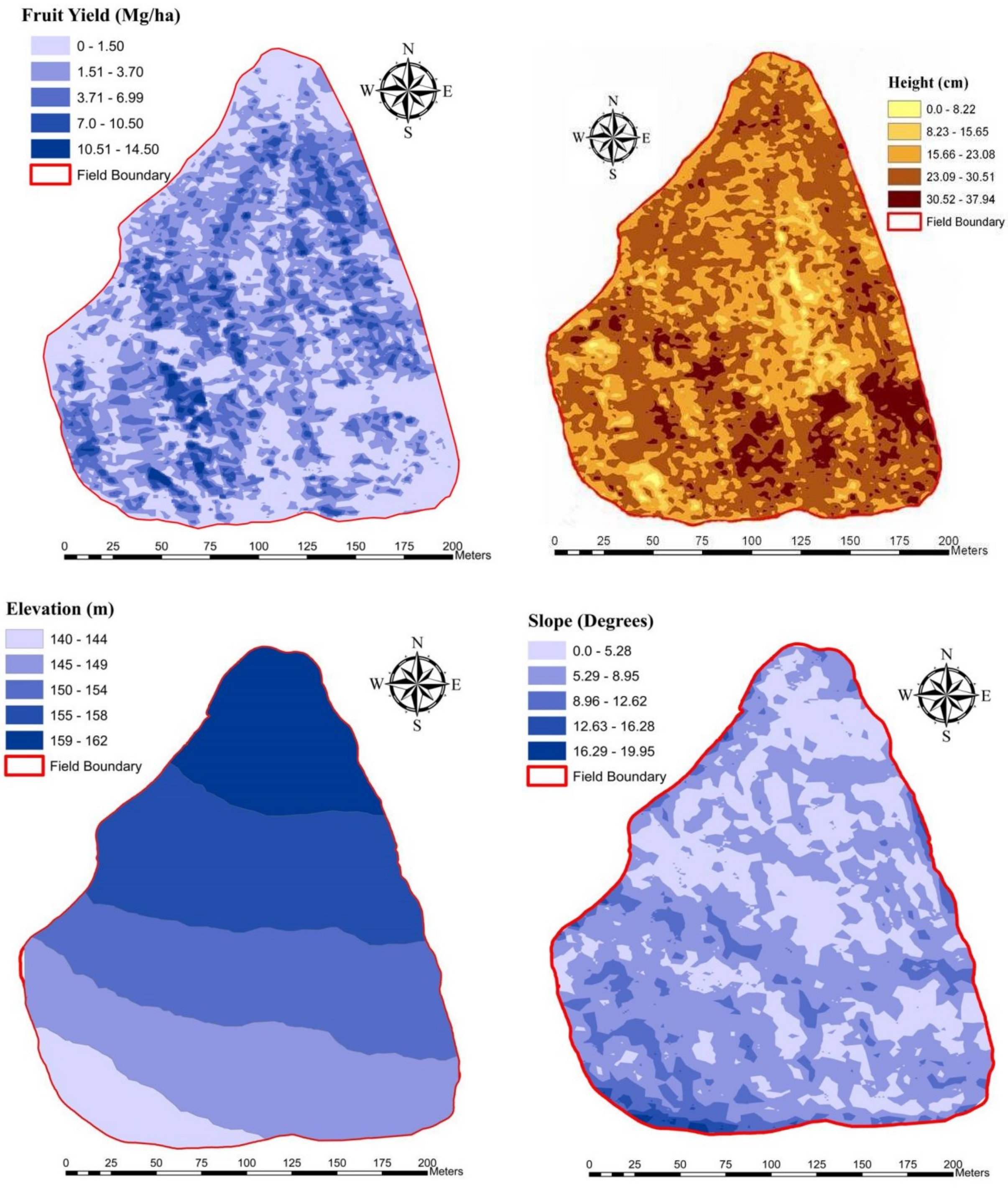


Figure 2-13: Kriged maps of fruit yield, plant height, elevation and slope for Cooper site.

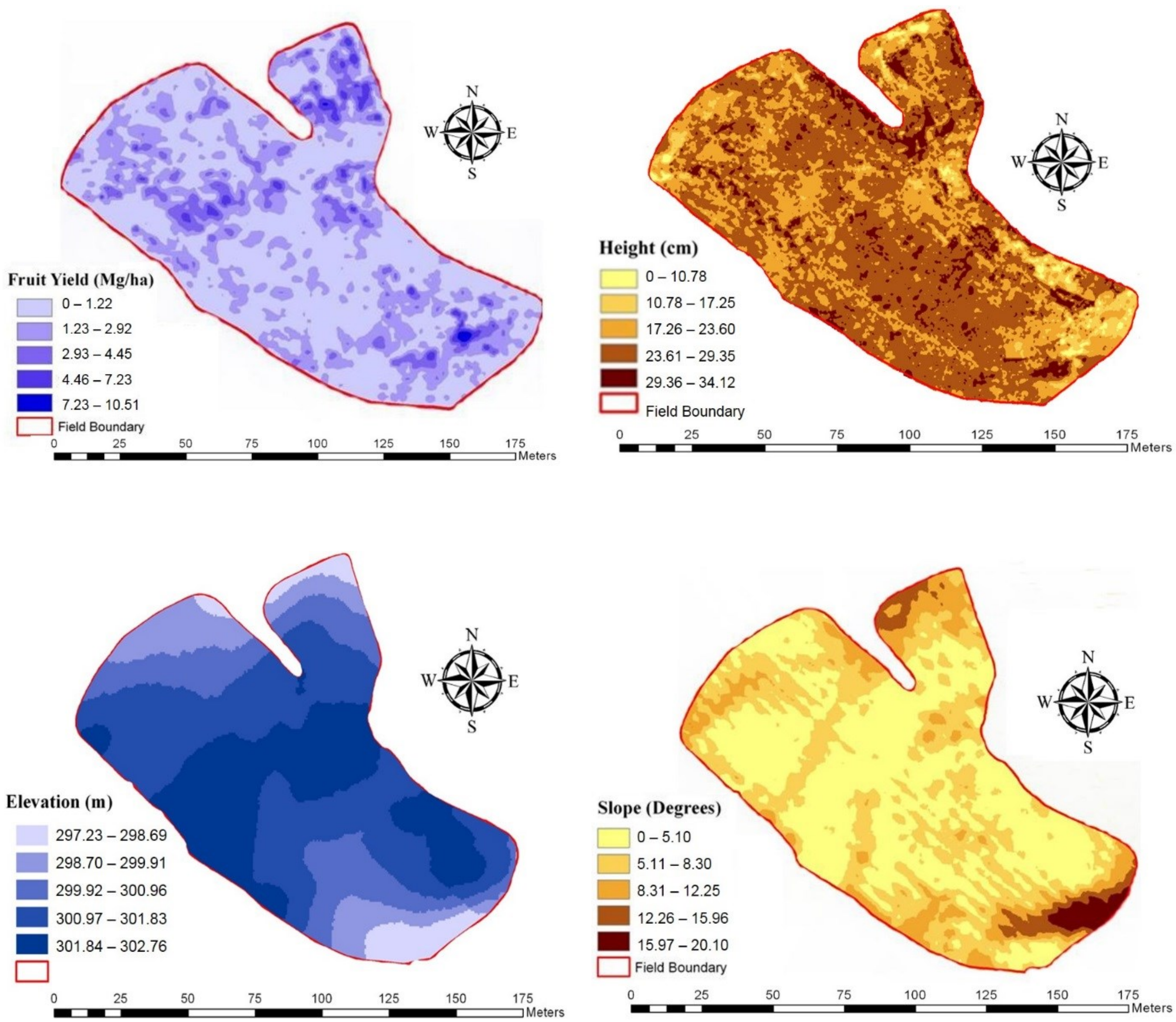


Figure 2-14: Kriged maps of fruit yield, plant height, elevation and slope for Small Scott site.

The range of influence from semivariograms also supported the results identified by the maps (Table 2-1 and Table A-1; Appendix A). In general, map comparison of plant height with fruit yield suggested that the fruit yield was lower in the areas where the plant height was higher (Figs. 2-13 and 2-14; Figs. A-4 and A-5; Appendix A) and vice versa. Map comparison suggested a negative relationship between fruit yield and plant height. Visual inspections also revealed the lower yield in the areas with more plant height suggesting more vegetative growth, emphasizing the need to apply fertilizer on as needed basis to avoid wastage and ensure environmental sustainability. Map comparison suggested that there was less influence of elevation on plant height and fruit yield as these parameters were present in all regions of elevation within the selected sites. Interpolated maps of fruit yield and slope suggested that fruit yield was higher in low lying areas (mild slope) and vice versa (Figs. 2-13 and 2-14; Figs. A-4 and A-5; Appendix A), which might be due to lower availability of nutrients at steep slope areas.

The accuracy of interpolated maps in ArcGIS 10 software was verified by comparing actual values with the kriged values at randomly selected points throughout the selected maps. Results of error assessment suggested that the kriged values were very close to actual fruit yield (*RMSE* = 0.21 Mg ha^{-1}, n = 26), plant height (*RMSE* = 1.33 cm, n = 26), slope (*RMSE* = 0.42 degrees, n = 26) and elevation (*RMSE* = 0.67 m, n = 26) within the selected fields (Fig. 2-15). Results of map error assessment revealed that the kriged estimates were very close to the actual values for selected wild blueberry fields (Fig. 2-15).

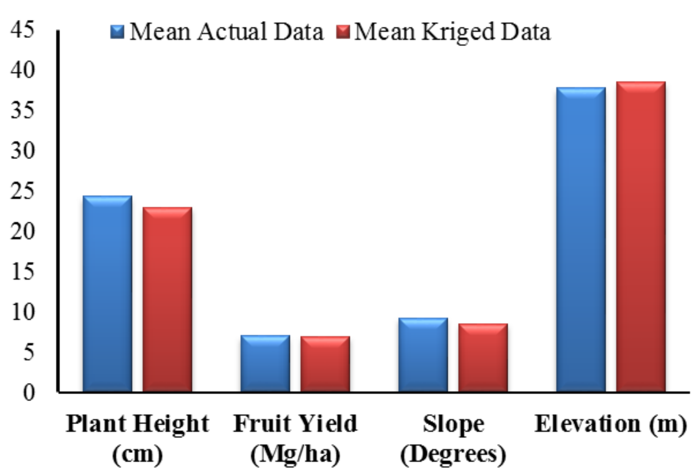


Figure 2-15: Map error assessment of interpolated values in comparison with actual data of plant height, fruit yield, slope and elevation.

Overall, the kriged maps and geo-statistical parameters showed large spatial variability in fruit yield, plant height, slope, and elevation for selected fields. Low yield in some parts of the field might be partially due to weeds and bare spots in those areas (Fig. 2-3; Figs. 2-13 and 2-14; Figs. A-4 and A-5; Appendix A). Another reason for spatial variation in fruit yield might be due to variability in soil properties and plant available nutrients within the field. Adjustments of ground speed and header revolutions of the commercial blueberry harvester in accordance with spatial variation in fruit yield might be helpful in increasing berry picking efficiency. Additionally, spatial patterns of variation in bare spots, weeds and fruit yield within the selected fields could be useful to develop prescription maps for variable rate applications to reduce fertilizer usage. Zaman et al. (2008) mapped bare spots/weed areas in different wild blueberry fields with a mobile mapper GPS. Bare spots/weeds varied from 30 to 50% of the newly developed field and were scattered throughout the fields. Farooque et al. (2012b) suggested defining bare spots as a separate class and allocate zero rate of fertilizer, while delineating management zones for variable rate fertilization. Unnecessary or over-fertilization in bare spots areas may deteriorate water quality, promote weed growth and increase production cost. Under-fertilization restricts yield and can reduce berry quality (Percival and Sanderson, 2004; Zaman et al., 2009). Hence, variable rate fertilization based on considerable variation in fruit yield, bare spots/weeds, plant height and slope could improve farm profitability and reduce environmental impacts.

Zonal statistics was performed to assess variations in fruit yield (estimated from μEye camera) and plant height (estimated from ultrasonic sensor) in different slope zones across the selected fields (Figs. 2-16 and 2-17; Figs. A-6 and A-7; Appendix A). Results of zonal statistics indicated the higher fruit yield and lower plant height in low lying areas (mild slope) and vice versa for Cooper, Small Scott and Frankweb sites (Figs. 2-16 and 2-17; Figs. A-6 and A-7; Appendix A). Plant height was observed to be higher in mild slope areas for Tracadie site (Fig. A-7; Appendix A), which might be due to relatively flat nature (average slope = 2.40 degrees) of this site. Fruit yield was found to be higher in tall plant areas of Tracadie site. Visual inspection revealed that the plants at Tracadie site contained less number of branches, which could be the reason for this variation.

In general, fruit yield was highest in mild slope (Zone 2) for selected sites (Figs. 2-16 and 2-17; Figs. A-6 and A-7; Appendix A). Low fruit yield on the steep slope areas might be due to erosion of nutrients, restricting yield potential. Fruit losses during harvesting can be reduced by lowering the ground speed and header revolutions in high yield areas. Visual observation also confirmed that the fruit losses were higher in high fruit yielding areas and vice versa. Variation in fruit yield and plant height corresponding with the variability in slope suggested that the automation of the blueberry harvester in relation to these variations can result in increased harvesting efficiency during harvesting. The automation of the harvester has the potential to reduce the stress level of the operator, who is continuously involved in changing the machine parameters manually. Zonal statistics also supported the negative relation between fruit yield and plant height. These results were in agreement with the findings of Farooque (2010). Yang et al. (1998) showed that topographic variables such as elevation, slope and aspect can explain 15 to 35% of wheat yield variability at field scale.

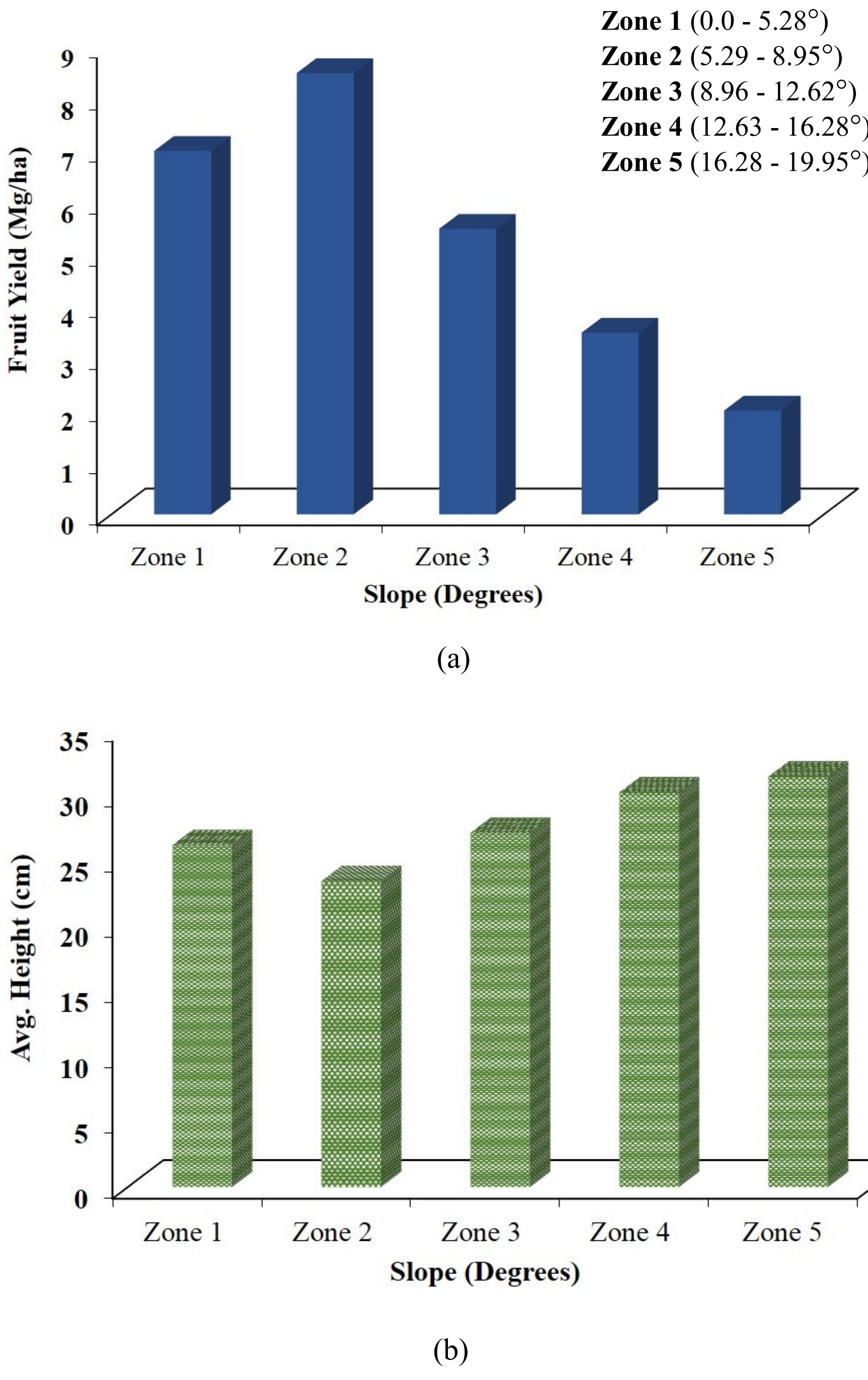
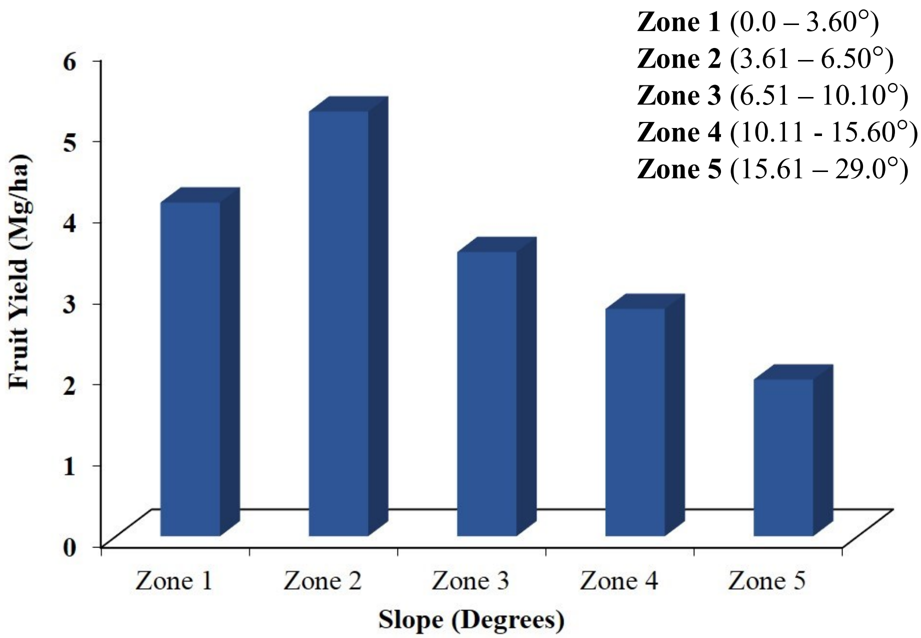
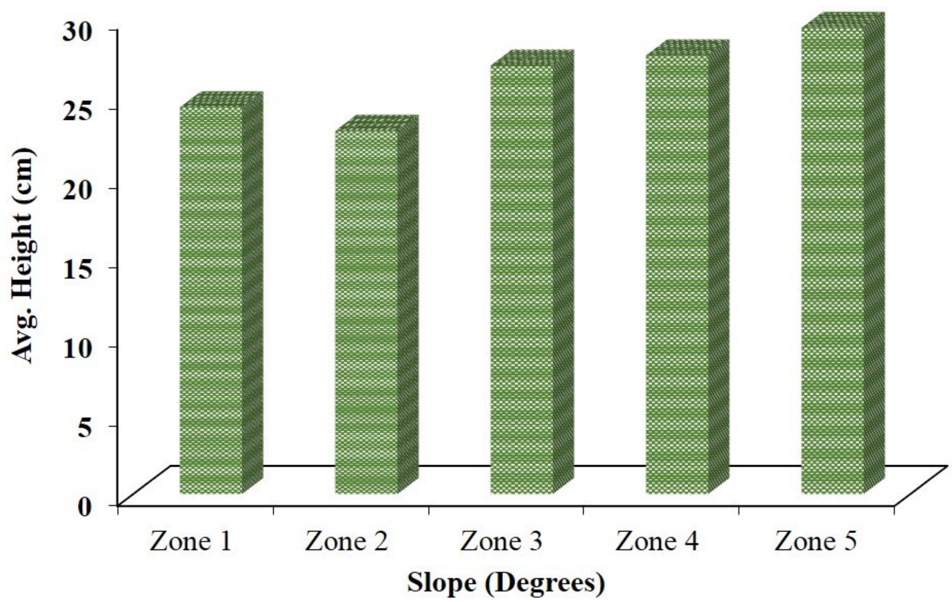


Figure 2-16: Bar graphs showing the variation of fruit yield and plant height within different slope zones for Cooper site.



(a)



(b)

Figure 2-17: Bar graphs showing the variation of fruit yield and plant height within different slope zones for Small Scott site.

The performance of μEye digital color camera to estimate pre-harvest fruit yield and quantify overall fruit losses non-destructively, the actual fruit yield collected at the shed was compared with the estimated fruit yield (Table 2-2). The μEye camera mounted on a commercial wild blueberry harvester took 50,640 images prior to harvest with an estimated fruit yield of 10,232 kg, while the actual yield collected in the harvester bin weighed at 9,100 kg for Cooper site, suggesting 11.07% loss of berries while harvesting. Total number of images taken at Small Scott site were 30,683 with an estimated fruit yield of 3,408 kg. The actual fruit yield collected by the harvester was 3,110 kg indicating 8.74% loss of berries for Small Scott site (Table 2-2). The μEye camera took 87,481 images prior to harvest with an estimated fruit yield of 42,622 kg, while the actual yield collected in the harvester bin weighed at 35,232 kg for Frankweb site, suggesting a 17.33% loss of berries during mechanical harvesting (Table 2-2). The total number of images were 63,224 with an estimated fruit yield of 18,588 kg for Tracadie site. The actual fruit yield collected at the shed was 16,172 kg indicating 14.65% loss of berries for Tracadie site (Table 2-3).

Table 2-2. Comparison of actual yield (from the shed) versus predicted yield using μEye digital color camera to quantify overall fruit losses during mechanical harvesting.

Site	Number of Data Points	Actual Yield (kg)	Predicted Yield (kg)	Fruit Loss (%)	Acreage (ha)
Cooper Site	50,640	10,232	9,100	11.07	3.2
Small Scott Site	30,638	3,408	3,110	8.74	1.9
Frankweb Site	87,481	35,232	42,622	17.33	4.6
Tracadie Site	63,224	16,172	18,588	14.65	2.9

Overall fruit losses were lower in Cooper and Small Scott sites when compared with Frankweb and Tracadie sites (Table 2-2). Possible reason for lower fruit losses at

Copper and Small Scott sites might be the low yielding nature of these fields. These results depicted that the fruit losses during harvesting are greatly influenced by the variation in fruit yield within the field. Non-destructive yield mapping confirmed that there were fruit losses during mechanical harvesting, which require physical quantification. Results emphasized the need to evaluate the blueberry harvester for picking efficiency in different fruit yielding (low, medium and high) fields to quantify various types of berry losses (un-harvested berries, berries on the ground and through blower) during mechanical harvesting. Performance evaluation of the commercial harvester will suggest optimal operating conditions in relation to variability in fruit yield to enhance berry recovery. This would help the wild blueberry industry to generate more revenue and increase profitability for the farmers.

2.4 CONCLUSIONS

The goal of this work was to develop and evaluate the multiple sensors system that comprises of μEye camera, ultrasonic sensor, slope sensor, and RTK-GPS for the wild blueberry fruit yield, plant height, slope, and elevation estimations, respectively. There was significant correlation between the percentage of blue pixels and actual fruit yield for selected sites. The correlations between actual and predicted fruit yield (validation) were also highly significant within the selected fields. Ultrasonic sensor output voltage was significantly correlated with actual plant height. Results suggested that the developed system (hardware and custom software) proved very efficient at measuring and mapping fruit yield, plant height, and topographic features in real-time within the wild blueberry fields.

Results of this work have shown that the mapping of wild blueberry fruit yield, plant height, and topographic features were valuable for understanding the relationships in the monitoring fields. Based on the results, it can be concluded that there is potential to estimate and map fruit yield, plant height and topographic features in real-time within the wild blueberry fields using multiple sensors. This would help the industry to generate more revenue and increase profitability with no additional expenditures. Additionally, this information could be used to implement site-specific management practices within the blueberry fields to optimize productivity while minimizing environmental impact of farming operations.

Chapter 2 highlights the integration of multiple sensors onto a commercial wild blueberry harvester to sense fruit yield, plant height and topographic features in real-time during mechanical harvesting. Non-destructive yield mapping prior to harvesting, quantified overall fruit losses, emphasizing the need for physical evaluation of the commercial harvester at different ground speeds and header revolutions to improve berry picking efficiency. Detailed evaluations of the blueberry harvester will suggest optimal machine operating parameters to reduce fruit losses. Chapter 3 of this dissertation concentrated on physical evaluations of the blueberry harvester in selected wild blueberry fields to optimize berry recovery during mechanical harvesting.

CHAPTER 3 EFFECT OF GROUND SPEED AND HEADER REVOLUTIONS ON THE PICKING EFFICIENCY OF A COMMERCIAL WILD BLUEBERRY HARVESTER

The wild blueberry industry is facing increased harvesting losses with the existing commercial harvester. These machines are no longer able to efficiently harvest the higher yields that result from improvements in plant growth and productivity. This study was designed to evaluate the performance efficiency of a commercial wild blueberry harvester for fruit losses during harvesting. Four wild blueberry fields were selected in the Nova Scotia and New Brunswick provinces of Canada. A 3 × 3 factorial experiment was constructed to examine the joint effect of ground speed and header revolution per minute (rpm) on picking efficiency of the harvester. Eighty one yield plots (0.91 × 3 m) were selected randomly in each field. The field boundaries, bare spots, weeds and yield plots were mapped with a RTK-GPS. The harvester was operated at specific levels of ground speed at 1.2, 1.6 and 2.0 km h^{-1} and header rpm of 26, 28 and 30. Total fruit yield, un-harvested berries on the plants, berries on the ground and losses through the blower were collected from each plot within the selected fields. Pre-harvest fruit losses were collected from each plot prior to harvest. The treatment combinations were assigned randomly within the selected fields. Slope, plant height and fruit zone were also recorded manually from each plot.

Results indicated that the pre-harvest fruit losses were lower in early season compared to those harvested later. Un-harvested berries on the plants and losses through the blower were significantly lower than losses on the ground. Significant relationship between fruit yield and total losses ($r = 0.54$ to 0.82) suggested that losses during harvesting were proportional to fruit yield. Factorial analysis of variance showed that the ground speed, header rpm and their interaction were found to have significant (p = 0.05) effects on picking efficiency of the harvester. Results of means comparison showed that a combination of 1.2 km h^{-1} and 26 rpm resulted in significantly lower losses when compared with other treatment combinations. Results also revealed that a suitable combination of ground speed and header rpm can minimize fruit losses during harvesting, which can increase harvestable yield and farm profitability.

The work presented in this chapter has been published in *Applied Engineering in Agriculture Journal* 30(4):535-546, entitled "Effect of ground speed and head revolutions on the picking efficiency of wild blueberry harvester".

3.1 INTRODUCTION

Wild blueberries are an important horticultural commodity native to Northeastern North America. Blueberry plants spread predominately via underground rhizomes with few blueberry seeds germinating in established fields (Glass and Percival, 2000). The stem height of the wild blueberry crop typically ranges from 5 to 30 centimeters (cm) and the fruit size ranges from less than 0.48 cm to greater than 1.27 cm. Most of the berries are medium sized, soft, blue/black fruit with favorable flavor; they are also resistant to cracking (Hayden and Soule, 1969). Wild blueberry fruit has the characteristic of remaining on the plant fully ripe until the greener berries reach maturity. Harvesting does not take place until approximately 90% of the berries are blue. Harvesting of the wild blueberry crop in Canada begins in early August and usually lasts for a month. Mechanical harvesting can cause damage to fruit, particularly bruising which lowers fruit quality by producing softer, leaky berries that are at increased risk of decay during postharvest storage (Dale et al., 1994; Mehra et al., 2012). Berries must be harvested before frost occurs (Kinsman, 1993).

Over the past 100 years the wild blueberry crop has been harvested with a hand rake that has a design similar to a cranberry scoop. Harvesting losses using hand raking varied from crew to crew, but the range had been estimated at 15 to 40% with an overall average of 20% (Kinsman, 1993). One of the biggest problems encountered by blueberry rakers is interference from weeds, which can result in reduced raking speed with many berries missed or spilled. The underlying factors for the development of mechanical harvester were the high labor costs, shortage and quality of labor, short harvesting seasons (Yarbrough, 1992 and 2001), and recent increase in fruit yield (Yarbrough, 2013). Challenges in development of a mechanical harvester were: uneven field topography, low plant height, presence of weeds and debris, and bare soil. Harvesting of blueberries constitutes the greatest expense in producing the crop. There was an interest in reducing this cost by mechanical harvesting (Yarborough, 2001). Mechanical harvesting has been considered as one of the most reliable methods for reducing labor costs (Porrás et al., 1994).

Research on the development of a mechanical harvester started in early 1950s but a viable harvester was not produced until the 1980s (Hall et al., 1983). Many mechanical harvesting systems were developed (Rhodes, 1961; Abdalla, 1963; Hayden and Soule, 1969; Grant and Lamson, 1972, Richard, 1982) during this time span but were not commercially adopted due to many unsolved technical difficulties such as rough terrain, inability to achieve good harvesting efficiencies and mechanical damage to the fruit. Past evaluations of the blueberry harvesters indicated that considerable cost savings may be realized by using the mechanical harvesters, but destruction of plants and reduced berry quality of the harvested crop may result (Marra et al., 1989). Achieving high harvesting efficiency with mechanized harvesting systems has been a challenge for the adoption, due to its impact on total cost of crop production. Harvesting efficiency reveals the extent to which effort/time is well used for the desired operation (Ravetti, 2012).

The first wild blueberry harvester was modified in 1956 from a mechanical cranberry picker consisting of a series of six raking combs that raked in a direction opposite to the travel of the machine. This design suffered from high fruit loss and soil digging during harvesting (Dale et al., 1994). Gray (1969) developed the hollow reel raking mechanism which has served as the basis of harvesters today. The picking efficiency of this machine was 80 to 85% of the berries on the vine (Hayden and Soule, 1969); but, it could only pick 30 to 35% of the fields due to limitations in field terrain. Towson (1969) evaluated the CRCO-UM blueberry harvester and found that the efficiency of this harvester ranged from 75 to 85% depending upon the field conditions. The picking efficiency of a harvester was defined as a ratio of the weight of harvested berries to the weight of berries on the plants before harvesting (Soule and Gray, 1972). They also reported that the wild blueberry harvester picked better on smooth ground with no weeds; it experienced performance efficiency problems in rough and weedy fields. Doug Bragg Enterprises (DBE) Limited, in Collingwood, Nova Scotia achieved great success by improving the harvester design by adding hydraulic control systems for the head and head rotational speed, by introducing speed controls for belts and conveyors, and by altering the width of the picking head (Malay, 2000).

Many researchers have evaluated the performance of different mechanical harvesters for fruit picking efficiency. Birger (2014) compared mechanical harvesting of olives with manual picking, suggesting that the picking efficiency of harvester was 80 to 95% with better quality of olives. Chen et al. (2012) reported that the vibratory shaker resulted in higher efficiency of fruit removal and less fruit damage compared with impact harvester for sweet cherry (*Prunusavium* L.) crop. Rabcewicz and Danek (2010) evaluated the raspberry mechanical harvester for fruit picking efficiency. They suggested that the harvester was 60 to 80% efficient with 1 to 5% raspberries on the ground. Van Dalfsen and Gaye (1999) evaluated three rotary mechanical harvesters for cultivated blueberries. They suggested higher fruit losses with the mechanical harvesters (14 to 30% on an average), when compared with hand raking. Peterson et al. (1997) reported that the highbush blueberries harvested by rotary mechanical harvester not only decreased berry recovery but also had 55% moderate and severe bruise damage to the fruit causing quality issues. They also reported that the bruise damage was only 22% for hand raking. Brown et al. (1996) and Takeda et al. (2008) suggested that the sway harvester significantly reduced the berry picking efficiency and quality for highbush blueberries. They also revealed that the berry quality was better with hand harvesting. Mainland (1993) suggested that the ground loss associated with the mechanical harvesting can be up to 30% of the harvested crop for cultivated blueberries. Strik and Buller (2002) stated that even with well pruned bushes, the ground losses could be 20% of the harvested crop.

Hall et al. (1983) estimated that the DBE blueberry harvester attains 68% (Weedy fields) to 75% (Smooth weed free fields) of total berry yields which is similar to manual raking. The effective field capacity of the DBE harvester was determined to be 1.16 ha/ 10 hr day which is consistent with the 2.24 ha/10 hr day for the double head harvester. Hand rakers picking efficiency was averaged to be 0.135 ha/ 6 hr day indicating that the DBE harvester can compensate for the work of 8 hand rakers (Marra et al., 1988). Sibley (1994) performed an engineering assessment of the DBE blueberry harvester and found that this harvester was 69% efficient. The lower harvesting efficiency was partially due to worn rollers and high ground speed of the chosen machine. Sibley (1992) suggested conducting a study on performance evaluation of a commercial wild blueberry harvester at various ground speeds and header rpm's, to analyze the sensitivity of machine operating parameters on picking efficiency. Farooque et al. (2013) mounted a digital color camera on a wild blueberry harvester to estimate pre-harvest yield in order to quantify overall losses. Results of their study emphasized the need to physically quantify berry losses during harvesting in variable blueberry fields.

Today, the mechanically harvested wild blueberry area is more than 80% of the total wild blueberry area in Canada and only the fields in rough terrain are still hand raked (PMRA, 2005). The DBE is the largest manufacturer of the wild blueberry harvesters. Over 1,500 harvesters, with single, double or triple picking heads are in operation in Atlantic Canada, Quebec and the State of Maine, United States of America. Many researchers have attempted to evaluate the wild blueberry harvesters for fruit losses up to the early 1990s (Rhodes, 1961; Abdalla, 1963; Hayden and Soule, 1969; Hall et al., 1983; Sibley, 1992; Yarborough, 1992), but no work has been done in last 25 years. In the last two decades, improved management practices using selective herbicides, fertilizers, pesticides, pollination and pruning have resulted in healthy and tall plants, higher plant density, tall weeds and significant increases in fruit yield. The wild blueberry industry is facing increased harvesting losses because of these changes in crop conditions. Therefore, the objective of the work presented in this chapter was to evaluate the existing commercial wild blueberry harvester for fruit losses during harvesting to determine an ideal combination of ground speed and header rpm for most efficient fruit recovery and to identify the relationships between the berry losses and measured parameters. Increased berry picking efficiency has the potential to enhance farm profitability of the farmer's community.

3.2 MATERIALS AND METHODS

3.2.1 Study Area

Four wild blueberry fields were selected in Colchester County, Nova Scotia and Tracadie, New Brunswick, Canada to evaluate the commercial blueberry harvester and to quantify fruit losses. The selected fields were the Cooper (Field A) site (45.480573°N, 63.573471°W; 3.2 ha), Small Scott (Field B) site (45.600641°N, 63.086512°W; 1.9 ha), Tracadie (Field C) site (47.2824117°N, 65.1440212°W; 1.6 ha) and Frankweb (Field D) site (45.241900°N, 63.401143°W; 2.57 ha). Fields A and B were in their vegetative sprout year of the biennial crop production cycle in 2010 and crop year in 2011, while fields C and D were in sprout year in 2011 and crop year in 2012. The selected fields had been under commercial management over the past decade and received biennial pruning by mowing for the past several years along with conventional fertilizer, weed and disease management practices. The soils at the experimental fields were classified as sandy loam (Orthic Humo-Ferric Podzols), which is a well-drained acidic soil (Webb and Langille, 1996). The geographical locations of the monitoring sites are presented in Figure 3-1.

3.2.2 Harvester Operating Mechanism

Wild blueberry harvesters manufactured by the DBE are designed to be operated mounted on tractors. These are the only high capacity, reliable harvesters available to the

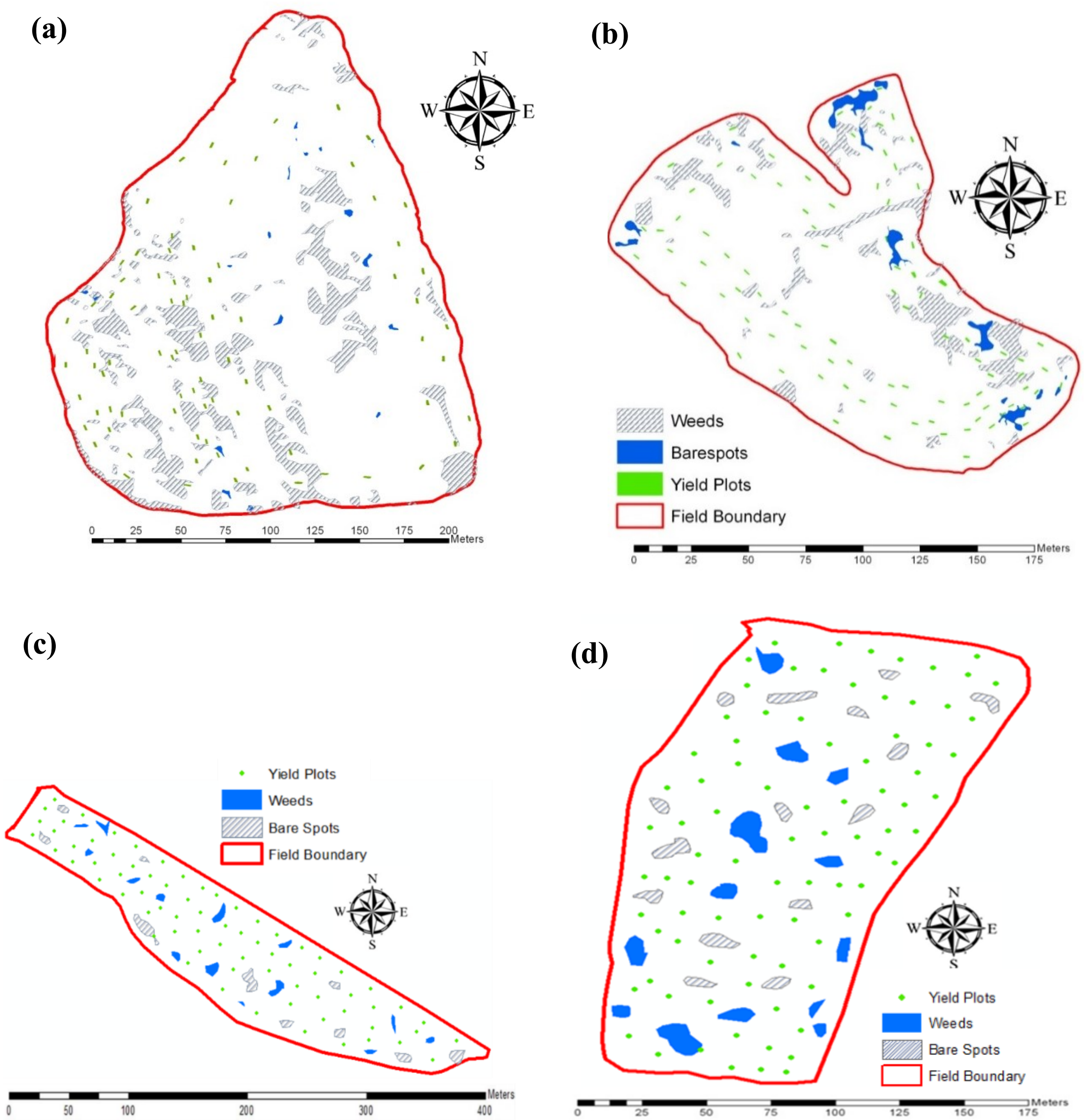


Figure 3-1: Layouts of the selected wild blueberry fields, (a) Cooper site, (b) Small Scott site, (c) Tracadie site and (d) Frankweb site.

blueberry industry. The operating concept of the picking reel is illustrated in Figure 3-2. The picking head of harvester is driven by a hydraulic motor, which is controlled manually by the operator (Fig. 3-2) inside the tractor cabin. The picking reel contains sixteen teeth bars with sixty seven equally spaced curved teeth on each bar attached to the periphery of the reel or head (Fig. 3-2). The teeth bars mounted on the picking reel are operated in a clockwise direction, opposite to the direction of the forward speed of tractor to pick wild blueberry crop. The hydraulic motor can vary the rotational speed (rpm) of the harvester head as desired by the operator. The speed of upward movement of the teeth through the plants can be altered by changing the reel rpm. By appropriately altering the reel rpm the operator can provide the gentle lift necessary to pick berries and reduce losses with minimal mechanical damage.

The cleaning brush installed at the top of the picking reel can be operated in the direction opposite to the picking reel (Fig. 3-2). The purpose of the cleaning brush is to remove any debris and plant shoots from the toothed bars that would interfere with effective berry picking. The picked berries are dropped off onto the inside conveyer and transported to the side conveyer for storage in the bin behind the tractor (Fig. 3-2). The blower fan installed at the conveyer is used to blow off any debris and soil prior to storage in the bin. To achieve most efficient picking the guide wheel in front of the harvester is utilized to maintain the height of the harvester from the ground. The operator has to adjust the height of the harvester head manually to adjust for changes in the plant height.

3.2.3 Experiment Design

The single head wild blueberry harvester was mounted on a 62.5 kW John Deere tractor (Fig. 3-3). The experiments were designed as 3 × 3 factorial analysis with levels of ground speed (1.2, 1.6 and 2.0 km h^{-1}) and header revolutions (26, 28 and 30 rpm). All treatment combinations were assigned randomly with nine replications at each experimental field. Factorial designs are widely used in experiments involving several factors, where it is required to study the joint effect of the factors on response variables. Traditionally, the wild blueberry harvester has been operated at a ground speed of 1.6 km

h^{-1} and 28 rpm. Eighty one plots with the same width as the harvester head, 0.91 m, and 3 m length were made randomly using a measuring tape in the path of the operating harvester. The harvester head was raised with the machine running to expel all the previously harvested fruit in the storage bin prior to harvesting the experimental plot. Experimental plots were harvested at chosen levels of ground speed and header rpm within the selected fields. The field boundaries, bare spots, weeds and yield plots were mapped with a RTK-GPS in each field (Fig. 3-1).

3.2.4 Pre-harvest Fruit Losses

Pre-harvest fruit losses were estimated prior to the harvesting of yield plots in selected fields. A wooden quadrat of 0.91 × 3 m was placed on the selected plots (n = 81) to collect pre-harvest fruit losses manually at each field. The collected berries were placed in labeled Ziploc bags and weighed using a balance (Denver Instruments Inc., NY, USA) to quantify the amount of berry losses at the onset of experiment. The percentage of pre-harvest fruit losses was calculated using the following formula.

$$\text{Preharvest fruit losses (\%)} = \frac{PHL}{TFY} \text{ X } 100 \quad (3\text{-}1)$$

$$TFY = PHL + Fruit\ yield\ collected\ from\ harvesting\ plot \quad (3\text{-}2)$$

where *PHL* is pre-harvest fruit losses prior to harvest (kg) and *TFY* is total fruit yield (kg).

3.2.5 Fruit Losses during Harvesting

Prior to harvest experimental plots, the harvester head was raised and moved back (approximately, 25 m) to attain the selected level of ground speed and header rpm. The harvester head was lowered at a chosen combination to harvest the yield plot and raised again at the end of each plot. Fruit yield was collected from each plot by attaching a bucket

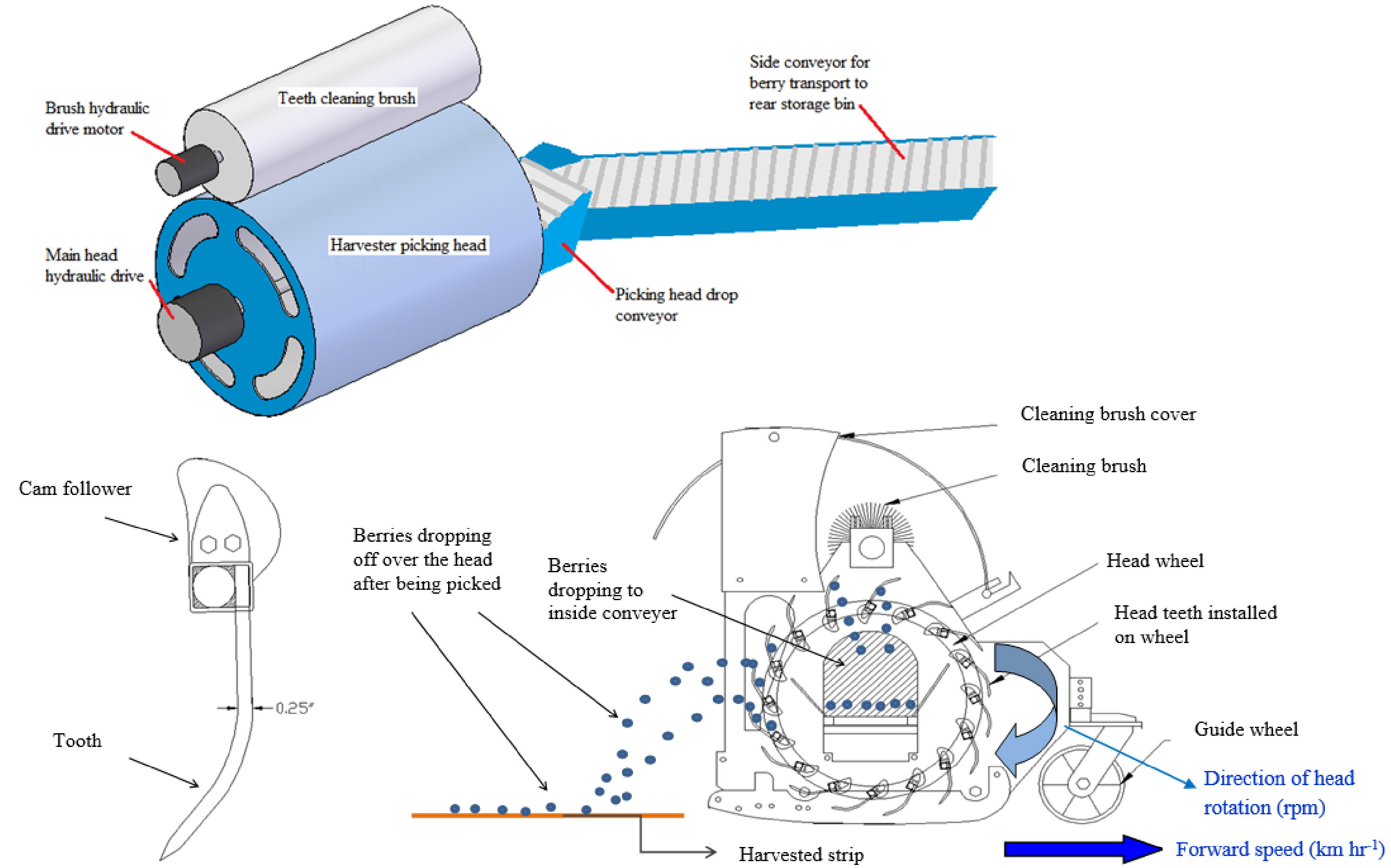


Figure 3-2: Schematic diagrams to show the working principle of a commercial wild blueberry harvester.

Figure 3-3: Single head wild blueberry harvester mounted on a John Deere tractor.

to the harvester conveyer belt (Fig. 3-4 b). Three types of losses were calculated from the harvested plot, *i.e.* un-harvested berries on the plant, berries knocked onto the ground due to the impact of the harvester head and losses through the blower (Fig. 3-4). The loss through the blower was collected by attaching a bucket under the blower fan to collect any berries that would be blown away (Fig. 3-4). Berries on the ground and un-harvested berries on the plants were manually picked from each plot (Fig. 3-4 a). The berries were separated from leaves and debris to record the actual weight of fruit yield and losses from each plot. The cleaned berries were placed in labeled Ziploc bags and weighed using a balance. Fruit yield and losses data were recorded in kilograms (kg). The purpose of calculating these losses at chosen levels of ground speed and header rpm was to assess the picking efficiency of the harvester and to find a suitable combination with minimum yield losses during harvesting.

Five plant height and fruit zone readings were recorded using a ruler to get an average value for plant height and fruit zone within the selected plots (Fig. 3-5). Slope angle was also measured manually using a Craftsman SmartTool Plus digital level (Sears Holdings Corp., Hoffman Estates, IL, USA). Five slope measurements were made at each harvesting plot within a radius of one meter and averaged to obtain the representative slope in each plot for selected fields (Fig. 3-5). Pre-harvest fruit losses were not brought into consideration while evaluating the performance of blueberry harvester because these were not caused by the harvester. Picking efficiency of the blueberry harvester was examined using the following equations.

(a) **(b)**

Figure 3-4: (a) Manual collection of loss on the ground and un-harvested berries on the plants; (b) Collection of fruit losses through the blower and total fruit yield from the harvested plot.

$$\text{Un} - \text{harvested berry losses } (\%) = \frac{UHBP}{TFY} \text{ X } 100 \tag{3-3}$$

$$\text{Losses on the ground } (\%) = \frac{BOG}{TFY} \text{ X } 100 \tag{3-4}$$

$$\text{Losses through the blower } (\%) = \frac{LTB}{TFY} \text{ X } 100 \tag{3-5}$$

$$\text{Total loss } (\%) = \frac{TFL}{TFY} \text{ X } 100 \tag{3-6}$$

$$TFY = YC + UHBP + BOG + LTB \quad (3\text{-}7)$$

$$TFL = UHBP + BOG + LTB \quad (3\text{-}8)$$

$$\text{Picking Efficiency of the Harvester} = \left(1 - \frac{TFL}{TFY}\right) \text{X } 100 \quad (3\text{-}9)$$

where *UHBP* is un-harvested berries on the plants, *YC* is yield collected by the harvester from the experimental plot, *TFY* is total fruit yield collected from the harvested plot, *BOG* is berries on the ground, *LTB* is losses through the blower and *TFL* is total fruit losses. All variables were recorded in kg.

Figure 3-5: Manual measurement of plant height and fruit zone (left) and slope of the ground (right).

3.2.6 Statistical Analysis

The statistical analysis was performed using Minitab 16 (Minitab Inc. NY, USA) and SAS 9.3 (SAS Institute Inc., NC, USA) statistical software. The total variability in fruit losses can be due to main effects, interaction effects and the uncontrollable factors. Normal probability plot of residuals was used to check the normality of error terms using Anderson-Darling (A-D) test at a significance level of 5%. Residual versus fitted values plot was utilized to check the constant variance of error terms. Treatments were applied in random order to achieve independence of error terms. Classical statistics were utilized to calculate minimum, maximum, mean, standard deviation, coefficient of variation and skewness of collected data. A factorial analysis of variance (ANOVA) using general linear model (GLM) procedure was performed to study the joint effect of ground speed and head rpm on fruit losses during mechanical harvesting. Multiple mean comparisons were performed using least squares (LS) means to determine which specific means significantly differ from each other in the treatment combinations. Regression analyses were performed to develop correlations among the fruit yield, fruit losses, slope and crop parameters.

3.3 RESULTS AND DISCUSSION

The validity of the model assumptions (normal distribution, constant variance and independence of the error terms) was tested by examining the residuals at 5% level of significance. The non-normal data were normalized using logarithmic transformations for analysis and were back transformed to the original scale for reporting results. The coefficient of variation (CV) is a first approximation of 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%. Descriptive statistics revealed that the fruit yield and pre-harvest fruit losses were highly variable (CV > 34%) within the selected fields (Table 3-1). Field D was found to have the highest fruit yield when compared with A, B and C fields (Table 3-1). Higher yield at field D could have been due to low coverage of weed/bare spots (8.2%), when compared with A (18%), B (15%) and C (9.2%) fields. Other contributing factors could be better nutrient plans, favorable weather conditions and effective pollination for field D.

Pre-harvest fruit losses were 4.68%, 7.33%, 7.31% and 5.42% for fields A, B, C and D, respectively (Table 3-1). The later harvest dates from August 28 to September 10 contributed to higher pre-harvest losses in fields B and C. Visual inspection also revealed that more berries were present on the ground during late season harvesting when compared with early season (August 5 to August 25), which might be due to the occurrence of senescence causing increased fruit drop as it ripens. Results suggested that early season harvesting would increase harvestable berry yield by reducing pre-harvest fruit losses.

Table 3-1. Summary statistics of fruit yield and pre-harvest fruit losses for selected fields.

Pre-harvest Fruit Losses (kg ha^{-1})							
Field	Min	Max	Mean	Mean (%)	S.D	C.V (%)	Skewness
A	80	360	182	4.68	83.3	46.29	0.76
B	40	400	207	7.33	99.6	47.27	0.09
C	80	460	439	7.31	40.74	40.74	0.83
D	110	515	467	5.42	117.8	36.27	0.64
Fruit Yield (kg ha^{-1})							
Field	Min	Max	Mean		S.D	C.V (%)	Skewness
A	305	9914	3887		2014	54.35	0.82
B	254	7635	2825		1570	59.98	0.89
C	1690	10445	5995		1942	34.96	0.11
D	2218	17968	8603		2915	35.81	0.83

Summary statistics suggested that fruit yield, un-harvested berries on the plants, berries on the ground, loss through the blower, total loss and slope were highly variable with the CV > 35% (Table 3-2). Plant height and fruit zone were moderately variable for fields A, B and D (Table 3-2). The selected parameters were observed to be moderate to highly variable with CV ranging from 14% to 54% for field C (Table 3-2). The variability in fruit yield, plant height, fruit zone and berry losses could be due to the intrinsic sources (natural soil variations and yielding nature of different clones) and extrinsic sources (harvester operation, operator skills, field topography and crop management practices) (Hepler and Yarborough, 1991).

Since pre-harvest losses were not caused by the harvester, they were excluded from the evaluation of picking efficiencies of the blueberry harvester (Table 3-2). The un-harvested berries were found to be significantly higher (244.30 kg ha^{-1}) for field D when compared with other fields (< 100 kg ha^{-1}) indicating that the most of the berries on the plants were either picked by the harvester or dropped on the ground from the impact force of harvester head (Table 3-2). The un-harvested berries on the plants were 2.26%, 1.52% 1.66% and 3% of the total losses for fields A, B, C and D, respectively. Higher percentage of un-harvested berries for fields A and D might be because the berries were not ripe enough to fall off the plants as these fields were harvested during early season.

Results reported that the berries on the ground after harvesting the experimental plots were 7.85%, 6.32%, 11.29% and 13.49% for fields A, B, C and D, respectively (Table 3-2). Significantly higher percentage of losses on the ground suggested that the berries were picked by the harvester but not effectively moved to the conveyer for transportation to the storage bin. The visual inspections also revealed that the picked berries were dropped off over the harvested strip which might be due to the impact (force) of the harvester head, and the centrifugal force developed by the higher header rpm, pushing the berries away from the center and contributing to ground losses (Fig. 3-2). Results showed that the losses through the blower were 1.17%, 0.8%, 1.14% and 1.74% for fields A, B, C and D, respectively (Table 3-2). The total losses were observed higher for field D (18.24%) when compared with fields A (11.28%), B (8.68%) and C (14.10%). These results suggested that the fruit losses were proportional to fruit yield within the selected fields (Fig. 3-6).

Table 3-2. Summary statistics of fruit yield, berry losses, slope, plant height and fruit zone for selected fields.

Field A

Parameters	Min	Max	Mean	Mean (%)	S.D	C.V (%)	Skewness
Fruit Yield	305	9914	3705	-	2014	54.35	0.82
Un-harvested Berries	4.90	342.70	83.58	2.26	77.41	92.61	1.50
Berries on the Ground	19.6	891	291	7.85	186	63.94	1.15
Loss through Blower	4.92	225.21	43.47	1.17	39.05	89.83	1.99
Total Losses	58.7	1096.7	418	-	225.6	53.96	0.79
Total Losses (%)	3.73	25.5	11.28	11.28	5.86	46.38	0.62
Plant Height (cm)	10.60	32.80	23.64	-	4.06	17.18	-0.38
Fruit Zone (cm)	7.80	25.30	19.35	-	3.56	18.42	-0.45
Slope (degrees)	0.5	19.53	7.47	-	4.40	58.88	0.89

Field B

Parameters	Min	Max	Mean	Mean (%)	S.D	C.V (%)	Skewness
Fruit Yield	253	7635	2618	-	1570	59.98	0.89
Un-harvested Berries	0	299.37	39.68	1.52	62.47	157.95	3.12
Berries on the Ground	3.38	708.4	165.4	6.32	127.3	76.99	1.44
Loss through Blower	0	220.23	22.16	0.80	33.01	148.94	3.50
Total Losses	5.1	833.7	227.2	-	167.3	73.60	1.51
Total Loss (%)	0.99	26.85	8.68	8.68	5.07	56.02	1.45
Plant Height (cm)	13	34	22.99	-	3.63	15.80	0.06
Fruit Zone (cm)	7.40	30.5	19.07	-	3.62	18.99	-0.05
Slope (degrees)	0.20	23.66	7.04	-	4.47	63.58	1.35

Field C

Parameters	Min	Max	Mean	Mean (%)	S.D	C.V (%)	Skewness
Fruit Yield	1690	10445	5556	-	1942	34.96	0.11
Un-harvested Berries	23.77	319.54	92.23	1.66	38.34	41.57	2.77
Berries on the Ground	147.9	1056.3	627.5	11.29	234.12	39.17	0.10
Loss through Blower	21.13	110.92	63.67	1.14	18.62	29.25	0.22
Total Losses	192.8	1228	783.5	-	256.7	34.07	-0.01
Total Loss (%)	7.99	22.34	14.10	14.10	3.09	22.20	-0.02
Plant Height (cm)	19	39	26.95	-	3.96	14.70	0.44
Fruit Zone (cm)	11.23	34.60	23.09	-	3.92	17.01	-0.24
Slope (degrees)	0	6.56	2.58		1.40	54.45	1.04

Field D							
Parameters	Min	Max	Mean	Mean (%)	S.D	C.V (%)	Skewness
Fruit Yield	2218	17968	8136	-	2915	35.81	0.83
Un-harvested Berries	42.9	574.71	244.30	3.0	115.7	47.37	0.67
Berries on the Ground	131.5	1847	1098.12	13.49	385.3	35.97	-0.34
Loss through Blower	31.6	528.9	142.21	1.74	90.6	63.78	2.16
Total Losses	240.2	2616.10	1484.6	-	545.9	37.42	0.0
Total Losses (%)	4.70	29.47	18.24	18.24	4.68	25.69	-0.25
Plant Height (cm)	13.10	31.80	22.37	-	3.65	16.35	0.48
Fruit Zone (cm)	11	24.75	17.55	-	3.43	19.55	0.06
Slope (degrees)	0.73	21.69	7.86	-	5.16	65.69	0.89

Note: Fruit yield, un-harvested berries, berries on the ground, loss through the blower and total losses were recorded in kg ha^{-1} unless otherwise specified.

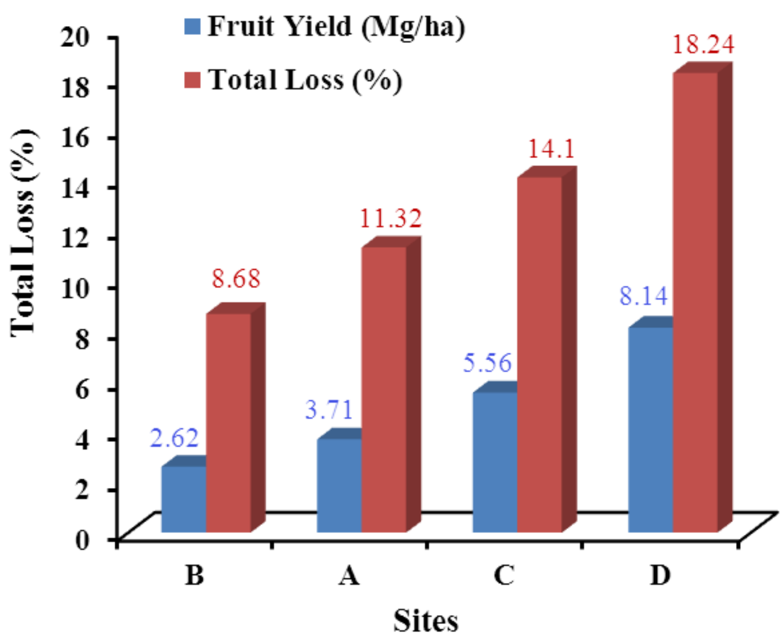


Figure 3-6: Overall variation in fruit losses with respect to fruit yield within the selected fields.

Significant relationship between fruit yield and total losses (r = 0.54 to 0.82) for selected fields (Table 3-3) also support the concept that the losses during harvesting increased with an increase in fruit yield and vice versa. Overall, the picking efficiency of the blueberry harvester was 88.72%, 91.32%, 85.90% and 81.76% for fields A, B, C and

D, respectively. These results also confirmed the accuracy of non-destructive estimates of pre-harvest fruit losses from digital color camera mounted on the commercial wild blueberry harvester (Table 2-2) as the actual fruit losses were very close to the estimated losses during mechanical harvesting. Plant height, fruit zone and slope were similar for the selected fields except field C (Table 3-2), where the plants were taller with a higher fruit zone (Table 3-2). A fruit zone higher above the ground can result in better picking efficiency of the blueberry harvester. Un-harvested berries on the plants were significantly correlated with plant height (r = -0.22 to -0.40) suggesting that the un-harvested berries were lower in the tall plants and vice versa (Table 3-3). Negative correlations of the un-harvested berries on the plants, on the ground and for total losses with the plant height and fruit zone indicated that the tall plants with higher fruit zone provided better opportunity for the harvester to pick more effectively (Table 3-3). Visual inspections revealed that the lodging of crop at the edges of bare spots lowered the fruit zone resulting in an increased losses. Soule and Gray (1972) indicated that a blueberry harvester can perform better in flat fields when compared with rough terrain. Higher losses (14.10%) for field C, although the field was relatively flat (Table 2), might be due to the late season harvesting (August 28 – September 10). Visual observations suggested that the plants were less dense at field C when compared with the fields A, B and C.

Significant correlations of fruit yield with berry losses during harvesting (r ~ 0.23 to 0.78) suggested a linear trend indicating that the fruit losses were greatly influenced by the variations in fruit yield (Table 3-3). Berries on the ground were found to have a significant relationship with total losses (r = 0.91 to 0.98) suggesting that losses on the ground increased with an increase in total losses. Significant positive correlation of total losses with the slope for fields A (r = 0.23) and B (r = 0.38) indicated that the total losses increased with the steepness of the slope (Table 3-3), revealing that the topography of the ground seems to have an impact on the picking efficiency of the harvester. Topography was addressed as one of the challenges during development process of the wild blueberry harvester (Yarbrough, 2001; Hall et al., 1983). Total fruit losses were non-significantly correlated with slope, indicating that there was no effect on fruit losses during harvesting for fields C and D (Table 3-3). This could be due to the flat nature of field C and significantly higher yields at field D (Table 3-2).

Table 3-3. Correlation matrix among fruit yield, berry losses, crop parameters and slope for selected fields.

Field A

	Fruit Yield	Un-harvested Berries	Berries on the Ground	Berries through Blower	Total Losses	Plant Height	Fruit Zone
Un-harvested Berries	0.25*						
Berries on the Ground	0.47***	0.24*					
Loss through Blower	0.40***	-0.03 NS	0.15 NS				
Total Losses	0.54***	0.51***	0.93***	0.28**			
Plant Height (cm)	-0.34**	-0.40 ***	-0.21 NS	0.19 NS	-0.28 *		
Fruit Zone (cm)	-0.35**	-0.50***	-0.22*	0.23 *	-0.32**	0.94***	
Slope (degrees)	-0.29**	0.43**	0.16 NS	-0.03 NS	0.23*	0.02 NS	-0.03 NS

Field B

	Fruit Yield	Un-harvested Berries	Berries on the Ground	Berries through Blower	Total Losses	Plant Height	Fruit Zone
Un-harvested Berries	0.42***						
Berries on the Ground	0.59***	0.33**					
Loss through Blower	0.47***	0.09 NS	0.14 NS				
Total Losses	0.70***	0.64***	0.91***	0.34**			
Plant Height (cm)	-0.20 NS	-0.27 *	-0.22 *	0.06 NS	-0.25 *		
Fruit Zone (cm)	-0.12 NS	-0.17 NS	-0.17 NS	0.02 NS	-0.18 NS	0.80***	
Slope (degrees)	0.03 NS	0.26*	0.37 **	-0.02 NS	0.38**	-0.42 **	-0.25 *

Field C							
	Fruit Yield	Un-harvested Berries	Berries on the Ground	Berries through Blower	Total Losses	Plant Height	Fruit Zone
Un-harvested Berries	0.23*						
Berries on the Ground	0.77***	0.23*					
Loss through Blower	0.09 NS	0.19 NS	0.09 NS				
Total Losses	0.78***	0.38**	0.98***	0.13 NS			
Plant Height (cm)	-0.36 **	-0.22 *	-0.26 *	-0.05 NS	-0.29 *		
Fruit Zone (cm)	-0.02 NS	-0.06 NS	-0.10*	0.04 NS	-0.10 NS	0.47***	
Slope (degrees)	-0.12 NS	-0.07 NS	0.12 NS	-0.20 NS	0.09 NS	0.15 NS	0.02 NS
Field D							
	Fruit Yield	Un-harvested Berries	Berries on the Ground	Berries through Blower	Total Losses	Plant Height	Fruit Zone
Un-harvested Berries	0.70***						
Berries on the Ground	0.78***	0.79***					
Loss through Blower	0.69 ***	0.63***	0.62***				
Total Losses (kg ha^{-1})	0.82***	0.87***	0.97***	0.51 ***			
Plant Height (cm)	-0.34 **	-0.30* *	-0.28 *	-0.31**	-0.32* *		
Fruit Zone (cm)	0.09 NS	-0.13 NS	-0.07 NS	-0.24*	-0.11 NS	0.45***	
Slope (degrees)	-0.17 NS	0.03 NS	0.04 NS	-0.01 NS	0.04 NS	0.12 NS	-0.14 NS

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. Note: Fruit yield, un-harvested berries, berries on the ground, loss through the blower and total losses were recorded in kg ha^{-1} unless otherwise specified.

Results of ANOVA suggested that the main effects of ground speed and header rpm were found to be non-significant for un-harvested berries on the plants and berries on the ground, while the interaction effects (Speed × revolution) were significant for fields A and B (Table 3-4). The un-harvested berries on the plants and berries on the ground were found to have a significant interaction for field C, while the main effects were significant in field D (Table 3-4). The ground speed was found to produce a significant loss through the blower for field C, while for field D, both ground speed and interaction effects were significant (Table 3-4).

Table 3-4. Analysis of variance using two factor factorial design for selected fields.

Source	Un-harvested Berries	Berries on the Ground	Loss through Blower	Total Loss	Total Loss (%)	Fruit Yield
Field A						
Speed	NS	NS	NS	NS	NS	NS
Revolution	NS	NS	*	NS	NS	NS
Speed*Revolutions	*	*	NS	*	*	*
Field B						
Speed	NS	NS	NS	NS	NS	NS
Revolution	NS	NS	NS	NS	NS	NS
Speed*Revolutions	*	*	*	*	*	*
Field C						
Speed	*	NS	*	NS	NS	NS
Revolution	NS	NS	NS	NS	NS	NS
Speed*Revolutions	*	*	NS	*	*	*
Field D						
Speed	*	*	*	*	*	NS
Revolution	*	*	NS	*	NS	NS
Speed*Revolutions	NS	NS	*	*	*	*

Significance indicated by * and *NS* = non-significant at $p = 0.05$.

In factorial experiments if the higher order interaction is significant, their main effects can be ignored. Main effect of revolution was found to have a significant impact on the losses through the blower for field A, while two way interaction effects were significant for field B (Table 3-4). Interaction effects were significant for total losses (% and kg ha^{-1}) and fruit yield for selected fields (Table 3-4). In summary, results reported that fruit losses during harvesting were influenced by the ground speed and header rpm either alone or in combination suggesting that a suitable combination could result in better picking efficiency of the blueberry harvester.

Results of means comparison indicated that the un-harvested berries on the plants and losses through the blower were significantly lower than the losses on the ground for selected fields (Table 3-5). The best combinations with minimum un-harvested berries on the plants were treatments 1, 4 and 8 for selected fields (Table 3-5). Treatment 8 was non-significantly different when compared with treatment 1 for field C (Table 3-5). In general, the un-harvested berries on the plants were lower at treatment 1 for selected fields, suggesting that operating the harvester at lower speed and rpm can minimize the un-harvested berries on the plants. Results of LS means reported that the berries on the ground were generally higher at 30 rpm for the selected fields (Table 3-5), which might be due to an impact of the harvester head and faster rpm of the picking reel. The best treatments with minimum loss of berries on the ground were 1, 2 and 7 for selected fields (Table 3-5). Results revealed that the 26 rpm provided more time for header to pick the berries more effectively with minimum losses on the ground.

The best treatments with minimum loss of berries through the blower (< 70 kg ha^{-1}) were 1, 2 and 7 for selected fields (Table 3-5). The mixed trend of losses through the blower for selected fields might be due to high fruit yield variability, suggesting that the blower losses during harvesting were not affected by treatment combinations. The best treatments for total losses were 2 for field A and 7 for field B (Table 3-5). Treatment 1 (1.2 km h^{-1} and 26 rpm) resulted in significantly lower total losses for the fields C and D (Table 3-5). In general, treatment 9 produced significantly higher losses, which could be due to higher radial and tangential forces applied by the harvester during fruit picking for fields C and D (Table 3-5). There was a mixed trend of total losses (kg ha^{-1}) at different treatment combinations for field B (Table 3-5), which could be due to low yield nature of this field. There were non-significant differences in total losses at 26 and 28 rpm for the ground speed of 1.2 km h^{-1} for field A (Table 3-5).

Table 3-5. Results of multiple means comparison using least-squares method to identify the two way interaction effects on fruit losses during harvesting.

Field A

Treatment	Un-harvested Berries	Berries on the Ground	Loss through Blower	Total Loss	Fruit Yield
1	80.5 AB	245.9 C	81.6 A	408 B	5116 A
2	90.3 AB	165.4 D	25.0 B	280.7 D	1899 D
3	105 AB	340.6 AB	32.2 B	477.8 A	3783 B
4	54.2 B	268.7 BC	41.3 B	364.2 BC	3437 BC
5	114.2 A	330.7 AB	41.9 B	486.8 A	4398 AB
6	59.8 B	403.6 A	43.5 B	506.9 A	4368 AB
7	81.6 AB	270.9 BC	59.8 AB	412.3 B	3490 BC
8	103.3 AB	281.8 BC	28.3 B	413.4 B	3877 B
9	63.1 B	311.3 B	37.5 B	411.9 B	3368 BC

Field B

Treatment	Un-harvested Berries	Berries on the Ground	Loss through Blower	Total Loss	Fruit Yield
1	20.1 B	144.6 B	29.8 BC	194.5 BC	2029 BCD
2	64.1 A	263.3 AB	65.9 A	393.3 A	3458 A
3	25.3 B	143.6 B	38.5 B	207.4 BC	2809 AB
4	64.4 A	183.9 AB	19.1 BC	267.4 ABC	3091 A
5	38.2 AB	90.1 C	10.3 BC	138.6 CD	1556 D
6	52.2 A	264.9 A	9.5 C	326.6 AB	3332 A
7	22.3 B	76.7 C	5.5 C	104.5 D	1752 D
8	27.5 B	137.7 B	12.5 BC	177.7 CD	2450 BCD
9	43.1 AB	183.8 AB	8.4 C	235.3 BC	3086 A

Field C					
Treatment	Un-harvested Berries	Berries on the Ground	Loss through Blower	Total Loss	Fruit Yield
1	74.2 CD	527 BC	60.4 B	661.7 C	6044 A
2	76.7 BCD	637.9 A	63.4 AB	778 AB	5726 A
3	88 BCD	603.9 ABC	62.5 AB	754.4 BC	5500AB
4	94.7 BCD	582.5 ABC	58.7 B	735.9 BC	5350AB
5	107.1 ABC	653.8 A	78.9 A	839.8 A	6300 A
6	79.5 BCD	635.9 A	65.7 AB	781.2 A	5435AB
7	130.3 A	505.6 C	56.6 B	692.5 CD	4510 B
8	71.9 D	652 A	62.2 AB	786.1 A	5604AB
9	108 AB	579 ABC	64.6 AB	751.5 AB	4575 B
Field D					
Treatment	Un-harvested Berries	Berries on the Ground	Loss through Blower	Total Loss	Fruit Yield
1	121.0 C	550.2 E	65.1 C	736.4 D	6347 C
2	196.7 BC	921.9 D	125.2 BC	1243.7 BC	7923 AB
3	202.7 BC	1155.4 AB	126.1 BC	1484.2 BC	8467 AB
4	191.3 BC	800.9 CD	121 BC	1113.2 C	6301 C
5	278 AB	1198.3 AB	189.3 AB	1665.6 AB	9190 A
6	209.7 B	1184 AB	115.9 BC	1509.62 B	8687 AB
7	322.5 A	1225.9 A	227.1 A	1775.5 A	9520 A
8	352.6 A	1250.1 A	181.1 AB	1783.81 A	9130 A
9	324.7 A	1362.5 A	128.0 BC	1815.20 A	7660 B

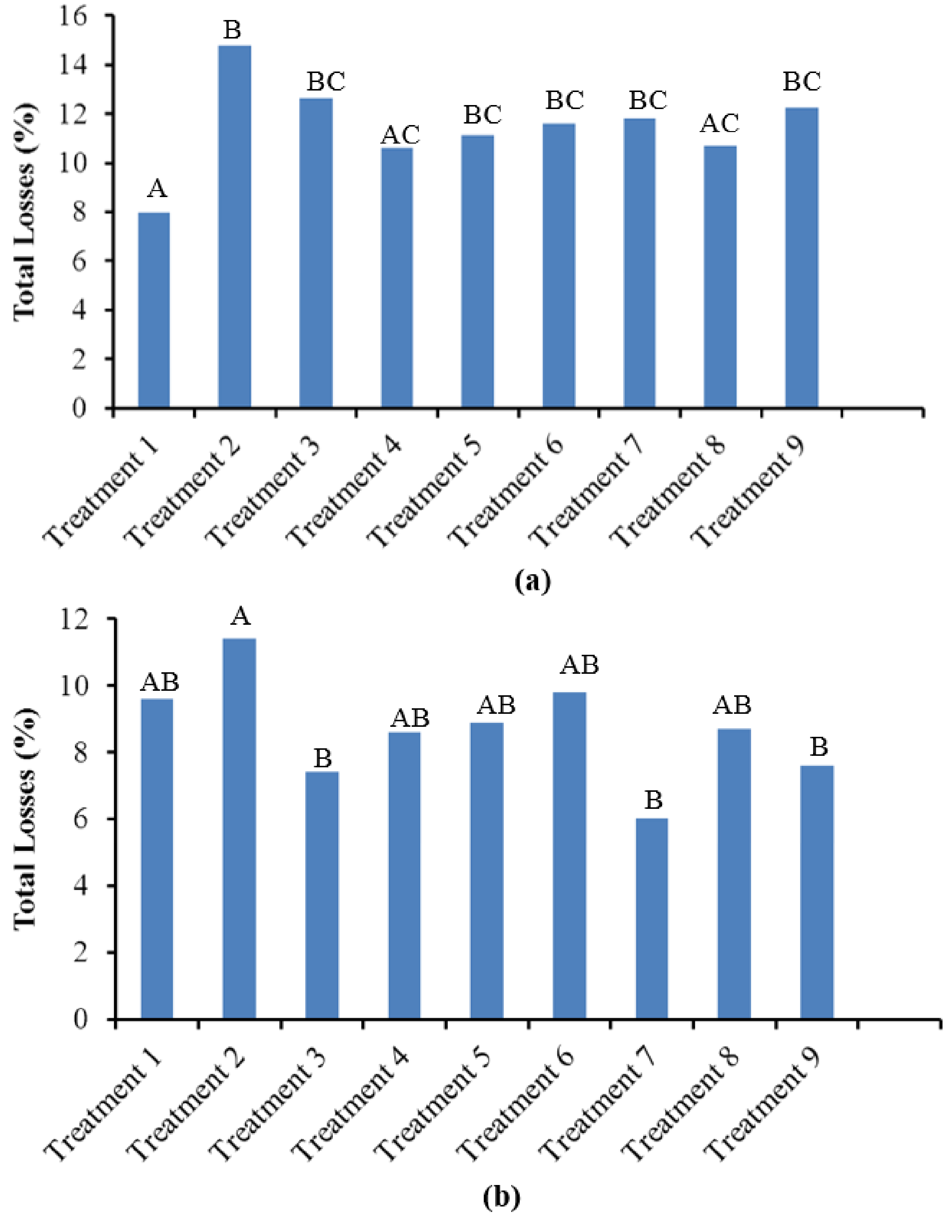
Means with no letter shared are significantly different at $p = 0.05$.
Note: The fruit yield and losses were recorded in kg ha^{-1}.
Where, **Treatment 1:** 1.2 km h^{-1} and 26 rpm, **Treatment 2:** 1.2 km h^{-1} and 28 rpm, **Treatment 3:** 1.2 km h^{-1} and 30 rpm, **Treatment 4:** 1.6 km h^{-1} and 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 and **Treatment 9:** 2.0 km h^{-1} and 30 rpm.

Total losses (%) were dependent upon the fruit yield collected from each treatment. The 1.2 km h-1 and 26 rpm (Treatment 1) was found to be the best combination with less than 8% berry losses during harvesting (Fig. 3-7a) for field A. Treatments 1, 4 and 8 were non-significantly different at fields A (Fig. 3-7 a). Treatment 1 was found to have < 12% fruit losses, which was significantly lower, when compared with other treatments for fields

C and D (Fig. 3.8). The mixed trend of fruit losses for field B (Fig. 3-7 b), suggested that the 2.0 km h^{-1} and 26 rpm was the best treatment combination with minimum losses. Non-significant differences among the treatment combinations (Fig. 3-7 b) were found for field B.

These results suggested that in low yielding fields, the chosen levels of ground and head rpm are not as important, however, in high yielding fields a careful selection of the operating parameters can enhance the picking performance of wild blueberry harvester. Treatment 9 was the worst combination with significantly higher losses for fields C and D (Fig. 3-8), emphasizing the need to reduce ground speed and header rpm in high yielding fields for better picking efficiency and berry recovery. Operating the harvester at lower ground speed and header rpm will provide a gentle upward movement of reel teeth bars through the plants to enhance harvesting efficiency by reducing the losses. Longer teeth with a slight tilt at the end of the teeth could provide better retention of berries for effective transportation to conveyer and finally to the storage bin.

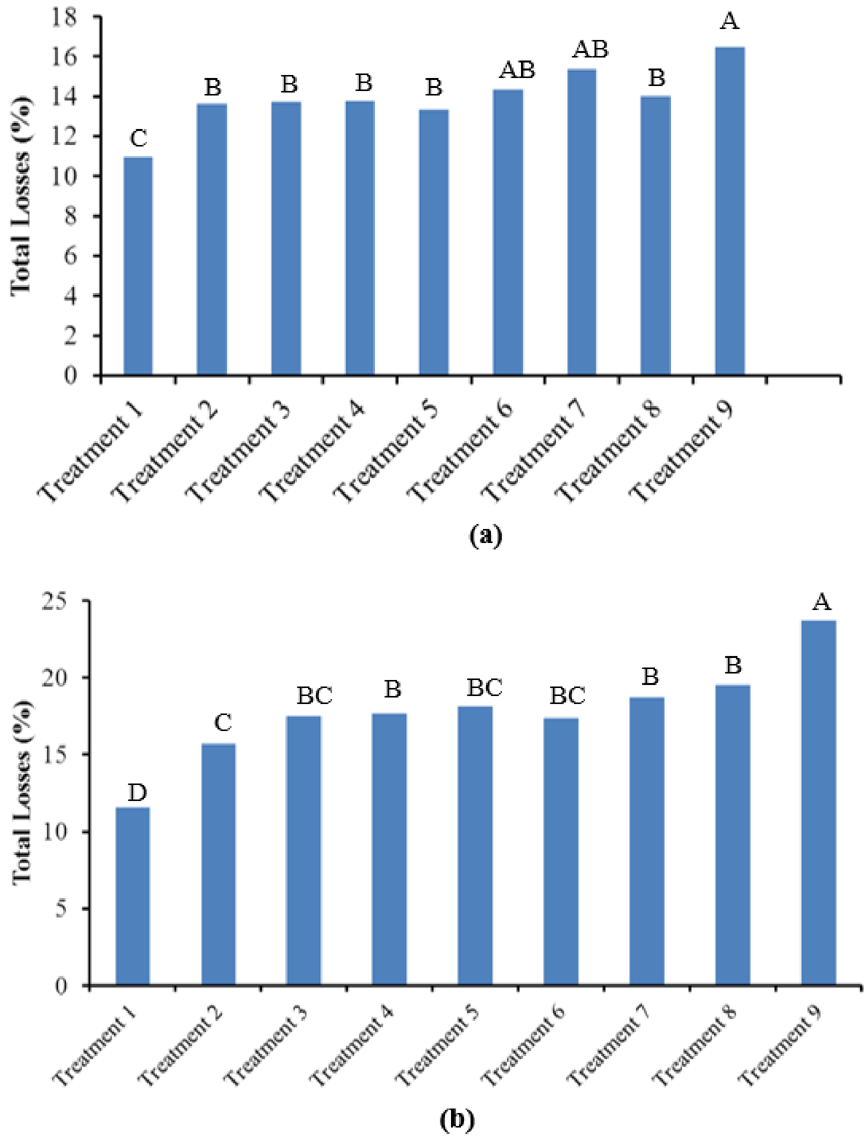
Based on these results, it can be concluded that in wild blueberry fields with yield over 3500 kg ha^{-1} a combination of 1.2 km h^{-1} and 26 rpm can result in significantly lower losses. In low yielding fields (< 3000 kg ha^{-1}) a combination of 2.0 km h^{-1} and 26 rpm can do a better job to increase berry picking efficiency of the blueberry harvester. Overall, the results of LS mean reported that the efficiency of the harvester was found to be 92% for field A and over 88% for fields C and D at 1.2 km h^{-1} and 26 rpm. The picking efficiency of the harvester was 94% (6% losses) at 2.0 km h^{-1} and 26 rpm for fields B.



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

Where, 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 and Treatment 9: 2.0 km h^{-1} and 30 rpm.

Figure 3-7: Least squares mean comparison of total fruit losses at different treatments, (a) Field A and (b) Field B.



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

Where, 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 and Treatment 9: 2.0 km h^{-1} and 30 rpm.

Figure 3-8. Least squares means comparison of total fruit losses at different treatments, (a) Field C and (b) Field D.

Fruit loss during harvesting are not only due to the machine itself but are a function of several parameters which can affect the picking efficiency. These parameters include operator skills, field conditions, crop maturity, crop characteristics, time of harvesting, weather conditions, bare spots, weed coverage and improper maintenance of the harvester. A newly manufactured harvester was used in this study; therefore no contribution from low maintenance was expected. Results of this study revealed that by choosing a good combination of ground speed and header rpm based on fruit yield variation can minimize the fruit losses during harvesting. The reduced berry losses during harvesting will generate more revenue for the farmers to justify their input cost related to wild blueberry production.

3.4 CONCLUSIONS

Results of this study suggested that the pre-harvest fruit losses were found to be higher during the late season suggesting that early season harvesting could be helpful in reducing pre-harvest fruit losses. Results indicated that fruit losses during harvesting were highly variable within the selected fields. The major portion of the fruit losses during harvesting was on the ground when compared with un-harvested berries on the plants and losses through the blower. Fruit loss during harvesting is a linear function of the fruit yield, as fruit yield increases the fruit losses increases and vice versa. Results of the harvester evaluation confirmed the accuracy of the camera technology in mapping the pre-harvest fruit yield and losses during mechanical harvesting. Actual fruit losses (manually collected) were very close to the estimated fruit losses (from digital color camera).

Based on the results of ANOVA, it can be concluded that ground speed, header rpm and their interaction can cause significant differences in picking efficiency of the wild blueberry harvester. Results of means comparison showed that a treatment combination of 1.2 km h^{-1} and 26 rpm can result in significantly lower losses as compare to higher ground speed and header rpm in wild blueberry fields with yield over 3500 kg ha^{-1}. In low yielding fields (< 3000 kg ha^{-1}) a combination of 2.0 km h^{-1} and 26 rpm can do a better job to increase berry picking efficiency of the blueberry harvester. Proper selection of ground speed and header rpm in relation to spatial variability can minimize fruit losses to increase farm profitability.

Chapter 3 evaluated the role of ground speed and header rpm on picking performance of a commercial wild blueberry harvester in selected fields. Results of the harvester's physical evaluation confirmed the accuracy of camera technology in estimating pre-harvest fruit losses during mechanical harvesting. Fruit losses were highly variable within the selected fields, with the majority of losses being on the ground. Fruit losses were greatly influenced by the ground speed and header rpm and their interaction. Significant variability in fruit losses at different machine operating parameters, crop characteristics, fruit yield and slope of the ground, emphasized the need to study the response of spatial variations in fluctuating fruit losses during mechanical harvesting. Chapter 4 highlighted the variability in fruit losses in accordance with spatial variations in crop characteristics, fruit yield and ground slope.

CHAPTER 4 RESPONSE OF WILD BLUEBERRY FRUIT LOSSES TO SPATIAL VARIABILITY IN CROP CHARACTERISTICS AND GROUND SLOPE

Knowledge of spatial variability in fruit yield, crop characteristics, fruit losses and slope of the ground is critical for planning and implementing the operational recommendation for mechanical harvesting. Wild blueberry growers are facing increased harvesting losses because of changes in crop conditions caused by improved management practices. The goal of this work was to characterize and quantify spatial pattern of variability in crop characteristics, fruit yield and slope in relation to fruit losses during harvesting. Factorial experiments were designed and yield plots (0.91 × 3 m) were constructed randomly in selected fields. Total fruit yield, un-harvested berries on the plants, berries on the ground, and loss through the blower were collected from each plot within the selected fields. Pre-harvest fruit losses were collected from each plot prior to harvest. Slope, plant height and fruit zone were also recorded manually from each plot to examine their impact on fruit losses.

The coefficient of variations (CVs) for fruit yield, berry losses, slope, plant height and fruit zone suggested moderate to high variability (CV > 15%) within the selected fields. Results of correlation analysis showed higher fruit losses in high yielding areas and vice versa. Results reported that the fruit yield, berry losses, slope, plant height and fruit zone had a large spatial variation (range of influence ~ 20 to 50 m) within the selected fields. Kriged maps also showed substantial variation in mapped parameters within the selected fields. Regression analysis in conjunction with zonal statistics showed that the fruit losses increased with an increase in fruit yield and steepness of slope. Variability in fruit losses corresponding with the spatial variations in crop characteristics, fruit yield and slope suggested that these parameters had significant effect on fruit losses during harvesting. Results emphasized the need to model these spatial relationships mathematically to propose optimal harvester operational settings to increase harvestable yield. Improved berry picking efficiency by considering these spatial variations has the potential to increase profit margins for wild blueberry industry.

The work presented in this chapter has been submitted in *Applied Engineering in Agriculture Journal*, entitled “Response of wild blueberry fruit losses to spatial variability in crop characteristics and slope of the ground”.

4.1 INTRODUCTION

Soil properties, crop characteristics and fruit yield vary spatially, and temporally within the fields on most farms. Many factors including site characteristics, crop parameters, environmental conditions and management practices have an influence on fruit yield and quality (Farooque et al., 2012a; Patzold et al., 2008; Wong and Asseng, 2006; Ping et al., 2005). Characterization and quantification of spatial variability is essential to achieve a better understanding of the complex interactions (Wong and Asseng, 2006) in order to determine appropriate management practices including harvesting recommendations. Different techniques including color infrared images (CIR), remote sensing, soil survey maps, non-destructive mapping via EMI sensors and arial photographs have been used to address the spatial variability for various cropping systems. However, these methods are expensive, the quality of data may be inadequate, and data processing (arrangement and analysis of data) is normally intensive and complicated (Zaman et al., 2008). Therefore, within field variability can be described using sampling methods that allow a field to be divided into different management zones. With the introduction of geostatistical tools, a sampling strategy can be established based on range of influence, which not only reduces the number of samples but also the cost of analysis (McBratney and Pringle, 1999; Broulder et al., 2005).

Spatial variations in fruit yield are mainly caused by heterogeneity in crop characteristics, soil physical and chemical properties and weather conditions (Wong and Asseng, 2006; Rogerio et al., 2006). Heterogeneity may occur at small scale or large scale, even in the same variable of interest (Du Feng et al., 2008). The CV is mostly used to describe the overall variation within the field, which hypothesize that the variability is randomly distributed; however, it does not quantify the spatial pattern of variability. Samples close to each other have similar properties when compared with those far from each other. Geostatistics is a powerful tool for characterization and quantification of spatial variability (Sauer et al., 2006). Geostatistical procedures use statistical and mathematical functions for interpolation of data. Geostatistics combined with GIS provides interpolation of data from sampled points to un-sampled locations based on autocorrelation and spatial relationships for estimation of range of influence accurately (James and Charles, 1988).

Research benefits of geographical information system (GIS) technique were described in many scientific studies (Bradshaw and Muller 1998, Wang et al. 2006). The GIS can be utilized to spatially analyze the variable of interest in a monitoring study. Interpolated maps can be generated in GIS for visualization of spatial variability. Geostatistical analysis was recognized as the most confident, strongest, and widest method for interpolation which considers spatial variance, location and distribution of collected data (Kersic, 1997). Semivariograms calculated from geostatistical analysis provide spatial dependency of the variables both anisotropically and isotropically (Burgess and Webster, 1980). Spatial variability on a small scale plays a significant role in crop performance and productivity (Haefele and Wopereis, 2005). Site characteristics (humidity, soil properties, texture and rainfall) influence soil moisture and strength (McBratney and Pringle, 1999), which can cause higher fruit losses during harvesting by reducing the traction of tractor tires and slippage of berries from the periphery of the harvester head.

With the installation of sensors and yield monitors on mechanical harvesters, it has been evident that the yields for various crops exhibits significant spatial variability (Bramley and Hamilton, 2004). Many growers are aware of this variability which not only affects crop production, but also fruit quality (Bramley, 2005), and fruit losses during harvesting. Consequently, it is difficult to estimate fruit yield (Martınez- Casasnovas and Bordes, 2005), quality and losses that are actually encountered because of these spatial variations. Poor knowledge of spatial variability also limits the possibility of differentiating fruit losses caused by different factors within the field. Hence, there is an emerging need for increased harvesting efficiency, which can be achieved by implementing the optimal operational settings of the mechanical harvester in relation to spatial variability to achieve better berry recovery.

Spatial variability in crop characteristics, topographic features, soil properties and yield has been well documented (Cambardella et al., 1994; Gaston et al., 2001; Wong and Asseng, 2006; Cemek et al., 2007, Mann et al., 2010; Farooque et al., 2012a). Cambardella (1994) studied the field scale spatial variation in different soil properties in Central Iowa soils. Cemek et al. (2007) examined the spatial patterns of variability in hydraulic conductivity, soil EC, soil pH and soil ESP suggesting that hydraulic conductivity was the most variable, while the pH was least variable. Mann et al. (2010) described the spatial variability in soil properties at four sampling depths for Florida citrus production and delineated management zones for site-specific fertilization. Farooque et al. (2012a) characterized and quantified spatial variability in soil properties and fruit yield for wild blueberry cropping system. The authors also differentiated productive and un-productive areas based on spatial variability in soil properties and fruit yield. Schumann and Zaman (2003) mapped water table depth in flatwood soils of Florida and found that 81% of the variation in the water table depth could be explained with vertical dipole of the EMI instrument. Bramley and Lamb (2003) revealed that the spatial variation of grape quality coincided with the spatial distribution of the yield. Cheng et al. (2007) suggested that the spatial variability in biomass for shrub lands was greater than the grasslands. Spatial relationships between plant and soil were very clear for grassland (Zhao et al., 2007) and found to have an impact on crop productivity. Accurate estimation of spatial variability is important for environmental predictions, precise agriculture recommendations, ecological modeling and management of natural resources (Hangsheng et al., 2005; Wang, 2009). Spatial variations in fruit yield, crop characteristics and topographic features can have an impact on fruit losses during harvesting.

Heterogeneous growing scenarios in cultivated land require spatial and temporal attention when estimating crop growth and fruit yields to reduce fruit losses. Crop yield estimations are often performed using dynamic growth models that assume homogeneous field conditions, ignoring spatial differences and their effects on growth and yield (Hu and Mo, 2011; Irmak et al., 2001). Analyzing and quantifying relationships between heterogeneous soil conditions, crop growth and yield is often constrained by a lack of data due to high costs and time demands associated with data collection (Heil and Schmidhalter, 2012). Crop growth is greatly influenced by landscape attributes and differences in site characteristics, which reflect soil heterogeneity patterns (Hakojärvi et al., 2013). Variation in topography of the agricultural fields influences the redistribution of soil particles, organic matter, texture and nutrients due to erosion, causing large spatial variability (Ovalles and Collins, 1988). Differences in elevation within the field also affect water availability to crops and hence crop yield (Kaleita et al., 2007). Due to their role in influencing soil and yield variability, topographic attributes are generally used to map areas of high and low productivity within a field. Wild blueberry producers typically harvest their fields uniformly on a block basis, with block size varying from one or two to several hectares, hence ignoring within field variability in fruit yield, crop characteristics and topographic features. Variation in soil texture and slope of the ground can create imbalance of the harvester head during mechanical harvesting, which can affect picking performance of the harvester.

Many researchers have attempted to characterize and quantify the spatial variation in soil properties, crop parameters, topographic features and fruit yield for different cropping systems (Hakojärvi et al., 2013; Farooque et al., 2012a; Hu and Mo, 2011; Mann et al. 2010; Zhao et al., 2007; Wong and Asseng, 2006; Irmak et al., 2001; McBratney and Pringle, 1999). However, to date little attention has been paid to wild blueberry production system. Wild blueberry fruit yield is greatly influenced by spatial variation in soil properties (Farooque et al., 2012a). Farooque et al. (2012a and b) also reported that the soil spatial variability produces variable patches fruit yield (high, medium and low yielding) across the field. Currently, mechanical harvesting operating recommendations are implemented uniformly with inadequate attention being given to substantial variations within the wild blueberry fields. Harvesting of spatially variable fields at standard ground speed and header revolutions without characterizing spatial variability in crop parameters, fruit yield and slope can result in an increased fruit losses during harvesting. Therefore, the objectives of the work presented in this chapter were to characterize and quantify variability in plant characteristics, fruit yield and slope in relation to fruit losses during mechanical harvesting for wild blueberry cropping system. The ultimate goal is to study the variation in fruit losses and establish operational recommendations for increased berry recovery using the commercial blueberry harvester.

4.2 MATERIAL AND METHODS

4.2.1 Study Area

Four wild blueberry fields were selected in Atlantic Provinces of Canada to evaluate the impact of spatial variability in fruit yield, plant characteristics and slope on fruit losses during mechanical harvesting. The selected fields were the Cooper site (45.480573°N, 63.573471°W; 3.2 ha), Small Scott site (45.600641°N, 63.086512°W; 1.9 ha), Tracadie site (47.2824117°N, 65.1440212°W; 1.6 ha), and Frankweb site (45.241900°N, 63.401143°W; 2.57 ha) (Fig. 4-1). The Cooper and Small Scott sites were in their vegetative sprout year of the biennial crop production cycle in 2010 and crop year in 2011. The Tracadie and Frankweb sites were in crop year during 2012. Selected fields were managed commercially over the past decade with conventional fertilizer application, weed and disease controls and other management practices (mowing, pollination, etc.).

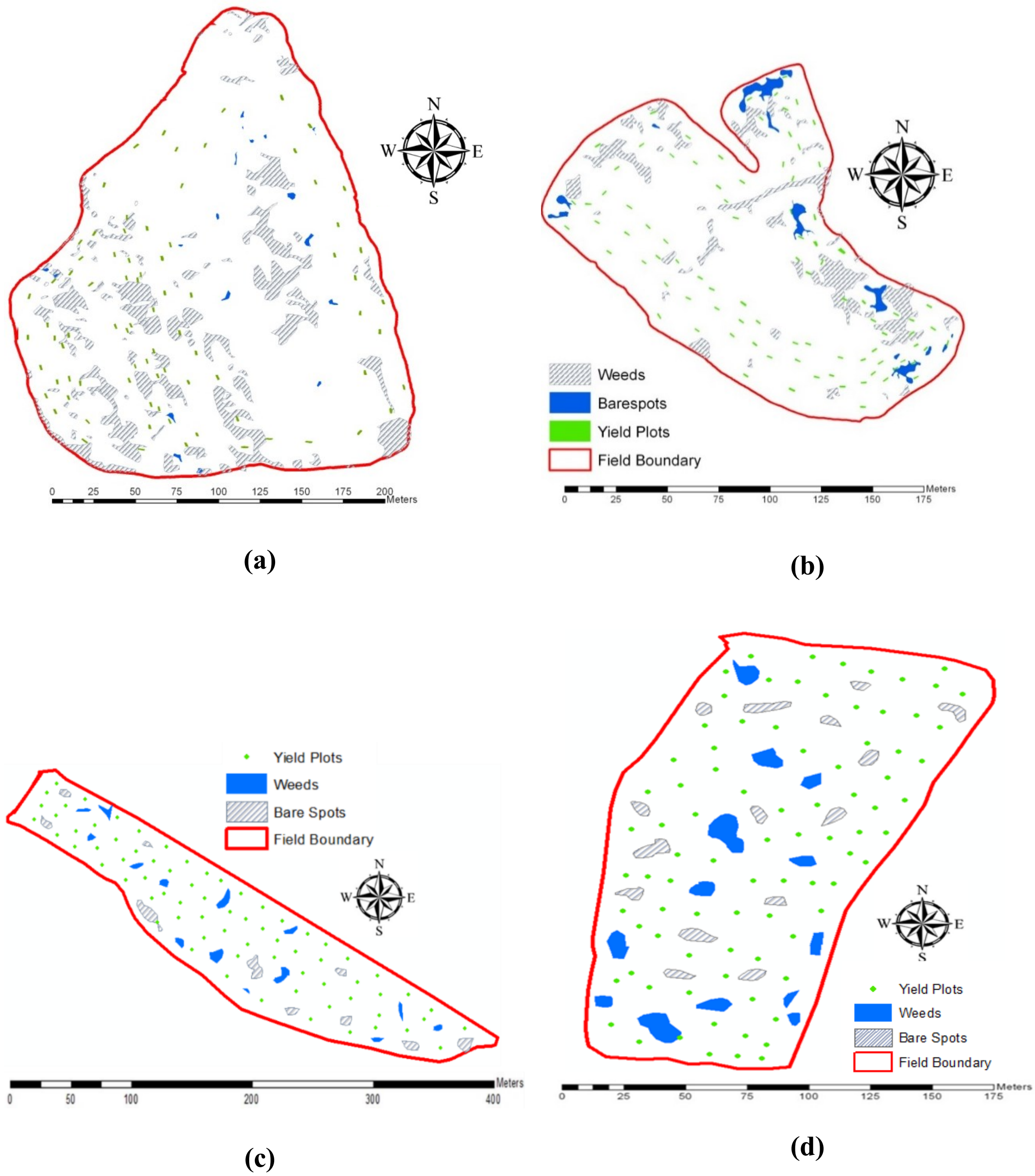


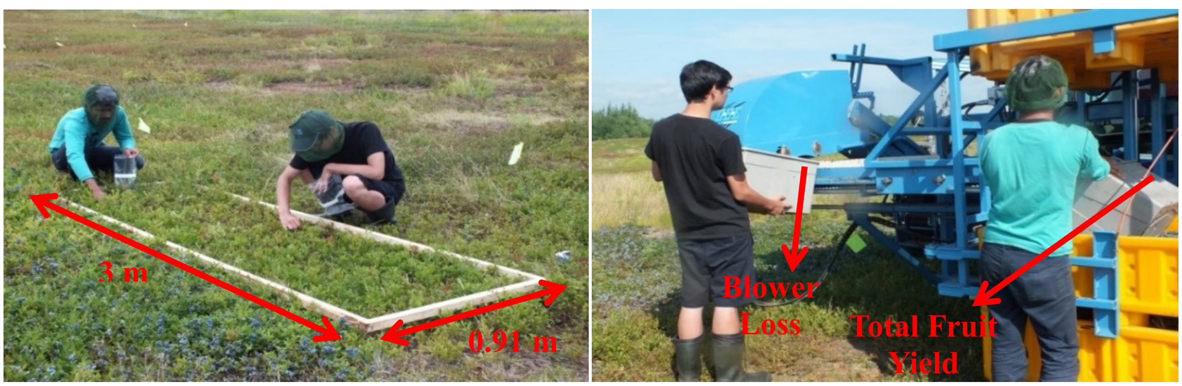
Figure 4-1: Layouts of the selected wild blueberry fields, (a) Cooper site, (b) Small Scott site, (c) Tracadie site, and (d) Frankweb site.

4.2.2 Data Collection

Completely randomized factorial experiments were designed within the selected fields to study the response of spatial variations on fruit losses during mechanical harvesting. The single head commercial blueberry harvester was mounted on a 62.5 kW John Deere tractor. Eighty one yield plots with the same width as the harvester head, 0.91 m and 3 m length were made randomly in each field using a measuring tape. Two marker flags were punched into ground, to indicate the end points of plots for the ease of operator's tracking. Experimental plots were constructed in the path of the operating harvester. Field boundaries, bare spots, weeds and yield plots were mapped with a RTK-GPS in each field. Pre-harvest fruit losses were estimated prior to harvesting the yield plots in selected fields. A wooden quadrat of 0.91 × 3 m was placed on randomly selected plots (n = 81) to collect pre-harvest fruit losses manually at each field. The collected berries were placed in labeled Ziploc bags and weighed using a balance to quantify the amount of berry losses at the onset of experiment. Pre-harvest fruit losses were recorded in kg. Details procedure for calculation of percentage pre-harvest fruit losses are provided in Chapter 3, Section 3.2.5.

Five plant height and fruit zone readings were measured prior to harvest from each experimental yield plots using a ruler to get an average value. Slope angle was recorded manually using a Craftsman SmartTool Plus digital level. Five slope measurements were randomly made at each harvesting plot within a radius of one meter for selected fields and averaged to obtain representative slope in each plot. After measuring the pre-harvest fruit losses, plant height, fruit zone and slope, the experimental plots were harvested using a commercial blueberry harvester. The harvester head was raised with the machine running to expel all the previously harvested fruit in the storage bin before harvesting the experimental plots.

Prior to harvesting the experimental plots, the harvester was moved back (approx. 25 m) to attain the ground speed and header rpm. Harvester head was lowered to harvest the yield plot and raised again at the end of each plot. Fruit yield was collected from each plot by attaching a bucket to the harvester conveyer belt (Fig. 4-2b). Three types of losses were calculated from the harvested plot, *i.e.* un-harvested berries on the plant, berries on the ground and losses through the blower (Fig. 4-2). Loss through the blower was collected by attaching a bucket under the blower fan to collect any berries that would be blown away (Fig. 4-2). Berries on the ground and un-harvested berries on the plants were manually picked from each plot (Fig. 4-2a).



(a) **(b)**

Figure 4-2: (a) Manual collection of loss on the ground and un-harvested berries on the plants; (b) Collection of fruit losses through the blower and total fruit yield from the harvested plot.

Berries were separated from leaves and debris to record the actual weight of yield and losses from each plot. Cleaned berries were placed in labeled Ziploc bag and weighed using a balance. Fruit yield and losses data was recorded in kg. The purpose of calculating these losses was to assess the picking performance of the harvester in relation to spatial variations in fruit yield, plant height, fruit zone and slope. Pre-harvest fruit losses were not brought into consideration while evaluating the performance of the blueberry harvester because these were not caused by the harvester. Details showing the procedure for calculation of fruit losses are given in Chapter 3; Section 3.2.5.

4.2.3 Statistical Analysis

The statistical analysis was performed using Minitab 16 (Minitab Inc. NY, USA) and SAS 9.3 (SAS Institute Inc., NC, USA) statistical software. Normality of the error terms was examined through Anderson Darling test and non-normal data were normalized using logarithmic transformations. Logarithmic conversion of the data are considered as the best method (Webster and Oliver, 2001) to assure normal distribution. Residual versus fitted values plot was utilized to check the constant variance of error terms. Yield plots were made randomly to assure independence of error terms. Classical statistics were utilized to calculate minimum, maximum, mean, standard deviation, CV and skewness. Classical statistics provides overall variability in the collected data, however, it does not provide the spatial trend. Therefore, geostatistical analysis was performed using GS+ Geostatistics for the Environmental Sciences Version 9 software (Gamma Design Software, LLC, Woodhams St, Plainwell, MI, USA) to characterize spatial variability in fruit yield, berry losses, plant parameters and slope. Semivariograms were produced for each variable to ascertain the degree of spatial variability between neighboring observations. The sill, nugget, range and sill to nugget ratio were calculated form semivariogram analysis for detailed description of spatial variability. Geostatistical analysis is based on spatial correlation between observations which can be expressed as a mathematical model. Variogram expresses the spatial pattern of variability in the data (Hassanipak, 2007) and can be described by the following formula:

$$\gamma(h) = \frac{1}{2N(h)}\left\{\sum_{i=1}^{N(h)}[Z(x_i + h) - Z(x_i)]^2\right\} \tag{4.1}$$

where γ is the semivariance for interval class (h), $N(h)$ is the number of sample pairs that are separated by distance (h) from each other, $Z(x_i)$ are the values of regionalized variable at spatial location x_i, $Z(x_i + h)$ are the values of regionalized variable at spatial location $x_i + h$.

Several authorized semivariogram models can be fitted to the data and the one with minimum nugget is selected (Oliver, 1987). There was no anisotropy evident in directional semivariograms, therefore, isotropic models were fitted using GS+ software. Correlation matrices were developed to study the relationships between fruit yield, fruit losses, plant characteristics and slope. Geostatistics combined with GIS was applied to generate detailed maps in Arc GIS 10 (ESRI, Redlands, CA), to analyze spatial variability visually. All parameters were interpolated using kriging interpolation technique. Kriging interpolation is a statistical estimator that assigns weight to each sampling location for an unbiased and reduced estimation of variance (Kumke et al., 2005). Kriging interpolation is considered to be more accurate and reliable than other methods such as inverse distance weighting (IDW) or trend surface models (Mulla et al., 1992; Farooque et al., 2013). Maps of fruit yield, un-harvested berries on the plants, berries on the ground, loss through the blower, plant height, fruit zones and slope were generated at same scale and equal number of classes for fair comparison. Zonal statistics function of ArcGIS 10 was utilized to assess the variation in fruit losses with respect to fruit yield, plant height and slope.

4.3 RESULT AND DISCUSSIONS

4.3.1 Descriptive Statistics of the Collected Data

The validity of the model assumptions (constant variance and normal distribution of the error terms) was verified by examining the residuals at 5% level of significance. Independence of error terms was assumed to be valid through the randomization. Anderson Darling test of normality reported that the fruit yield, berry losses and slope followed a non-normal distribution, while the plant height and fruit zone were normally distributed for Cooper, Small Scott and Frankweb sites. Fruit yield, loss through the blower, plant height, fruit zone and slope were normally distributed at the Tracadie site. Non-normal ($p < 0.05$) data were normalized using logarithmic transformations for analysis and were back transformed to original scale for reporting results. The underlying reason for non-normal and normal distributions of fruit yield, berry losses and slope at monitoring sites are unknown, but management practices, operator skills, weather conditions and timing of harvest seem to be likely causes.

Table 4-1. Summary statistics of fruit yield and pre-harvest losses for selected fields.

Pre-harvest Fruit Losses (kg ha^{-1})							
Field	Min	Max	Mean	Mean (%)	S.D	C.V (%)	Skewness
Cooper	80	360	182	4.68	83.3	46.29	0.76
Small Scott	40	400	207	7.33	99.6	47.27	0.09
Tracadie	80	460	439	7.31	40.74	40.74	0.83
Frankweb	110	515	467	5.42	117.8	36.27	0.64
Fruit Yield (kg ha^{-1})							
Field	Min	Max	Mean		S.D	C.V (%)	Skewness
Cooper	305	9914	3887		2014	54.35	0.82
Small Scott	254	7635	2825		1570	59.98	0.89
Tracadie	1690	10445	5995		1942	34.96	0.11
Frankweb	2218	17968	8603		2915	35.81	0.83

The CV is a first indication of the field variability. Wilding (1985) reported that collected data are least variable if the CV is less than 15%, moderately variable with CVs ranging from 15 to 35%, and most variable with CV greater than 35%. Summary statistics revealed that the fruit yield and pre-harvest fruit losses were highly variable (CVs > 34%) within the selected sites (Table 4-1). Large variation in fruit yield and pre-harvest fruit losses was also evident from the minimum, maximum and skewness values of the descriptive statistics (Table 4-1). Skewed distribution of fruit yield and pre-harvest fruit losses might be due variation in management practices and harvesting of blueberries at different times during the season. These results were in agreement with the findings of Farooque et al. (2012b). They reported large variation in fruit yield for wild blueberry cropping system.

Summary statistics suggested that fruit yield, un-harvested berries on the plants, berries on the ground, loss through the blower, total loss and slope were highly variable with the CV > 35% for selected sites (Table 4-2). Plant height and fruit zone exhibited moderate variability for Cooper, Small Scott and Frankweb sites (Table 4-2). Selected parameters were observed to be moderate to highly variable with CV ranging from 14 to 54% for Tracadie site (Table 4-2). The variability in fruit yield, plant height, fruit zone, and berry losses could be due to the intrinsic sources (natural soil variations and yielding nature of different clones) and extrinsic sources (harvester operation, operator skills, field topography and crop management practices) (Hepler and Yarborough, 1991; Cemeck et al., 2007; Rao and Wagenet, 1985). Since pre-harvest losses were not caused by the harvester, they were excluded from the evaluation of picking efficiencies of blueberry harvester (Table 4-2).

Table 4-2. Summary statistics for fruit yield, berry losses, slope, plant height and fruit zone for selected blueberry fields.

			Cooper Site				
Parameters	Min	Max	Mean	Mean (%)	S.D	C.V (%)	Skewness
Fruit Yield	305	9914	3705	-	2014	54.35	0.82
Un-harvested Berries	4.90	342.70	83.58	2.26	77.41	92.61	1.50
Berries on the Ground	19.6	891	291	7.85	186	63.94	1.15
Loss through Blower	4.92	225.21	43.47	1.17	39.05	89.83	1.99
Total Losses	58.7	1096.7	418	-	225.6	53.96	0.79
Total Losses (%)	3.73	25.5	11.28	11.28	5.86	46.38	0.62
Plant Height (cm)	10.60	32.80	23.64	-	4.06	17.18	-0.38
Fruit Zone (cm)	7.80	25.30	19.35	-	3.56	18.42	-0.45
Slope (degrees)	0.5	19.53	7.47	-	4.40	58.88	0.89
			Small Scott Site				
Parameters	Min	Max	Mean	Mean (%)	S.D	C.V (%)	Skewness
Fruit Yield	253	7635	2618	-	1570	59.98	0.89
Un-harvested Berries	0	299.37	39.68	1.52	62.47	157.95	3.12
Berries on the Ground	3.38	708.4	165.4	6.32	127.3	76.99	1.44
Loss through Blower	0	220.23	22.16	0.80	33.01	148.94	3.50
Total Losses	5.1	833.7	227.2	-	167.3	73.60	1.51
Total Loss (%)	0.99	26.85	8.68	8.68	5.07	56.02	1.45
Plant Height (cm)	13	34	22.99	-	3.63	15.80	0.06
Fruit Zone (cm)	7.40	30.5	19.07	-	3.62	18.99	-0.05
Slope (degrees)	0.20	23.66	7.04	-	4.47	63.58	1.35
			Tracadie Site				
Parameters	Min	Max	Mean	Mean (%)	S.D	C.V (%)	Skewness
Fruit Yield	1690	10445	5556	-	1942	34.96	0.11
Un-harvested Berries	23.77	319.54	92.23	1.66	38.34	41.57	2.77
Berries on the Ground	147.9	1056.3	627.5	11.29	234.12	39.17	0.10
Loss through Blower	21.13	110.92	63.67	1.14	18.62	29.25	0.22
Total Losses	192.8	1228	783.5	-	256.7	34.07	-0.01
Total Loss (%)	7.99	22.34	14.10	14.10	3.09	22.20	-0.02
Plant Height (cm)	19	39	26.95	-	3.96	14.70	0.44
Fruit Zone (cm)	11.23	34.60	23.09	-	3.92	17.01	-0.24
Slope (degrees)	0	6.56	2.58		1.40	54.45	1.04

Frankweb Site							
Parameters	Min	Max	Mean	Mean (%)	S.D	C.V (%)	Skewness
Fruit Yield	2218	17968	8136	-	2915	35.81	0.83
Un-harvested Berries	42.9	574.71	244.30	3.0	115.7	47.37	0.67
Berries on the Ground	131.5	1847	1098.12	13.49	385.3	35.97	-0.34
Loss through Blower	31.6	528.9	142.21	1.74	90.6	63.78	2.16
Total Losses	240.2	2616.10	1484.6	-	545.9	37.42	0.0
Total Losses (%)	4.70	29.47	18.24	18.24	4.68	25.69	-0.25
Plant Height (cm)	13.10	31.80	22.37	-	3.65	16.35	0.48
Fruit Zone (cm)	11	24.75	17.55	-	3.43	19.55	0.06
Slope (degrees)	0.73	21.69	7.86	-	5.16	65.69	0.89

Note: Fruit yield, un-harvested berries, berries on the ground, loss through the blower and total losses were recorded in kg ha^{-1} unless otherwise specified.

The CVs reported large variability in fruit yield and fruit losses for selected sites, which was also supported by the minimum and maximum values (Table 4-2). Mean fruit yield was the lowest for Small Scott site (2618 kg ha^{-1}) and highest for Frankweb site (8136 kg ha^{-1}). Large CVs for fruit yield and slope corresponding with the high CVs for un-harvested berries on the plants, berries on the ground and loss through the blower showed that the fruit losses during harvesting were influenced by these variations (Table 4-2). Lower fruit yield at Cooper and Small Scott sites as compared to Tracadie and Frankweb sites might be due to more bare spots and grasses (Fig. 4-1), rocky nature of soil, lower pollination, winter kill and availability of nutrients for plant growth and development. Fruit losses were generally higher for high yielding fields and vice versa (Table 4-2). Selected fields were not expected to behave identically, although they were representative of the geomorphology and agricultural practices of the local area. The variations in results also probably reflect the influence of temporal dynamics on the measured parameters due to sampling at different times during the study. This experiment was not designed to evaluate the temporal effects but spatial aspect of variation in fruit yield, crop parameters, fruit losses and topographic features. In the future, more explorations may be required to quantify the variability caused by the temporal variations.

4.3.2 Spatial Variation of the Collected Data

Nugget, sill and range of influence are the three major components of semivariogram (Brouder et al., 2005). Semivariance ideally increases with the lag distance between sample locations which is known as spatial dependence. Sampling locations separated by short distances (lower than the range of influence) are spatially correlated than those separated by the large distances. Nugget semivariance is the variance at zero distance (h = 0). Sill is a semivariance at which the sampling locations are not influenced by neighboring points. Range of influence is the distance at which the values of one variable become spatially independent from close by points (Oliver, 1987). Best fitted semivariogram models for pre-harvest fruit losses were exponential and spherical for selected sites (Table 4-3). Fruit yield, berry losses, plant height, fruit zone and slope were modeled using exponential, spherical, gaussian and linear models of semivariograms for the monitoring sites (Tables 4-4 and Table 4-5). The criterion for the best fitted models was the coefficient of determination (R^2) and residual sum of squares.

Pre-harvest fruit losses showed large spatial variation with the lower range of influence (< 19 m) within the selected fields (Table 4-3). Nugget to sill ratio is also an indicator of spatial dependence of a variable; low nugget to sill ratio represents high spatial dependence. A parameter is strongly spatial dependent if the nugget to sill ratio is < 25%. If the ratio is between 25 to 75%, the variable is assumed to have moderate spatial dependency. Weak spatial dependency is reported when the ratio > 75% (Chien et al., 1997;

Cambardella et al., 1994). Nugget to sill (C_0/C_0+C) ratio generally reflects the spatial autocorrelation (Li and Reynolds, 1995). Semivariogram of pre-harvest fruit losses indicated strong spatial dependence within the selected fields (Table 4-3). Strong spatial dependency of the pre-harvest fruit losses might be controlled by the weather conditions and time of the harvest, since these losses were not caused by the mechanical harvester.

Table 4-3. Semivarigram parameters of pre-harvest fruit losses for selected fields.

Pre-harvest Fruit Losses (kg ha^{-1})						
Sites	Nugget	Sill	Range (m)	Nugget Sill ratio (%)	R^2	Model
Cooper	2.63	14.56	21.58	17.86	0.73	Spherical
Small Scott	35.60	233.42	18.86	15.25	0.67	Exponential
Tracadie	4.23	33.42	17.30	12.66	0.68	Spherical
Frankweb	66.98	361.13	26.33	18.55	0.61	Exponential

Geostatistical analysis showed large spatial variability in fruit yield, un-harvested berries on the plants, berries on the ground and loss through the blower as indicated by their range of influence (< 38 m) for Tracadie and Frankweb sites (Table 4-4). Semivariograms reported that the Cooper and Small Scott sites also exhibited large spatial variability in fruit yield and berry losses during harvesting (Table 4-5). Plant height and fruit zone were also highly variable with the range of influence 16 to 22 m within the Tracadie and Frankweb sites (Table 4-4). Similar pattern of variation for plant height and fruit zones was observed at Cooper and Small Scott sites (Table 4-5). The Frankweb, Cooper and Small Scott sites were found to have large spatial variability in slope with the range of influence < 23 m (Tables 4-4 and 4-5). Slope exhibited moderate variability (range of influence = 50.58 m) for Tracadie site. Visual inspections also revealed that the Tracadie site was relatively flat when compared with the other experimental sites. Large spatial variations in collected data suggested that the standard harvesting operation by ignoring this variability can increase fruit losses during mechanical harvesting. Adjustments in the harvester ground speed and header revolution in accordance with spatial variability in fruit yield, plant parameters and slope can reduce berry losses during harvesting.

Table 4-4. Semivarigram parameters of fruit yield, plant height, fruit zone, slope and fruit losses for Tracadie and Frankweb sites.

Tracadie Site						
Parameters	Nugget	Sill	Range (m)	Nugget Sill ratio (%)	R^2	Model
Fruit Yield	53.06	467.41	16.90	11.34	0.60	Spherical
Un-harvested Berries	3.12	10.15	14.10	30.74	0.52	Exponential
Berries on the Ground	147.04	462.10	12.60	31.81	0.66	Exponential
Loss through Blower	77.04	214.03	24.56	35.98	0.35	Exponential
Total Losses	58.01	155.35	19.25	37.34	0.49	Exponential
Plant Height (cm)	2.47	13.95	15.87	17.71	0.42	Exponential
Fruit Zone (cm)	3.15	15.36	20.27	20.51	0.43	Exponential
Slope (degrees)	1.82	18.28	50.58	9.96	0.63	Linear
Frankweb Site						
Parameters	Nugget	Sill	Range (m)	Nugget Sill ratio (%)	R^2	Model
Fruit Yield	77.03	882.0	15.10	8.73	0.54	Spherical
Un-harvested Berries	28.31	59.6	16.70	47.48	0.53	Gaussian
Berries on the Ground	55.37	152.3	14.20	36.30	0.44	Spherical
Loss through Blower	290.03	795.0	38.20	36.48	0.47	Gaussian
Total Losses	19.70	54.80	15.80	35.94	0.62	Spherical
Plant Height (cm)	2.95	13.83	20.90	21.33	0.40	Gaussian
Fruit Zone (cm)	2.22	12.41	17.90	17.89	0.73	Exponential
Slope (degrees)	27.91	279.14	23.56	10.0	0.70	Linear

Note: Fruit yield, un-harvested berries, berries on the ground, loss through the blower and total losses were recorded in kg ha^{-1} unless otherwise specified.

Fruit yield, plant height, fruit zone and slope were found to be strongly spatial dependent (< 25%) for selected sites (Tables 4-4 and 4-5). Strong spatially dependent variables may be controlled by intrinsic factor (soil texture, structure, mineralogy and microorganism) (Cambardella et al., 1994). Fruit yield and plant growth may also be influenced by the nutrient availability and uptake by plants, which is primary controlled by the intrinsic factors. Strong auto-correlation for fruit yield, plant height and fruit zone also supported the large spatial variability in these parameters within the selected sites (Tables 4-4 and 4-5).

Another class of variables such as un-harvested berries on the plants, berries on the ground, loss through the blower and total loss showed moderate to low spatial dependence with the nugget to sill ratio > 25% for selected fields (Tables 4-4 and 4-5). Moderate to low spatial dependence is controlled by the extrinsic factors (Cambardella et al., 1994; Chien et al., 1997). Extrinsic variations such as weather conditions, machine operational settings and operator skills may control the spatial variability in fruit losses during mechanical harvesting. Large spatial dependency and lower range of influence were found to have great influence on crop yield and quality for various cropping systems (Li et al., 2008; Rogerio et al., 2006; Zhao et al., 2007; Zaman and Schumann, 2006). Spatial variation in intrinsic and extrinsic factors may strongly reflect variations in fruit yield (Mulla and Bhatti, 1997; Schepers et al., 2004), which can have an impact on fruit losses during mechanical harvesting of wild blueberries. Hence, understanding the spatial variability in fruit yield, plant parameters, fruit losses and slope is the key factor for implementing the optimal machine settings to enhance berry picking efficiency of the blueberry harvester.

Scale of spatial correlation for fruit yield, plant height, fruit zone and slope varied in distance from 12 to 50.58 m for selected sites (Tables 4-4 and 4-5). Most of the variables in this study were found to have the range of influence ranging from 15 to 40 m. Variability in collected data is assumed to be non-random at distances shorter than the range of influence (Oliver, 1987). Results showed that the selected parameters were highly variable and there were correlations between fruit yield, berry losses, plant characteristics and slope (Table 4-4; Table 4-5 Appendix B). Kerry and Oliver (2003) suggested that the sample spacing should be from one third or less than half the range of influence from semivariogram. The accuracy of spatial correlations described by geostatistical analysis can be improved by increasing the sample size (McBratney and Webster, 1983).

Table 4-5. Semivarigram parameters of fruit yield, plant height, fruit zone, slope and fruit losses for Cooper and Small Scott sites.

			Cooper Site			
Parameters	Nugget	Sill	Range (m)	Nugget Sill ratio (%)	R^2	Model
Fruit Yield	10.03	371.80	20.40	2.69	0.59	Spherical
Un-harvested Berries	16.01	36.10	27.42	34.32	0.47	Spherical
Berries on the Ground	43.06	97.03	24.40	44.36	0.49	Spherical
Loss through Blower	349.10	762.07	27.50	45.80	0.39	Gaussian
Total Losses	3.07	8.30	26.30	36.14	0.63	Spherical
Plant Height (cm)	0.86	16.62	17.60	16.87	0.69	Spherical
Fruit Zone (cm)	1.64	12.83	16.83	20.58	0.38	Exponential
Slope (degrees)	5.89	18.89	18.10	13.71	0.68	Spherical
			Small Scott Site			
Parameters	Nugget	Sill	Range (m)	Nugget Sill ratio (%)	R^2	Model
Fruit Yield	12.54	25.09	14.30	10.12	0.58	Exponential
Un-harvested Berries	161.04	382.38	15.90	44.42	0.48	Exponential
Berries on the Ground	10.08	27.40	16.50	36.49	0.75	Gaussian
Loss through Blower	6.53	11.03	26.50	57.52	0.56	Exponential
Total Losses	27.71	89.52	12.60	30.94	0.76	Gaussian
Plant Height (cm)	22.97	129.78	30.46	17.70	0.60	Linear
Fruit Zone (cm)	26.31	129.51	32.63	20.32	0.45	Spherical
Slope (degrees)	1.83	20.64	17.20	8.87	0.47	Spherical

Note: Fruit yield, un-harvested berries, berries on the ground, loss through the blower and total losses were recorded in kg ha^{-1} unless otherwise specified.

Overall, the higher CVs, lower range of influence and large to moderate spatial dependency suggested large spatial variability in fruit yield, berry losses, plant characteristics and slope for selected fields. Variations in fruit losses corresponding with the variability in fruit yield, plant height, fruit zone and slope provided strong evidence that the fruit losses during harvesting were caused by the variations in these parameters. Harvesting operational recommendation based on proper characterization and quantification of spatial variability can increase berry picking efficiency of the commercial wild blueberry harvester to improve profit margins for growers.

4.3.3 Relationships Among the Collected Data

Correlation matrix revealed significant relationships between fruit yield, berry losses, crop parameters and slope for selected sites (Tables 4-6 and 4-7). Fruit yield was significantly correlated with un-harvested berries on the plants, berries on the ground, loss through the blower and total losses for selected sites (Tables 4-6 and 4-7), except Tracadie site where loss through the blower was non-significantly correlated. Significant correlations of fruit yield with berry losses during harvesting (r~0.23 to 0.78) showed a linear trend indicating that the fruit losses were proportional to the fluctuations in fruit yield. Geostatistical results also reported that the fruit losses were greatly influenced by the variation in fruit yield (Tables 4-4 and 4-5). Negative significant relationship of fruit yield with plant height suggested that the fruit yield was lower in the areas where plants were taller for selected sites (Tables 4-6 and 4-7), except for Small Scott site. A possible reason for lower fruit yield in tall plants might be due to more vegetative growth causing reduction in fruit yield.

Table 4-6. Correlation matrix among fruit yield, berry losses, crop parameters and slope for Tracadie and Frankweb sites.

Tracadie Site							
	Fruit Yield	Un-harvested Berries	Berries on the Ground	Berries through Blower	Total Losses	Plant Height	Fruit Zone
Un-harvested Berries	0.23*						
Berries on the Ground	0.77***	0.23*					
Loss through Blower	0.09 ^{NS}	0.19 ^{NS}	0.09 ^{NS}				
Total Losses	0.78***	0.38**	0.98***	0.13 ^{NS}			
Plant Height (cm)	-0.36 **	-0.22 *	-0.26 *	-0.05 ^{NS}	-0.29 *		
Fruit Zone (cm)	-0.02 ^{NS}	-0.06 ^{NS}	-0.10*	0.04 ^{NS}	-0.10 ^{NS}	0.47***	
Slope (degrees)	-0.12 ^{NS}	-0.07 ^{NS}	0.12 ^{NS}	-0.20 ^{NS}	0.09 ^{NS}	0.15 ^{NS}	0.02 ^{NS}
Frankweb Site							
	Fruit Yield	Un-harvested Berries	Berries on the Ground	Berries through Blower	Total Losses	Plant Height	Fruit Zone
Un-harvested Berries	0.70***						
Berries on the Ground	0.78***	0.79***					
Loss through Blower	0.69 ***	0.63***	0.62***				
Total Losses (kg ha^{-1})	0.82***	0.87***	0.97***	0.51 ***			
Plant Height (cm)	-0.34 **	-0.30* *	-0.28 *	-0.31**	-0.32**		
Fruit Zone (cm)	0.09 ^{NS}	-0.13 ^{NS}	-0.07 ^{NS}	-0.24*	-0.11 ^{NS}	0.45***	
Slope (degrees)	-0.17 ^{NS}	0.03 ^{NS}	0.04 ^{NS}	-0.01 ^{NS}	0.04 ^{NS}	0.12 ^{NS}	-0.14 ^{NS}

Significance of correlations indicated by *, ** and ***, are equivalent to $p = 0.05$, $p = 0.01$ and $p = 0.001$. Where *NS*, non-significant at $p = 0.05$. Note: Fruit yield, un-harvested berries, berries on the ground, loss through the blower and total losses were recorded in kg ha^{-1} unless otherwise specified.

Un-harvested berries on the plants were significantly correlated with plant height (r = -0.22 to -0.40) suggesting that the un-harvested berries were lower in tall plants and vice versa for selected sites (Tables 4-6 and 4-7). Berries on the ground were found to have a significant relationship with total losses for selected sites (r = 0.91 to 0.98). Berries on the ground were directly proportional to total losses as indicated by the significant correlation. Results indicated that the major portion of fruit losses during harvesting was on the ground (Table 4-2). Negative correlations of un-harvested berries on the plants, on the ground, and total losses with plant height and fruit zone indicated that the tall plants with higher fruit zone provided better opportunity for the harvester to pick berries more effectively, and reduced magnitude of fruit losses during mechanical harvesting (Tables 4-6 and 4-7). Significant positive relationships of plant height with fruit zone revealed that the fruit zone was higher in the areas contained with tall plants and vice versa (Tables 4-6 and 4-7). Visual inspections narrated lodging of crop at the edges of bare spots resulting in lower fruit zone and increased losses during harvesting.

Table 4-7. Correlation matrix among fruit yield, berry losses, crop parameters and slope for Cooper and Small Scott sites.

Cooper Site							
	Fruit Yield	Un-harvested Berries	Berries on the Ground	Berries through Blower	Total Losses	Plant Height	Fruit Zone
Un-harvested Berries	0.25*						
Berries on the Ground	0.47***	0.24*					
Loss through Blower	0.40***	-0.03 NS	0.15 NS				
Total Losses	0.54***	0.51***	0.93***	0.28**			
Plant Height (cm)	-0.34**	-0.40 ***	-0.21 NS	0.19 NS	-0.28 *		
Fruit Zone (cm)	-0.35**	-0.50***	-0.22*	0.23 *	-0.32**	0.94***	
Slope (degrees)	-0.29**	0.43**	0.16 NS	-0.03 NS	0.23*	0.02 NS	-0.03 NS
Small Scott Site							
	Fruit Yield	Un-harvested Berries	Berries on the Ground	Berries through Blower	Total Losses	Plant Height	Fruit Zone
Un-harvested Berries	0.42***						
Berries on the Ground	0.59***	0.33**					
Loss through Blower	0.47***	0.09 NS	0.14 NS				
Total Losses	0.70***	0.64***	0.91***	0.34**			
Plant Height (cm)	-0.20 NS	-0.27 *	-0.22 *	0.06 NS	-0.25 *		
Fruit Zone (cm)	-0.12 NS	-0.17 NS	-0.17 NS	0.02 NS	-0.18 NS	0.80***	
Slope (degrees)	0.03 NS	0.26*	0.37 **	-0.02 NS	0.38**	-0.42 **	-0.25 *

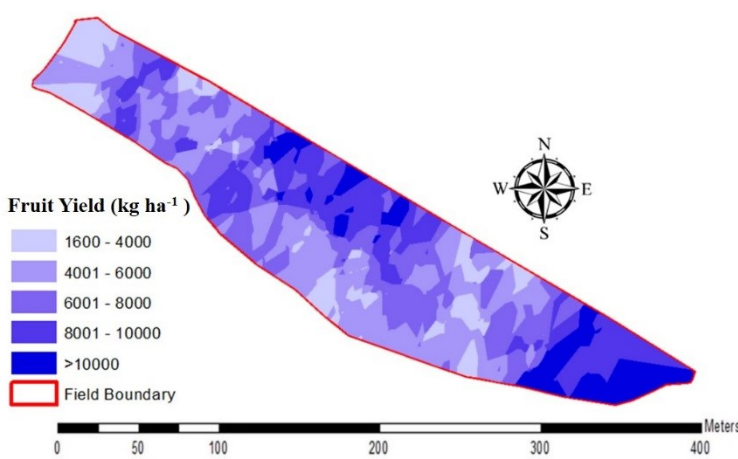
Significance of correlations indicated by *, ** and ***, are equivalent to p = 0.05, p = 0.01 and p = 0.001.Where *NS*, non-significant at p = 0.05. Note: Fruit yield, un-harvested berries, berries on the ground, loss through the blower and total losses were recorded in kg ha^{-1} unless otherwise specified.

Significant positive correlation of total losses with slope for Copper ($r = 0.23$) and Small Scott ($r = 0.38$) sites suggested that the total losses increased with the steepness of slope (Table 4-7), revealing that the topography of ground seems to have a negative effect on picking efficiency of the blueberry harvester. Topography of the field was addressed as one of the challenges during development process of the commercial wild blueberry harvester (Yarbrough, 2001; Hall et al., 1983). Total losses were non-significantly correlated with slope, indicating no effect on fruit losses during harvesting for Frankweb and Tracadie sites (Table 4-6). This could be due to relatively flat nature of Tracadie site and significantly higher yields at Frankweb site (Table 4-2).

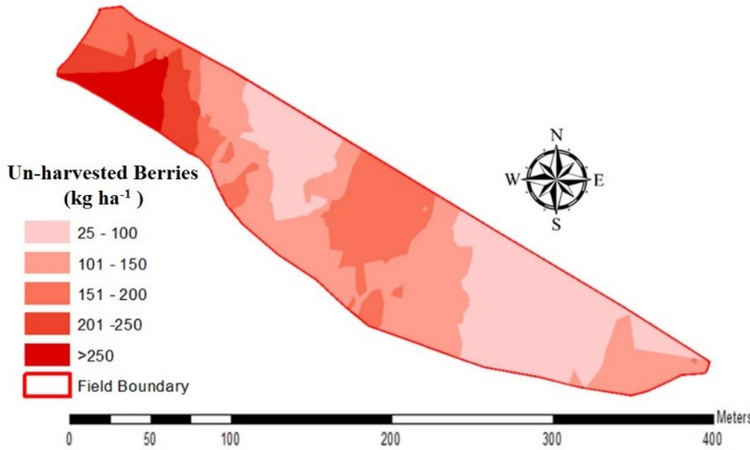
There are a variety of factors other than the machine contributing to fruit loss variability which have not been addressed. Operator skill and proper maintenance of the blueberry harvester are obvious examples. Seasonal variations, harvesting at different time schedules, soil properties and rocky nature of the fields can also have negative effect on picking efficiency of the harvester. A newly manufactured harvester was used in this study; therefore no contribution from maintenance is expected. Overall, the results of correlation matrix revealed that the berry losses during harvesting were influenced by the variations in fruit yield, plant height, fruit zone and slope within the selected fields. Results of the correlation matrix in conjunction with geostatistical analysis can be used to develop zones (low, medium and high yields), and the harvester operational settings (ground speed and head rpm) can be adjusted based on these variations to improve berry recovery and quality. Farooque et al. (2014) reported that the ground speed, header rpm and their interaction can cause significant losses during mechanical harvesting. Furthermore, the variability in collected data can be analyzed visually by generating detailed maps in ArcGIS 10 software.

4.3.4 Interpolation and Mapping of Collected Data

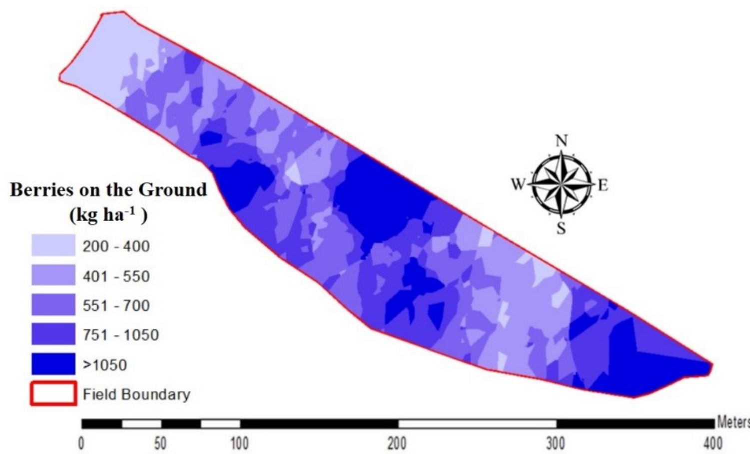
The interpolated maps of fruit yield, un-harvested berries on the plants, berries on the ground, loss through the blower, total loss, plant height, fruit zone and slope showed gradual and non-random spatial variability with significantly different values across the selected sites (Figs. 4-3 and 4-4; Figs. B-1 and B-2; Appendix B). Spatial patterns of variation in fruit yield, un-harvested berries on the plants, berries on the ground and total loss were almost similar for Tracadie and Frankweb sites (Figs. 4-3 a-e and 4-4 a-e). Higher values of fruit yield and berry losses were observed in mid north, south east and mid-south west of the Tracadie site (Fig. 4-3 a-e). Lower values were found in mid-south, west and mid-northeast of the Tracadie site. Maps revealed that the fruit losses were generally higher in high yielding regions and vice versa (Figs. 4-3 a-e). The slight variation in the trend for un-harvested berries on the plants might be due to late harvesting of the Tracadie site, resulting in lowering the grip of the berries with the plants. Pre-harvest fruit losses were also higher at Tracadie site (Table 4-1) indicating poor grip of berries with plants because of late harvesting.



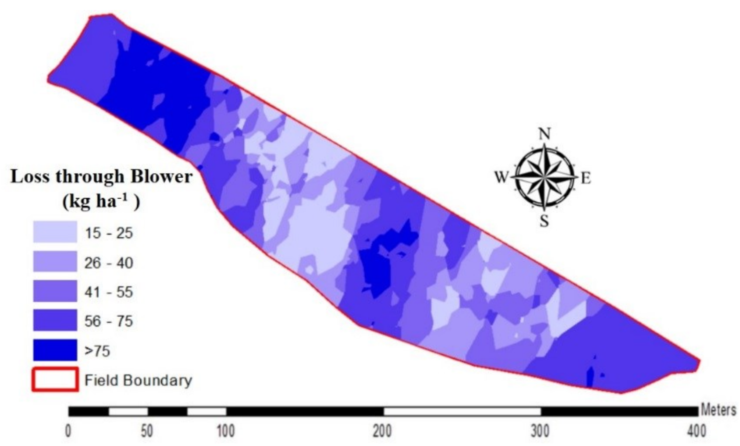
(a)


Un-harvested Berries
(kg ha-1)
25 - 100
101 - 150
151 - 200
201 -250
>250
Field Boundary
N
W
E
S
Meters
0
50
100
200
300
400

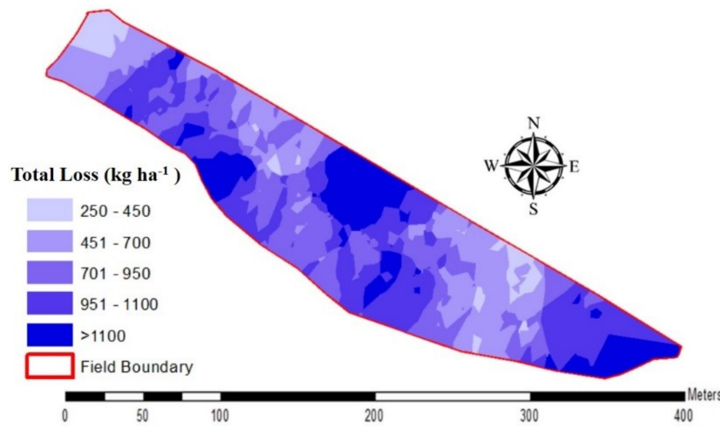
(b)


Berries on the Ground
(kg ha-1)
200 - 400
401 - 550
551 - 700
751 - 1050
>1050
Field Boundary
N
W
E
S
Meters
0
50
100
200
300
400

(c)

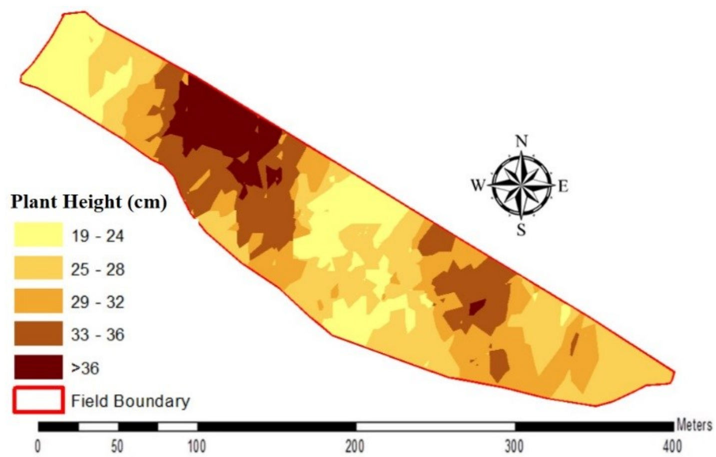

Loss through Blower
(kg ha-1)
15 - 25
26 - 40
41 - 55
56 - 75
>75
Field Boundary
N
W
E
S
Meters
0
50
100
200
300
400

(d)



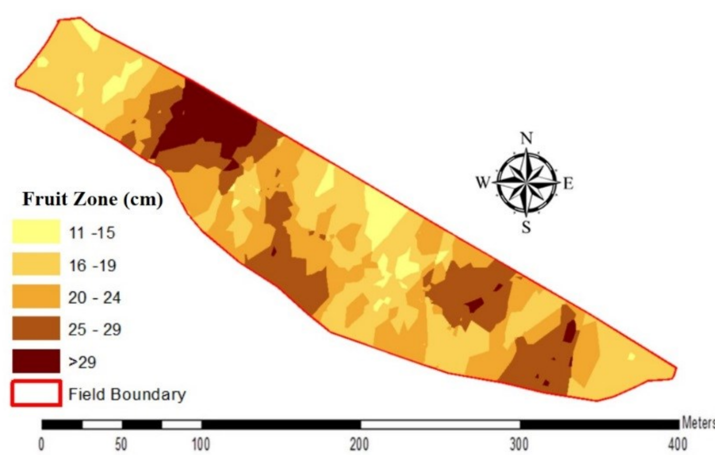
Total Loss (kg ha-1)
250 - 450
451 - 700
701 - 950
951 - 1100
>1100
Field Boundary
Meters
0
50
100
200
300
400
N
W
E
S

(e)



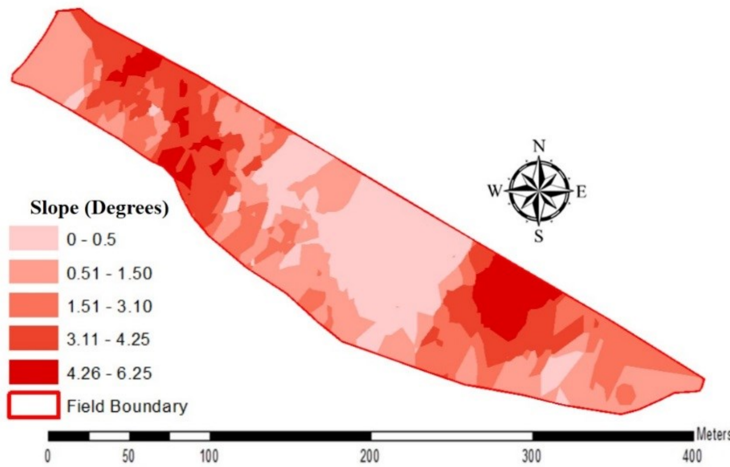
Plant Height (cm)
19 - 24
25 - 28
29 - 32
33 - 36
>36
Field Boundary
Meters
0
50
100
200
300
400
N
W
E
S

(f)



Fruit Zone (cm)
11 -15
16 -19
20 - 24
25 - 29
>29
Field Boundary
Meters
0
50
100
200
300
400
N
W
E
S

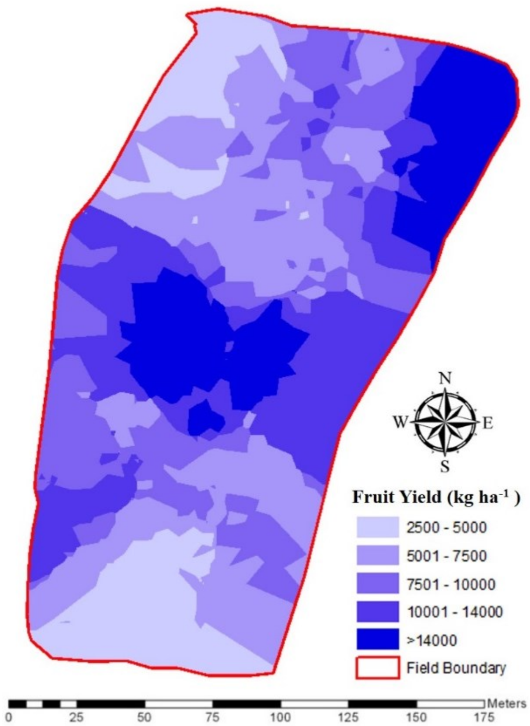
(g)



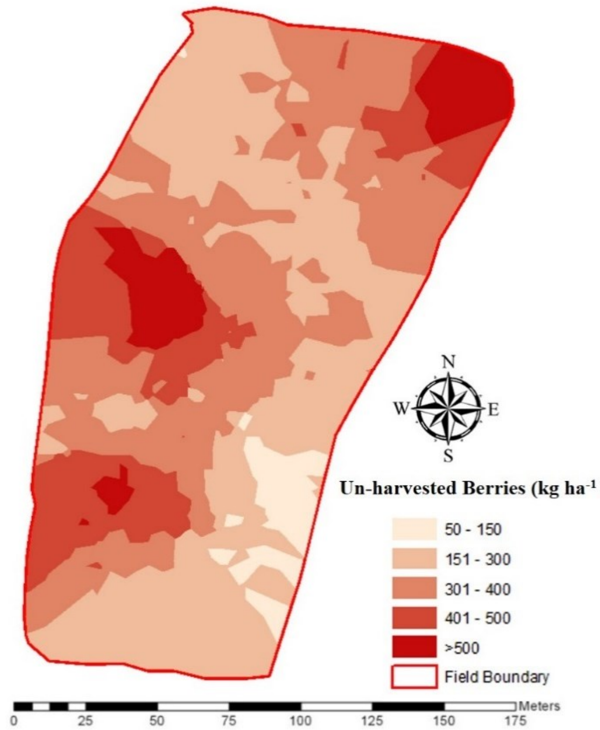
(h)

Figure 4-3: Interpolated maps, (a) Fruit yield, (b) Un-harvested berries, (c) Berries on the ground, (d) Loss through the blower, (e) Total loss, (f) Plant height, (g) Fruit zone and (h) Slope for Tracadie site.

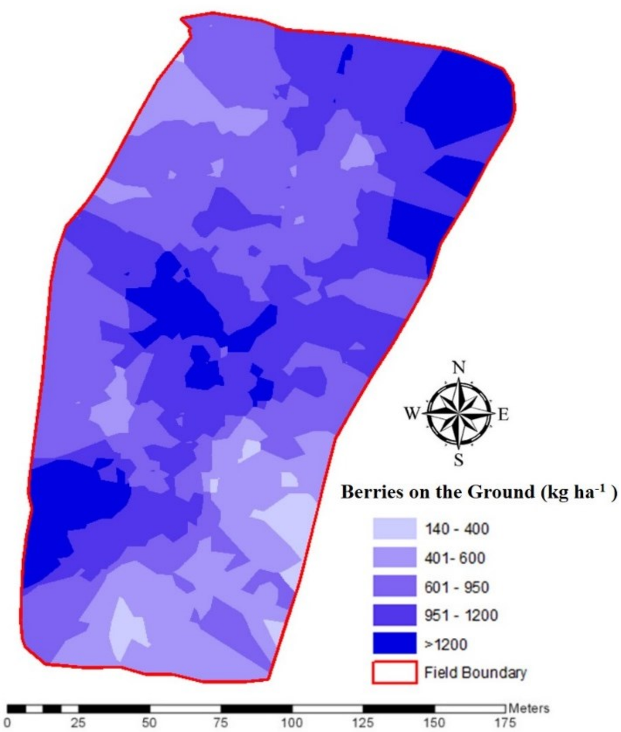
Kriged maps of fruit yield, un-harvested berries on the plants, berries on the ground, loss through the blower, total loss, plant height, fruit zone and slope suggested substantial variability within field for the Frankweb site (Fig. 4-4). Higher fruit yield and berry losses areas were contained in mid-east, mid-west and northeast of the Frankweb site (Figs. 4-4 a-e). Fruit yield and berry losses were found to be lower in south and north-west of the Frankweb site. Map comparison suggested that the fruit losses were significantly correlated with fruit yield, indicating higher losses in high yield areas. Fruit losses during harvesting were observed to be lower in low yield regions (Figs. 4-4 a-e). Higher fruit losses in high yielding regions can be minimized by providing a gentle lift for berry pickup which can be achieved by lowering the ground speed and header rpm of the harvester. Farooque et al. (2014) reported that a combination of 1.2 km hr^{-1} and 26 rpm can enhance picking efficiency of the harvester in high yielding fields.


N
W
E
S
Fruit Yield (kg ha-1)
2500 - 5000
5001 - 7500
7501 - 10000
10001 - 14000
>14000
Field Boundary
0 25 50 75 100 125 150 175 Meters

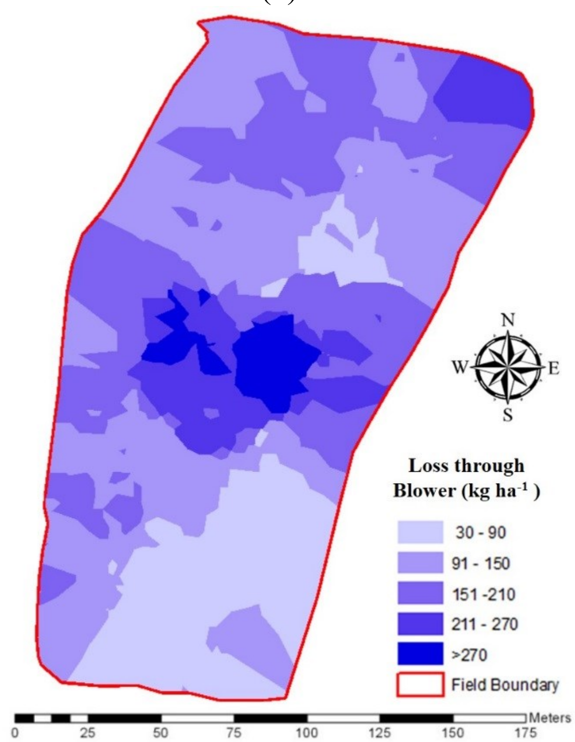
(a)


N
W
E
S
Un-harvested Berries (kg ha-1)
50 - 150
151 - 300
301 - 400
401 - 500
>500
Field Boundary
0 25 50 75 100 125 150 175 Meters

(b)


N
W
E
S
Berries on the Ground (kg ha-1)
140 - 400
401- 600
601 - 950
951 - 1200
>1200
Field Boundary
0 25 50 75 100 125 150 175 Meters

(c)


N
W
E
S
Loss through
Blower (kg ha-1)
30 - 90
91 - 150
151 -210
211 - 270
>270
Field Boundary
0 25 50 75 100 125 150 175 Meters

(d)

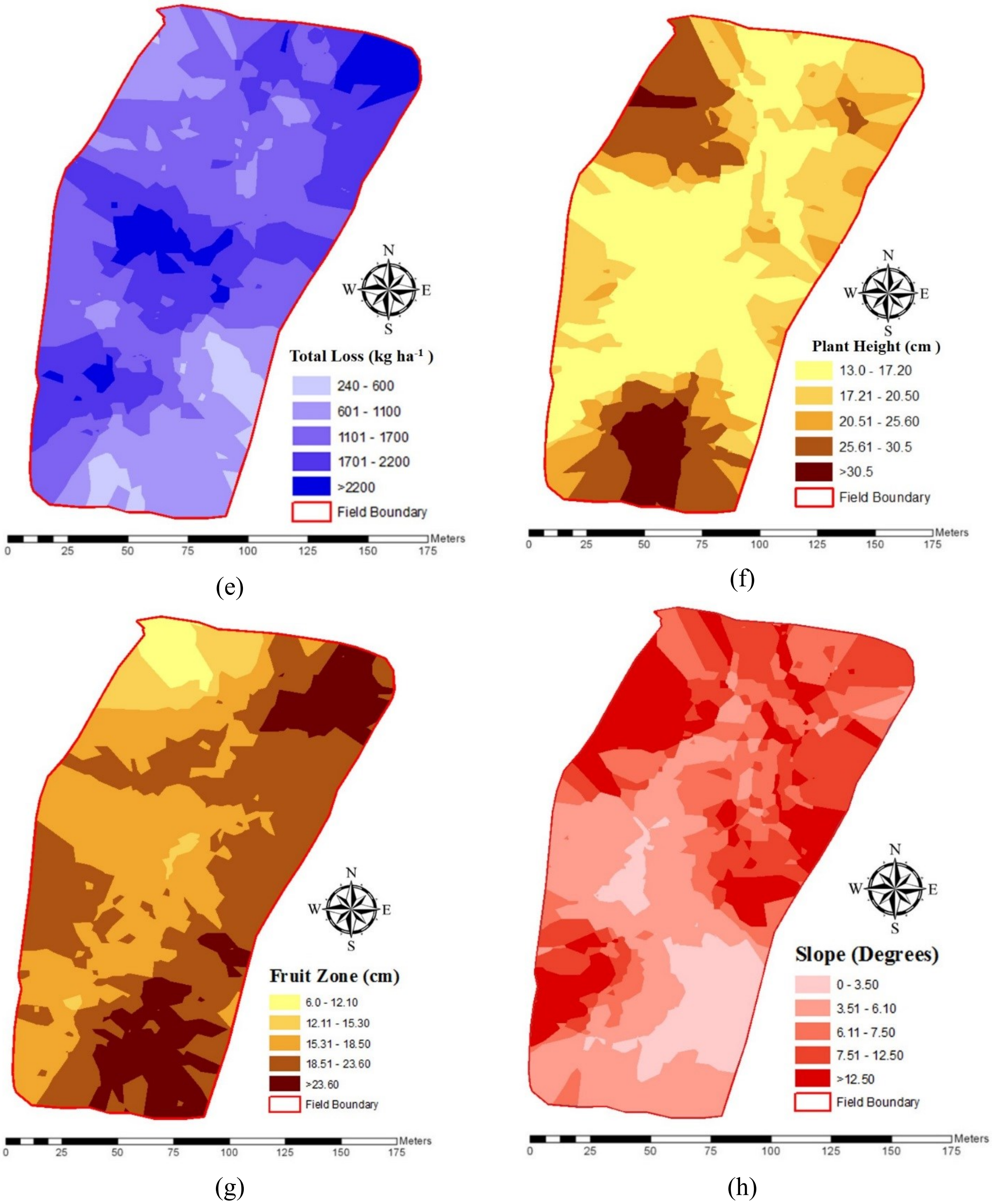


Figure 4-4: Interpolated maps, (a) Fruit Yield, (b) Un-harvested berries, (c) Berries on the ground, (d) Loss through the blower, (e) Total Loss, (f) Plant height, (g) Fruit zone and (h) Slope for Frankweb site.

Variation in loss through the blower did not match with spatial variability in fruit yield for Tracadie and Frankweb sites (Figs. 4-3 d and 4-4 d), suggesting that the blower loss were not controlled by the variation in fruit yield. Relationships identified by the maps were in agreement with the results of correlation analysis (Tables 4-6 and 4-7) for selected sites. Geostatistical analysis also revealed substantial variation in fruit yield and berry losses during harvesting. Spatial patterns of variation in fruit yield and berry losses were very similar for Cooper and Small Scott sites (Figs. B-1 a-e and B-2 a-e; Appendix B).

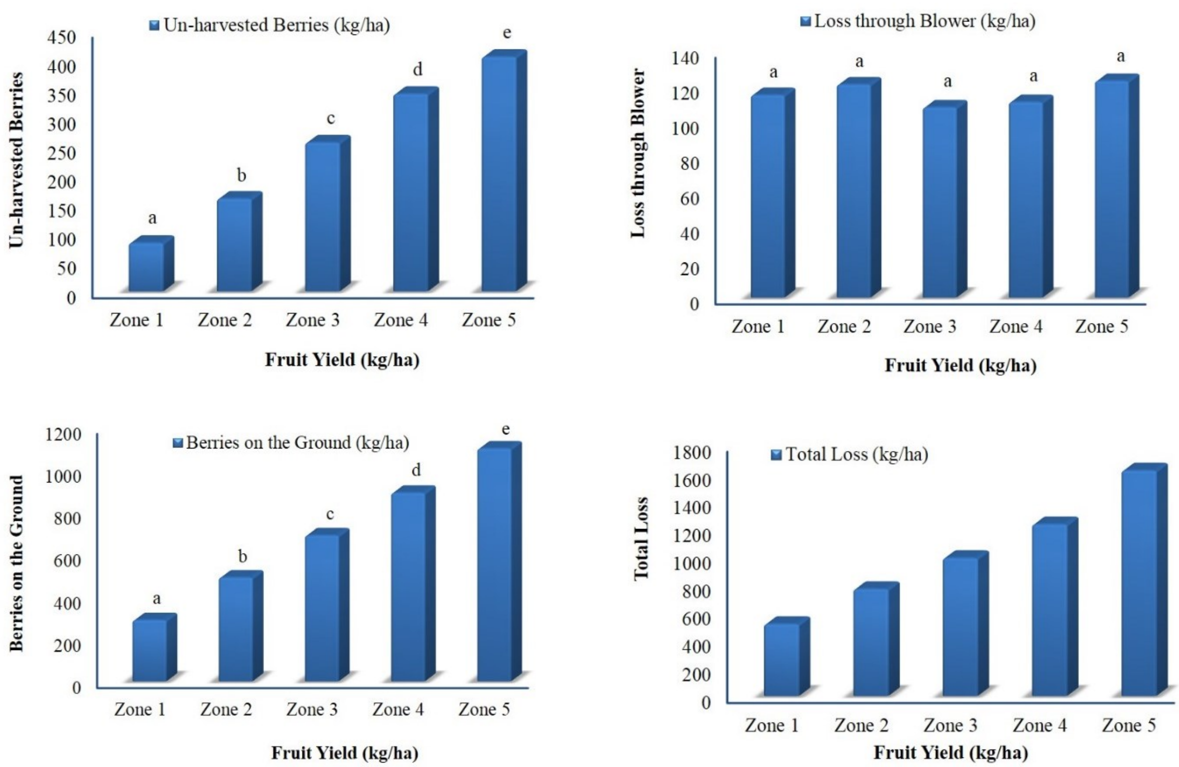
The interpolated maps of total losses, plant height and fruit zone revealed negative relationships (Figs. 4-3 e-g and 4-4 e-g). Higher values of total loss were observed in mid north, south east and north-west of the Tracadie site (Figs. 4-3 e-g). Map comparison reported that the plants were shorter with lower fruit zone in these areas, suggesting a negative relationship. Similar trend of variation for total loss, plant height and fruit zone were observed for Frankweb site (Figs. 4-4 e-g). Higher fruit losses in low plant height areas were due to lower fruit zone causing more losses during mechanical harvesting. Higher fruit zone areas provided the mechanical harvester a better opportunity to reduce berry losses and increased berry picking efficiency for selected sites. Significant positive correlations of plant height and fruit zone also supported these results (Tables 4-6 and 4-7). Results revealed that the picking performance of harvester was greatly influenced by the variations in plant height and fruit zone. Significant negative correlations of total loss with plant height and fruit zone also supported the relationships identified by the kriged maps (Tables 4-6 and 4-7). Spatial trend of variation for berry losses, plant height and fruit zone for Cooper and Small Scott sites were very similar to Tracadie and Frankweb sites (Figs. B-1 and B-2; Appendix B). Overall, the maps of berry losses, plant height and fruit zone showed substantial variability within the selected fields which was well supported by the geostatistical analysis.

Kriged slope maps suggested substantial variability within the selected fields (Figs. 4-3 h and 4-4 h; Figs. B-1 h and B-2 h; Appendix B). Geostatistical range of influence from semivariograms, and CVs also indicated large variability in slope for selected sites. Results of map comparison for fruit losses and slope showed inconsistent trend of variation (Figs. 4-3 h and 4-4 h) for Tracadie and Frankweb sites. These inconsistencies in variation of fruit losses with respect to slope were supported by the correlation analysis (Tables 4-6 and Table 4-7), which showed non-significant relationships. A possible reason for the inconsistent trend of variation at Tracadie and Frankweb site might be due to exceptionally high yielding nature of these sites (Table 4-2). High yielding nature of these sites might be dominating the slope effect resulting in inconsistent variations within the fields. Another reason for Tracadie site could be the flat nature of this field. Results of map comparison suggested that the fruit losses were higher in steep slope areas when compared with flat to mild slope areas for Cooper and Small Scott sites (Figs. B-1 h and B-2 h; Appendix B). Relationships identified by the map were supported by the correlation analysis for Cooper and Small Scott sites (Table 4-7). Results reported that the slope can have an impact on picking performance of the harvester. Operational adjustments corresponding with these variations can enhance berry picking efficiency of the harvester. Overall, maps of fruit yield, berry losses, plant characteristics and slope (Figs. 4-3 and 4-4; Figs. B-1 and B-2; Appendix B) showed substantial variation across the selected fields, which was supported by lower range of influence and high CVs.

4.3.5 Zonal Analysis of Fruit Losses

The variation in fruit losses with respect to fruit yield, plant height and slope were analyzed through zonal analysis using ArcGIS 10 software. Raster categories of data were extracted and analyzed statistically to compare the means of fruit losses in different fruit yield, plant height and slope zones. Results of zonal analysis suggested that the un-harvested berries on the plants, berries on the ground and total losses were significantly higher in high yielding Zones (Zone 5; Yield > 4000 kg ha^{-1}) for selected sites (Table 4-8; Fig. 4-5; Table B-1 and Fig. B-3; Appendix B). Fruit losses followed an increasing trend with an increase in fruit yield and observed to be lowest in low yielding areas (Zone 1) of selected sites. Results reported that the mean losses through the blower were similar for all fruit yield zones, indicating non-significant differences (Table 4-8; Fig. 4-5; Table B-1 and Fig. B-3; Appendix B). Variation of loss through the blower suggested that the blower losses were not controlled by the fluctuations in fruit yield. Loss through the blower might be controlled by the position and specifications of the blower fan installed on the harvester conveyer. Also, the clogging of debris in teeth bars and interference with weed patches during harvesting might be the other factors controlling the loss through the blower. Significant relationships between fruit yield and berry losses within the selected fields (Tables 4-6 and 4-7) also supported the results identified by the zonal analysis.

Variation in fruit losses with respect to plant height was examined using zonal analysis for selected sites (Table 4-8; Fig. 4-6; Table B-1 and Fig. B-4; Appendix B). Results revealed that the un-harvested berries on the plants, berries on the ground, and total losses were observed to be higher for Zone 1 (short plants) and Zone 5 (tall plants) for selected sites (Table 4-8; Fig. 4-6; Table B-1 and Fig. B-4; Appendix B). These results suggested inadequate picking performance of the blueberry harvester in short plants and very tall plants. Higher fruit losses in short plants within the selected sites might be due to the lower fruit zones, resulting in decreased picking efficiency of the commercial harvester. Higher fruit losses in short plants were also supported by the significant correlation between plant height and fruit zone for selected sites (Tables 4-6 and 4-7).



Fruit Yield (kg/ha) Zones

Zone 1 (2500 - 5000)
Zone 2 (5001 - 7500
Zone 3 (7501 - 10000)
Zone 4 (10001 – 14000)
Zone 5 (> 14000)

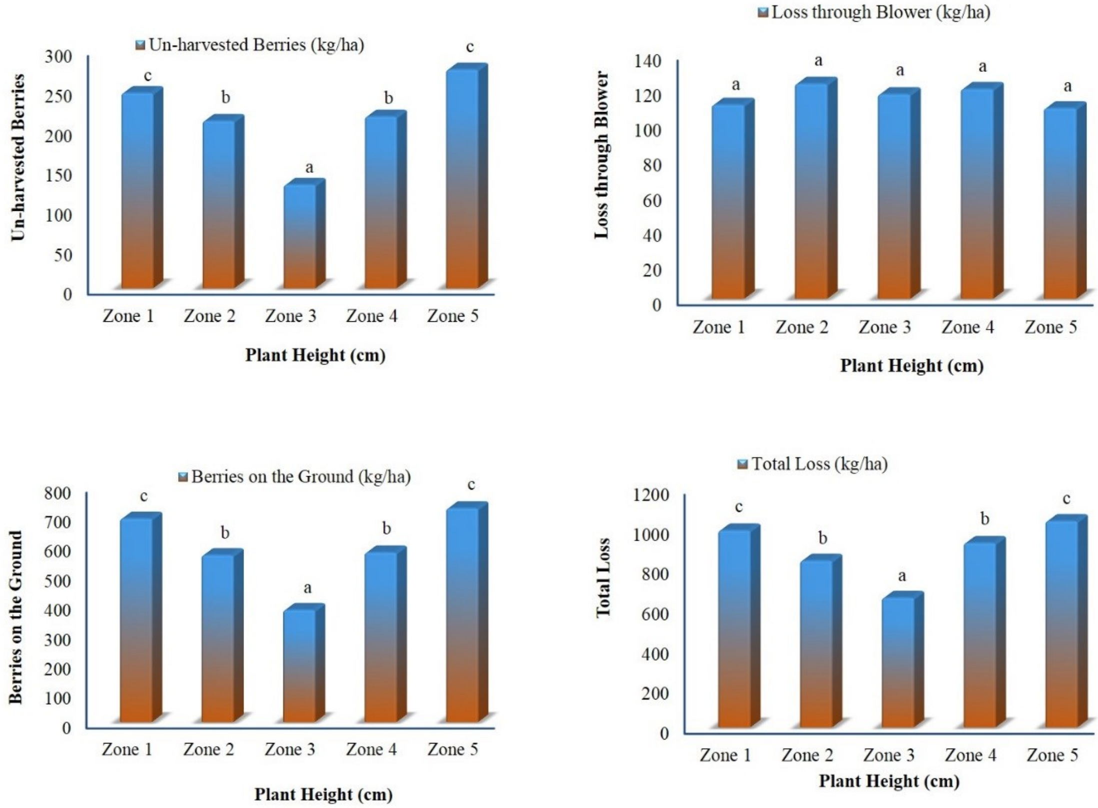
Figure 4-5: Multiple means comparison of fruit losses in relation to different zones of fruit yield for Frankweb site.

Table 4-8. Multiple means comparison of fruit losses in relation to different zones of fruit yield, plant height and slope for Tracadie site.

	Fruit Yield (Kg ha^{-1}) Zones				
Parameters	Zone 1 1600 to 4000	Zone 2 4001 to 6000	Zone 3 6001 to 8000	Zone 4 8001 to 10000	Zone 5 > 10000
Un-harvested Berries	39.5 a	70.6 b	95.3 c	119.4 d	159 e
Berries on the Ground	213.1 a	365.6 b	488.6 c	595.3 d	666.2 e
Loss through Blower	35.6 a	45.8 a	31.4 a	42.8 a	39.4 a
Total Losses	301.5 a	460.5 b	610.9 c	781.4 d	849.2 e
	Plant Height (cm) Zones				
Parameters	Zone 1 19 to 24	Zone 2 25 to 28	Zone 3 29 to 32	Zone 4 33 to 36	Zone 5 > 36
Un-harvested Berries	55.6 a	48.6 a	84.6 b	109.3 c	129.42 c
Berries on the Ground	361.3 b	233.4 a	476.3 c	586.1 d	641.7 e
Loss through Blower	33.5 a	38.9 a	31.3 a	43.6 a	37.6 a
Total Losses	430.4 b	310.6 a	490.5 c	645.8 d	790.5 e
	Slope (Degrees) Zones				
Parameters	Zone 1 0 to 0.50°	Zone 2 0.51 to 1.50°	Zone 3 1.51 to 3.10°	Zone 4 3.11 to 4.25°	Zone 5 > 4.25°
Un-harvested Berries	73.6 a	69.3 a	80.4 ab	75.6 a	95.5 b
Berries on the Ground	493.5 a	506.6 a	545.6 b	601.7 c	615.3 c
Loss through Blower	35.1 a	32.3 a	39.6 a	41.8 a	33.5 a
Total Losses	602.3 a	613.4 a	670.9 b	725.6 c	786.3 d

Means followed by different letters are significantly different at $p = 0.05$. Fruit losses were recorded in kg ha^{-1}.

Possible reason for higher losses in tall plants could be due to blockage of the harvester teeth bars with the excessive vegetation (leaves, shoots, branches), which might reduce berry carrying capacity of the harvester. Results suggested that the picking performance of the harvester was very good in Zone 3 of plant height, with significantly lower fruit losses during mechanical harvesting for selected sites (Table 4-8; Fig. 4-6; Table B-1 and Fig. B-4; Appendix B). Lower fruit losses in Zone 3 might be due to the optimum fruit zone interference during harvesting, providing the harvester an opportunity for effective berry picking and recovery.



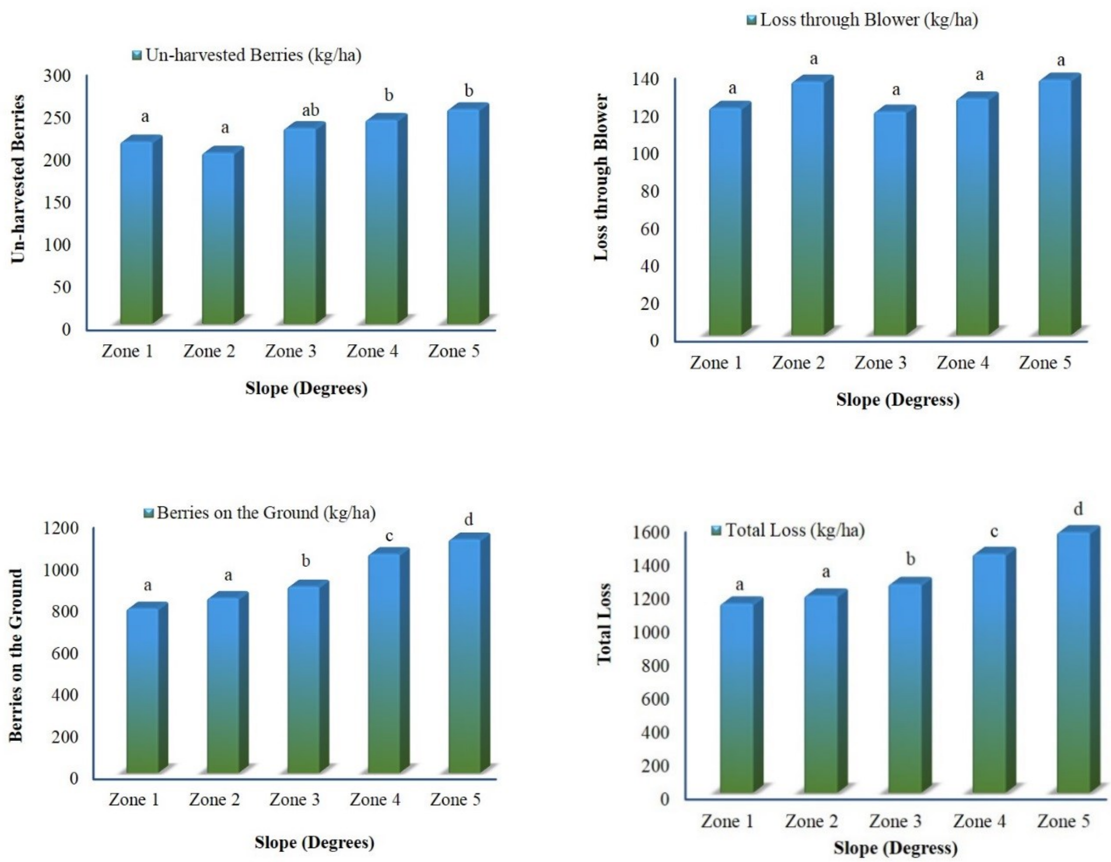
Plant Height (cm) Zones

Zone 1 (13- 17)
Zone 2 (18 - 21)
Zone 3 (22 - 26)
Zone 4 (27 – 30)
Zone 5 (> 30)

Figure 4-6: Multiple means comparison of fruit losses in relation to different zones of plant height for Frankweb site.

In general, results suggested that the fruit losses during harvesting were influenced by the variations in plant height. Loss through the blower were not affected by the variation in plant height for selected sites (Table 4-8; Fig. 4-6; Table B-1 and Fig. B-4; Appendix B). Correlation analysis between plant height and berry losses (Tables 4-6 and 4-7) also supported these results. Results of zonal analysis in five slope zones suggested that the un-harvested berries on the plants were non-significantly different for Tracadie and Frankweb sites (Table 4-8; Fig. 4-7). However, the un-harvested berries were observed to be higher in steep slope (Zone 5) areas and vice versa for the Tracadie and Frankweb sites. Un-harvested berries on the plants were significantly lower in mild slope areas for Cooper and Small Scott sites (Table B-1; Fig. B-5; Appendix B). Lower un-harvested berries were observed in steep slope of Cooper site (Fig. B-5; Appendix B), which might be due the low coverage of the steep slope areas within this field. Non-significant differences in un-harvested berries on the plants for Tracadie and Frankweb sites might be due to high yielding nature of these sites.

Exceptionally higher yield might be dominating the slope effect during mechanical harvesting. Berries on the ground followed an increasing trend with the steepness of the slope and were found to be highest in Zone 5 of the Copper and Small Scott sites (Table B-1; Fig. B-5; Appendix B). Significant positive correlations between fruit losses and slope sites (Table 4-7) also supported the results identified by the zonal statistics. The pattern of variation for berries on the ground were similar for Tracadie and Frankweb sites, except non-significant differences for Zones 1 and 2; and Zones 4 and 5 for Tracadie site, and Zones 1 and 2 for Frankweb site (Table 4-8; Fig. 4-7). Non-significant difference in various slope zones might be due to flat nature of Tracadie site, when compared with other monitoring sites. In general, berries on the ground were higher in steep slope areas for selected sites (Table 4-8 and Fig. 4-7; Table B-1 and Fig. B-5; Appendix B).



Slope (Degrees) Zones

Zone 1 (0 - 3.50)
Zone 2 (3.51 – 6.10)
Zone 3 (6.11 – 7.50)
Zone 4 (7.51 – 12.50)
Zone 5 (> 12.50)

Figure 4-7: Multiple means comparison of fruit losses in relation to different zones of slope for Frankweb site.

Loss through the blower were not seem to have any influence of slope and were found to be non-significantly different in various slope zones within the selected fields (Table 4-8 and Fig. 4-7; Table B-1 and Fig. B-5; Appendix B). Variation for total loss was very similar to berries on the ground for Cooper and Small Scott sites (Table B-1; Fig. B-

5; Appendix B). Total loss were non-significantly different for Zones 1 and 2 for Tracadie sites and observed to be highest in Zone 5 (Table 4-8). Total loss were non-significantly different for Zones 1 and 2; and Zones 3 and 4 for Frankweb site (Fig. 4-7) and observed to be lowest in Zone 1. Conclusively, the fruit losses during harvesting were influenced by the variation in slope during mechanical harvesting. Collectively, the results of classical statistics, geostatistical range of influence, correlation matrix, kriged maps and zonal analysis revealed that the crop characteristics, fruit yield, slope and fruit losses were spatially variable with selected sites. Adjustments in the machine operating parameters by keeping in view these spatial variations can enhance picking performance of the blueberry harvester, and increase profit margins for wild blueberry industry with no additional cost.

4.4 CONCLUSIONS

Results of CVs, semivariogram parameters, interpolated maps, correlation matrix and zonal analysis confirmed the existence of large spatial variability in fruit yield, plant parameters and topographic features. Results revealed the dependence of fruit losses on fruit yield, plant height, fruit zone and slope within the selected sites. In general, fruit losses increased with an increase in fruit yield and slope during mechanical harvesting. Zonal analysis suggested that the picking performance of the blueberry harvester was inadequate in short and very tall plants. Operational adjustments in the blueberry harvester in accordance with spatial variations can enhance berry picking efficiency. Farooque et al. (2014) reported that a combination of ground speed (1.20 km hr^{-1}) and header revolutions (26rpm) can improve berry recovery in high yielding fields (> 3,500 kg ha^{-1}). Variability in fruit losses corresponding with spatial variations in crop characteristics, fruit yield and slope suggested that these parameters had a significant effect on fruit losses during harvesting. Additionally, these results can be used to implement site-specific management practices in blueberry fields.

Chapter 4 confirmed the existence of large spatial variability in fruit yield, plant parameters and topographic features within the selected wild blueberry fields. Results of geo-statistical analysis, mapping in GIS and zonal analysis suggested that the fruit losses during harvesting were significantly influenced by the spatial variations in fruit yield, crop characteristics and slope of the ground. Mechanical harvesting of blueberry fields by ignoring these spatial variations can increase fruit losses during harvesting. Influence of spatial variations on picking performance of the harvester emphasized the need to model these spatial relationships mathematically to propose optimal operational settings (ground speed, head rpm, head height, *etc.*) to improve berry picking efficiency. Chapter 5 concentrated on development of mathematical models to study these spatial relationships using ANN and MR techniques.

CHAPTER 5 DEVELOP A PREDICTIVE MODEL FOR WILD BLUEBERRY FRUIT LOSSES DURING HARVESTING USING ARTIFICIAL NEURAL NETWORK

The wild blueberries are one of the most important fruit crops of Canada, producing more than 50% of the world's production. Understanding and predicting the relationships between the machine operating parameters, fruit losses, topographic features and crop characteristics can aid in better berry recovery during mechanical harvesting. This research suggested a modeling approach for prediction of fruit losses during harvesting using artificial neural network (ANN) and multiple regression (MR) techniques. Four wild blueberry sites were selected and completely randomized factorial (3 x 3) experiments were conducted at each site. One hundred sixty two plots (0.91 x 3 m) were made at each site, in the path of operating harvester. Total fruit yield and losses were collected from each plot within the selected sites. The harvester was operated at specific levels of ground speed (1.20, 1.60 and 2.00 km h^{-1}) and head rotational speed (26, 28 and 30 rpm). The slope, plant height and fruit zone were also recorded from each plot.

The collected data were normalized and 70% of the data were utilized for training, and 30% for validation of developed models using ANN and MR techniques. Results of root mean square error (*RMSE*) suggested that the tanh-sigmoid transfer function between the hidden layer and output layer was the best fit for this study. The developed models were validated internally and externally and the best performing configuration was identified based on *RMSE*, coefficient of efficiency, percent variation and coefficient of determination. Results of scatter plot among the *RMSE* and epoch suggested that an epoch size (iterative steps) of 15000 was appropriate to predict fruit losses using ANN approach.

Results revealed that the prediction accuracy of MR model was lower (R^2 = 0.46; *RMSE* = 0.14) than the ANN model (R^2 = 0.84; *RMSE* = 0.075) for training dataset. Results reported that the ANN model predicted fruit losses with higher (R^2 = 0.63; *RMSE* = 0.11) accuracy when compared with MR model (R^2 = 0.37; *RMSE* = 0.15) for external validation dataset. Overall, the results of this study suggested that the ANN model was able to predict fruit losses during harvesting accurately and reliably. These results can help to identify the factors responsible for fruit losses and to suggest optimal harvesting scenarios to improve harvesting efficiency.

The work presented in this chapter has been submitted in *Applied Engineering in Agriculture Journal*, entitled "Development of a predictive model for wild blueberry harvester fruit losses during harvesting using artificial neural network".

5.1 INTRODUCTION

Fruit losses during harvesting are consequence of complex interactions between mechanical parameters, crop characteristics, weather conditions, soil structure, operator skills and field topography (Adams et al., 1998; Bryant et al., 2000; Farooque et al., 2013; Salter et al., 1980). Owing to the dynamicity of these relationships, determination of ideal harvesting conditions to optimize yield and quality has always remained a challenge (Fritz and Weichmann, 1979). Inherently, the nature of the harvesting processes that govern the picking efficiency are complicated and non-linear, therefore, traditional single factor modeling techniques often lack the ability to model such complex systems (Chen et al., 2001). Modeling network of relationships requires an approach that is robust, scalable and flexible with a choice of various learning algorithms. In the case where inputs and outputs are intrinsically variable, a system that is intended to be predictive is more appropriate

(McCarthy et al., 2001; Reidsma et al., 2009). Therefore, a system which can 'learn' from successive field trials is ideal because it will certainly become more reliable through time and will be able to adapt to unforeseen changes in the data (Huang and Foo, 2002). The data-driven modeling which is very different from physically based approach, despite its similar purpose of connecting one set of data (output) with another corresponding set (input) to find relationships after proper training and validations.

Artificial neural networks (ANN) can effectively be used in scenarios where functional relationships are non-linear or unknown (Park et al., 2005). The ANN has been recognized as a powerful tool capable of performing better than statistical models, particularly for the case of non-linear and multiple processing systems (Alvarez, 2009; Huang and Foo, 2002). The architecture of ANN is designed based on the structure of human brain which learns the relationship between input and output variables and develops a hidden layer "black-box" understanding in terms of a complex series of associated weights (Setiono et al., 2000). Topology and structure of ANN model can be extremely complex or simple depending upon problem under study. The ANN model consists of a large number of simple processing elements called nodes. Each node is connected to the other nodes by means of direct communication links and an associated weight function. The nodes are arranged into: input layers (observations), hidden layer(s) (intermediate nodes) and output layers (conclusions).

The back-propagation (BP) multi-layer ANN is the most common and convenient (McCulloch and Pitts, 1943) for model development, training and predictions. The transfer and association of data between the layers are determined by transfer function and learning algorithms. The common transfer function used between the hidden layer and output layer is the sigmoid function, whereas linear function is applied to transfer data from the input layer to the hidden layer (Kaul et al., 2005). Based on the differences between actual and predicted values, the weight values between the variables are adjusted during each epoch based on the delta rule to compensate the errors. Error minimization process is achieved by using the gradient descent method (Bishop, 1994; Hornik et al., 1989). The ANN is not new technique, but research applications have increased significantly in past twenty years due to its generic nature, precise prediction capabilities and adaptability.

Application of ANN modelling requires an understanding of best procedures for training the network. Types of networks available and training algorithms are constantly evolving for better predictions (Haykin, 1999). Neural network modeling of a system requires selection of an appropriate network type, a training algorithm, a suitable training period, a best network structure and effective pre- and post-processing of data (Bishop, 1995). The ANN may be described as a network of interconnected nodes. The optimum number of nodes in the hidden layer can be determined by pruning out extraneous hidden nodes from a complex network during the training process. Shamseldin (1997) suggested that the best way to determine number of nodes in a hidden layer is trial and error. Training of ANN model is accomplished by presenting the network with a training data. Depending on the complexity of the problem, it may be necessary to train the network repeatedly until the underlying function is 'learned'. The over familiarization of ANN model with training data can lose its ability to generalize the problems, which it is going to encounter. Over training of network can be avoided by including regularization theory, which tries to smooth network predictions (Bishop, 1995) and cross validation via an independent dataset (Braddock et al., 1998).

The ANN model deals with both linear and non- linear concepts in a model architecture and can be used in dynamic input/output system (Tokar and Markus, 2000). The ANN has major advantages over traditional models, *i.e.* it does not require a prior knowledge of the system, it has more tolerance to incomplete data and noise levels, and it can minimize the effect of outlier. The ANN has been extensively used for exploring diverse areas such as bio-medical, engineering, image processing, water resources and others (Rumelhart et al., 1994; Shamseldin et al., 1997). It can be applied to solve many problems faster and with better accuracy than conventional techniques, even without human intervention. The ANN models complex tasks easily and simply, and requires very little theoretical knowledge of ANN users. The ANN can perform approximation, optimization, classification, prediction, generalization, relation, abstraction and adaptions of the complex systems under study (Hopfield and Tank, 1985; Kung et al., 1991).

The ANN have several applications such as, 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., 2002), stream flow estimations (Wright et al., 2002) and water level prediction (Patrick et al., 2002; Huang et al., 2003). Amini et al. (2005) predicted the cation exchange capacity of soil using ANN approach in comparison with multiple regression (MR) techniques. Chen et al. (2001) used the ANN model for prediction of quality changes during osmo-convective drying of the highbush blueberries for process optimization. Maftoonazad et al. (2008) predicted quality changes in coated and non-coated avocados during storage at different temperature using ANN models and hyper-spectral images.

Alvarez (2009) predicted wheat yields using ANN model suggesting that the ANN estimates were significantly closer to the actual values when compared with MR model. Huang and Foo (2002) assessed salinity variation responding to the multiple forcing functions of freshwater input, tide and wind using the ANN approach. Guo and Xue (2014) used ANN and suggested that it can produce highly satisfactory forecasting of wheat yield, when compared with other statistical tools. Shearer et al. (1999) incorporated fertility, elevation, electrical conductivity and satellite image features to develop BP-ANN for prediction of spatial variability in corn yield. The authors reported that the BP-ANN model showed promise in predicting spatial yield variability. Braga (2000) accurately predicted spatial patterns of corn yield in relation to agronomic variables, topographic features and seasonal variability using a BP-ANN model. Liu et al. (2001) suggested that the corn yield can be predicted using a BP-ANN with 80% accuracy. Sarangi and Bhattacharya (2005) reported the superiority of ANN over MR models in predicting sediment erosion.

Warner and Misra (1996) suggested learning algorithms for effective predictions and compared ANN and MR models in terms of accuracy and applications. Kaastra and Boyd (1996) used ANN for modeling financial and economic time series. Dewolf and Francl (1997) demonstrated the applicability of ANN for crop diseases predictions. Zhang et al. (1998) compared the relative performance of ANN with MR methods, suggesting that the ANN estimates were very close to the actual values. These authors indicated that the ANN had advantage over the MR models, owing its ability to handle multiple predictors exhibiting non-linear relationships. No work has been reported regarding the application of ANN for fruit losses prediction in wild blueberry cropping system.

Wild blueberry growers are facing increased harvesting losses with their existing harvesters due to changes in crop conditions (healthy and tall plants, high plant density, tall weeds and significant increase in fruit yield) caused by improved management practices (herbicides, fertilizers, pesticides, pollination, *etc.*) emphasizing the need to study the harvesting dynamics and to identify the sources responsible for losses. Therefore, there is an urgent need to develop a predictive model by employing ANN and MR techniques for quantification of fruit losses as a function of machine parameters, crop characteristics and slope of the field, and to evaluate the potential and efficiency of ANN and MR models against independent dataset. This practice will enable the industry to predict optimal harvesting scenarios to increase berry recovery and quality.

5.2 MATERIALS AND METHODS

5.2.1 Study Area

Four wild blueberry fields were selected in Atlantic Canada to model the fruit losses as a function of several input variables. The selected fields were the Cooper site (45.480573°N, 63.573471°W; 3.2 ha), Small Scott site (45.600641°N, 63.086512°W; 1.9 ha), Tracadie site (47.2824117°N, 65.1440212°W; 1.6 ha) and Frankweb site (45.404733°N, 63.669376°W; 2.57 ha). The Cooper and Small Scott sites were in sprout year of the biennial crop production cycle in 2010 and crop year in 2011, while the Tracadie and Frankweb sites were in vegetative year in 2011 and crop year in 2012. The selected sites were harvested using the commercial blueberry harvester at variable time span (early August to early September) each year to simulate early and late season harvesting. The selected fields had been under commercial management over the past decade and received biennial pruning by mowing for the past several years along with conventional management practices. The geographic location of the selected fields is presented in Figure 4-1; Chapter 4.

5.2.2 Experiment Design and Data Collection

A single head blueberry harvester was mounted on a 62.5 kW John Deere tractor. One hundred and sixty two plots (0.91 × 3 meters, same width as harvester head) were made randomly using a measuring tape in the path of the operating harvester at each site. A buffer of 0.30 m was constructed around each plot to avoid errors during data collection. Traditionally, the wild blueberry harvester has been operated at a ground speed of 1.6 km h^{-1} and 28 rpm. The experiments were designed as 3 × 3 factorial design with the selected levels of ground speed (1.20, 1.6 and 2.0 km h^{-1}) and head revolutions per minute (26, 28 and 30 rpm) to harvest the plots within the selected sites. All treatment combinations were assigned randomly with eighteen replications at each experimental site. Factorial designs are used to study the joint effect of the factors on response variables.

The harvester head was raised to expel all the previously harvested fruit in the storage bin and moved back (approximately, 25 m) to attain the selected level of ground speed and header rpm, prior to harvest of the experimental plots. Two flags were punched into the ground to indicate the starting and ending point of each plot. The harvester head was lowered at the chosen treatment combination to harvest the plot and raised at the end of each plot. Fruit yield was collected from each plot by attaching a bucket to the harvester conveyer belt (Fig. 5-1 a). Three types of losses were collected from the harvested plot, *i.e.* un-harvested berries on the plant, berries on the ground and losses through the blower. Fruit loss via blower was collected by attaching a bucket under the blower fan (Fig. 5-1 a).

Berries on the ground and un-harvested berries on the plants were manually picked from each plot (Fig. 5-1 b).

The collected berries were separated from leaves and debris, and placed in labeled Ziploc bags to record the actual weight of fruit yield and losses in kilograms (kg). Total losses (berries on the ground + un-harvested berries on the plants + loss through the blower) were calculated in percentage (%) based on the fruit yield collected from each plot. Five plant height and fruit zone readings were recorded using a ruler to get an average within the selected plots. Fruit zone represent the starting and ending points of the fruit clusters on the wild blueberry plants. Fruit zone helps an operator to adjust the head height from the ground surface for effective berry picking during mechanical harvesting. The slope angle was measured manually using a Craftsman SmartTool Plus digital level. Five slope measurements were made within a radius of one meter and averaged to obtain the representative slope in each plot for selected sites.

(a) **(b)**

Figure 5-1: (a) Manual collection of fruit losses through the blower and total fruit yield and (b) Collection of fruit losses on the ground and un-harvested berries on the plants from the harvested plot.

The purpose of collecting fruit yield, crop characteristic, machine parameters and slope of the ground in each plot was to model the relationships using ANN and MR techniques. Development of any mathematical model requires a minimum of two datasets; first one for development (training and internal validation) and the latter for external validation. Data collected from selected sites were pooled and mixed thoroughly prior to construct ANN and MR models. The 70% of data were utilized for training (n = 489), and 30% (n = 189) for validation (Mutangaa et al. 2015; Lee, 2014). A subset of training dataset (15%; n = 81) were utilized for internal validation of developed models. The data points that were outside the range of input variables were removed from validation data to avoid the extrapolation error. Nevertheless, the validation data comprised of all variability in fruit yields, plant height, fruit zone, fruit losses and slope. This practice allowed the evaluation of the generic ability of the models to predict fruit losses during harvesting.

5.2.3 Input and Output Variables

The variability in the training and validation datasets was examined through the summary statistics (minimum, maximum, mean, standard deviation and coefficient of variation). Correlation analysis was performed among the fruit yield, fruit losses, slope and crop parameters using Minitab 16 (Minitab Inc. NY, USA) software to identify the potential factors affecting the fruit losses during harvesting. Selection of ground speed and header rpm as input variables was examined via factorial analysis of variance (ANOVA) using fruit losses as response variable in SAS 9.3 (SAS Institute Inc., NC, USA) statistical software. Fruit losses (%) were considered as output variable for model development. The ground speed, header rpm, plant height, fruit zone and slope were the input variables for model development, training and validations. In order to enhance the performance of ANN models, the input data were normalized, and hence outputs obtained were also normalized quantities. The following relationship (Eq. 5-1) was used for the normalization of data.

$$u_i = \frac{(R_i - Min_i)}{(Max_i - Min_i)} \qquad (5\text{-}1)$$

where u_i is the normalized value of input, R_i is the actual value of input, Min_i is the minimum value of input and Max_i is the maximum value of input.

5.2.4 Multiple Regression Model

Multiple regressions predict a dependent variable (fruit losses) based on multiple input variables (crop characteristics, slope and machine operating parameters). A typical MR model can be presented in equation 5-2. Regression coefficients of the predictors were determined using the least-square method.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \ldots\ldots\ldots\ldots\ldots\ldots \beta_n x_n + \varepsilon \qquad (5\text{-}2)$$

where β_0 is intercept, β_i is regression coefficients, x_i are the input variables and ε is the error term. i = 1, 2, 3, 4………..n

The validity of model assumptions (normal distribution and constant variance of the error terms) was tested by examining the residuals at 5% level of significance. Independence of error terms was assumed to be valid through the randomization of treatment combinations. Non-normal data were normalized using logarithmic transformations and were back transformed to original scale for reporting results. Minitab 16 statistical software was employed to construct the MR model. The best MR model was selected on the basis of highest coefficient of determination (R^2), percent variation (*%E*), coefficient of efficiency (*CE*) and *RMSE*. The MR is one of the most commonly used empirical methods to develop model for different cropping systems (Shibayama and Akiyama, 1991). However, in some cases, the model tends to over-fit data thus reducing its applicability to unseen changes in data.

5.2.5 Artificial Neural Network Model

Commercial software, Peltarion Synapse (Peltarion Systems®, Netherlands) was utilized to develop ANN model for prediction of fruit losses during harvesting. This software allows the user to define the architecture of the network, offers a variety of training algorithms, transfer functions and ability to articulate the critical network parameters such as, learning rate, momentum rule and epoch size (iterative steps). The same array of input variables selected by the correlation analysis and factorial ANOVA were used for model development. Moreover, the use of same set of input variables between MR and ANN approaches allowed us a fair comparison.

A back-propagated artificial neural network (BP-ANN), multiple layers supervised learning system with a mathematical function and Levenberg-Marquard learning algorithm was used for model development. Difference between BP-ANN and other ANN algorithms is the way in which weights are adjusted for accurate predictions (Eq. 5-3). This equation explains how the input nodes are converted into output (H) using a transfer function. This mechanism is repeated for all preceding nodes in a network till the final layer is achieved. Training of architecture involves a mechanism of providing the network with the desired output with efficient network performance. Network will estimate the output value from the inputs, compares the model predicted output to the target value, and then adjusts the weights in order to reduce errors between the network output and the target values. The network training is achieved if the error is below a given value. Error minimisation process is achieved by using the gradient descent method (Bishop, 1994; Hornik et al., 1989).

$$H = I_1 W_1 + I_2 W_2 + I_3 W_3 + \ldots\ldots\ldots\ldots I_n W_n \qquad (5\text{-}3)$$

where I are the inputs, W is weight function and H is the output.

$n = 1, 2, 3 \ldots\ldots\ldots\ldots n$

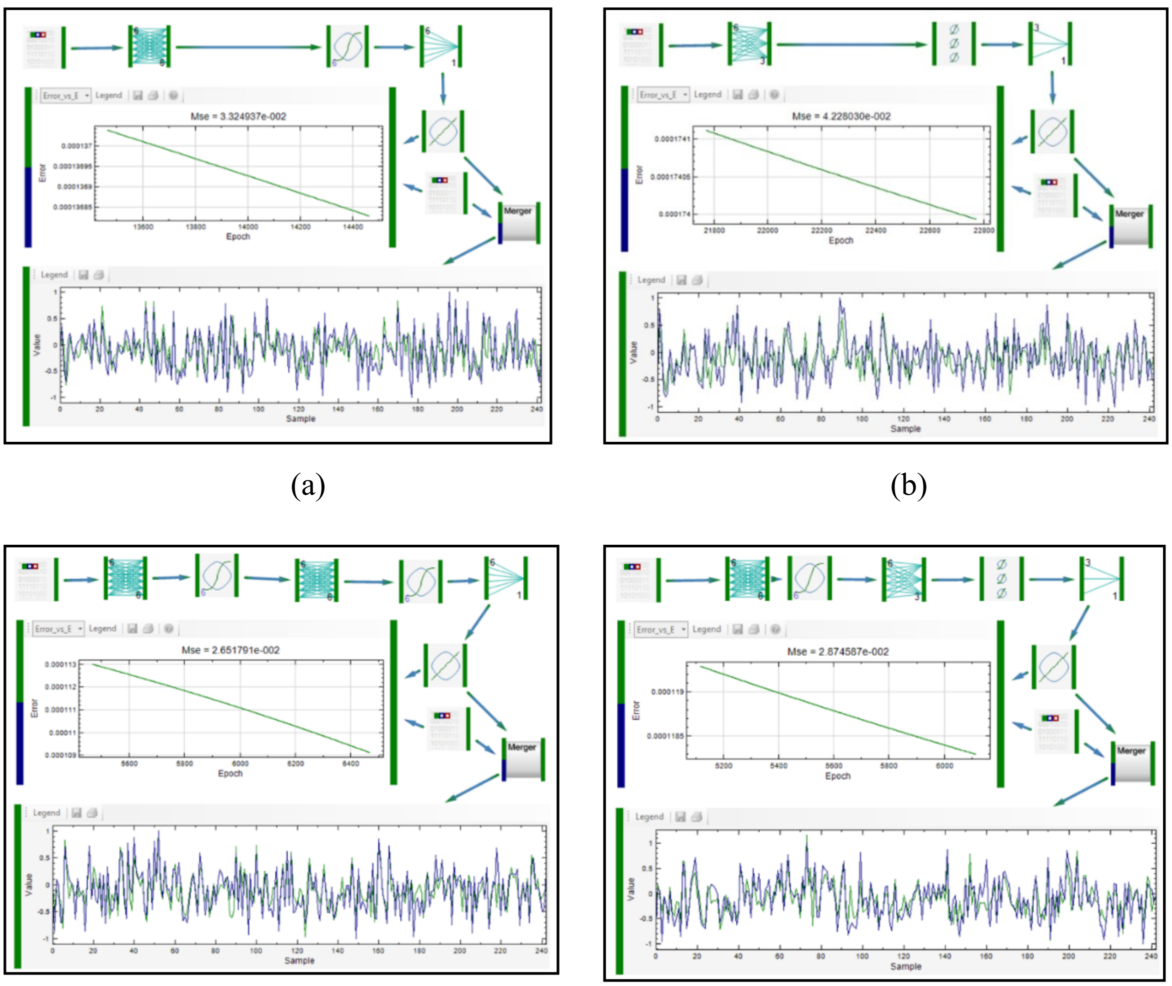
The size of the input layer neurons corresponded to the number of input parameters with one hidden layer is considered enough to model the majority of continuous non-linear function. More hidden layers may cause over and under fitting of the network (Torrecilla et al., 2004). In summary, the neural network performs a non-linear transformation on the input variables (X) to achieve an output (Y). This phenomenon is explained in equation 5-4.

$$\{Y\} = f(\{X\}) \qquad (5\text{-}4)$$

where Y is output, f is non-linear function and X are input variables.

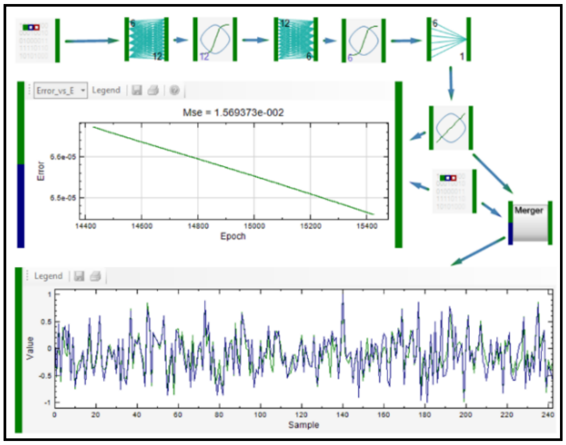
Seven architectures were developed (Fig.5-2) and tested to find a suitable mathematical function to process the data for prediction of fruit losses during harvesting. The software allowed the definition of the mathematical function, learning rate and momentum rule to articulate the performance of developed networks. Five mathematical functions (tanh sigmoid, linear, exponential, morlet and logistic sigmoid) were tested. Many simulations of the developed networks were performed to optimize the performance of developed networks. All networks were run at an epoch of 10000. The best mathematical function was selected based on the minimum *RMSE* by comparing the actual and predicted values.

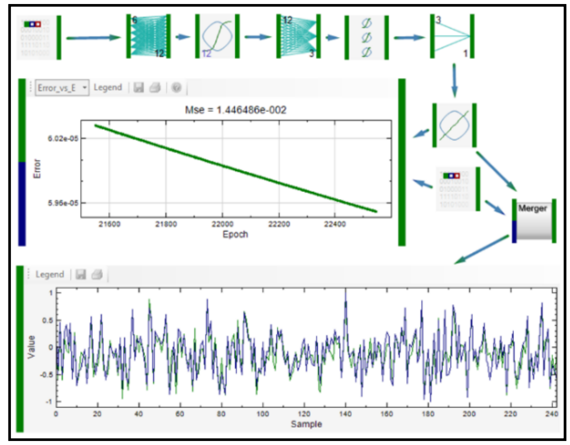
After determination of a mathematical function, all the developed architectures were tested and evaluated to configure the optimal settings of network (weight layers, function layers, nodes per hidden layer, epoch, etc.) for prediction of fruit losses. All networks were operated at an epoch of 25,000, Levenberg-Marquard learning algorithm, learning rate of 0.1 and momentum rule of 0.7 in order to have a fair comparison of the prediction accuracy of developed networks. In order to determine the optimal epoch size, the best selected ANN model was operated at different epoch values at an interval of 1000 and the values of *RMSE* were recorded at each interval. The epoch values were plotted against *RMSE* to find the optimum epoch for network to perform efficiently. Epoch size has been demonstrated to have a major influence on the error terms (Madadlou et al., 2009). The general concept of ANN model is shown in Figure 5-3.



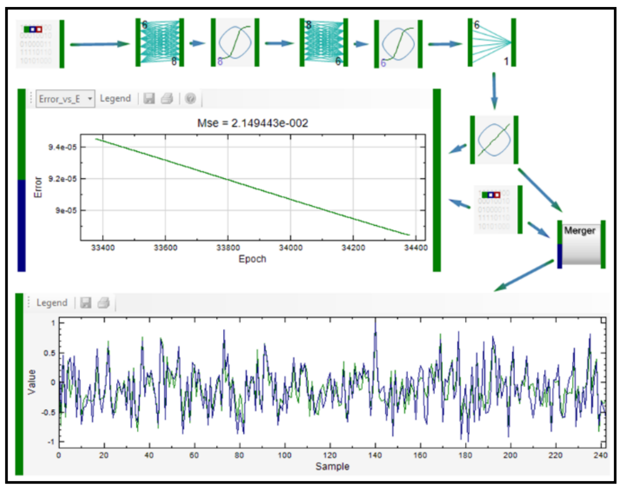
(a) (b)

(c) (d)





(e) (f)



(g)

Figure 5-2: Developed networks using tanh sigmoid function at an epoch size of 25,000, (a) 1 W (6/6) and 1 F (6/6) layers, (b) 1 W (6/6) and 1 F (6/3) layers, (c) 2 W (6/6) and 2 F (6/6) layers, (d) 2 W (6/6 and 6/3) and 2 F (6/6 and 3/3) layers, (e) 2 W (6/12 and 12/6) and 2 F (6/6 and 12/12) layers, (f) 2 W (6/12 and 12/3) and 2 F (12/6 and 3/3) layers and (g) 2 W (6/8 and 8/6) and 2 F (8/8 and 6/6).

Once the network had been structured and trained, the performance of developed model was tested by employing internal and external validations. The internal validation was performed by selecting a subset of training dataset, while the external validations were performed using an independent dataset. In order to perform validations, the trained model was extracted using the deployment postprocessor of the Peltarion Synapse software to make a separate and stand-alone WorkArea0.dll (.NET dynamic linking library). A DOS prompt based C# (Microsoft, Redmond, Wash.) program was developed to predict and validate external data by using WorkArea0.dll and save processed result as a comma separated value (CSV) file. The performance of developed model for internal and external validations was tested and evaluated in terms of R^2, *RMSE*, *%E* and *CE*. The ANN predictions were plotted against MR estimates to examine the prediction accuracy of both techniques. The operational protocol of developed BP-ANN model is presented in Figure 5-4.

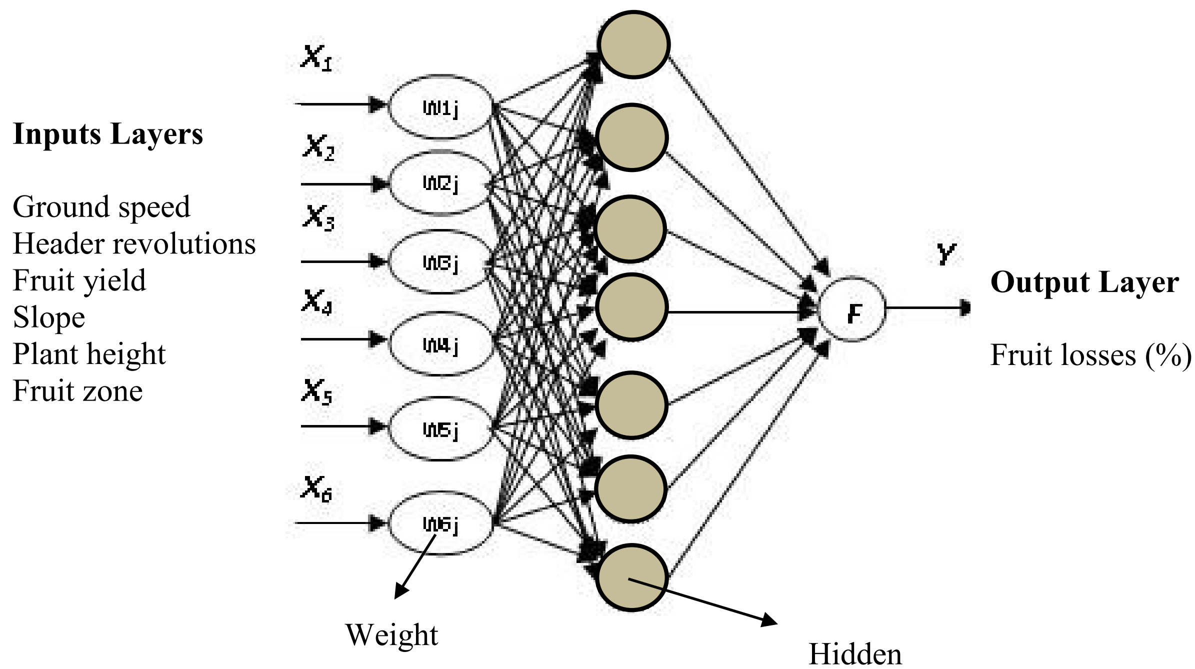


Figure 5-3: The architecture of a multilayer artificial neural network model.

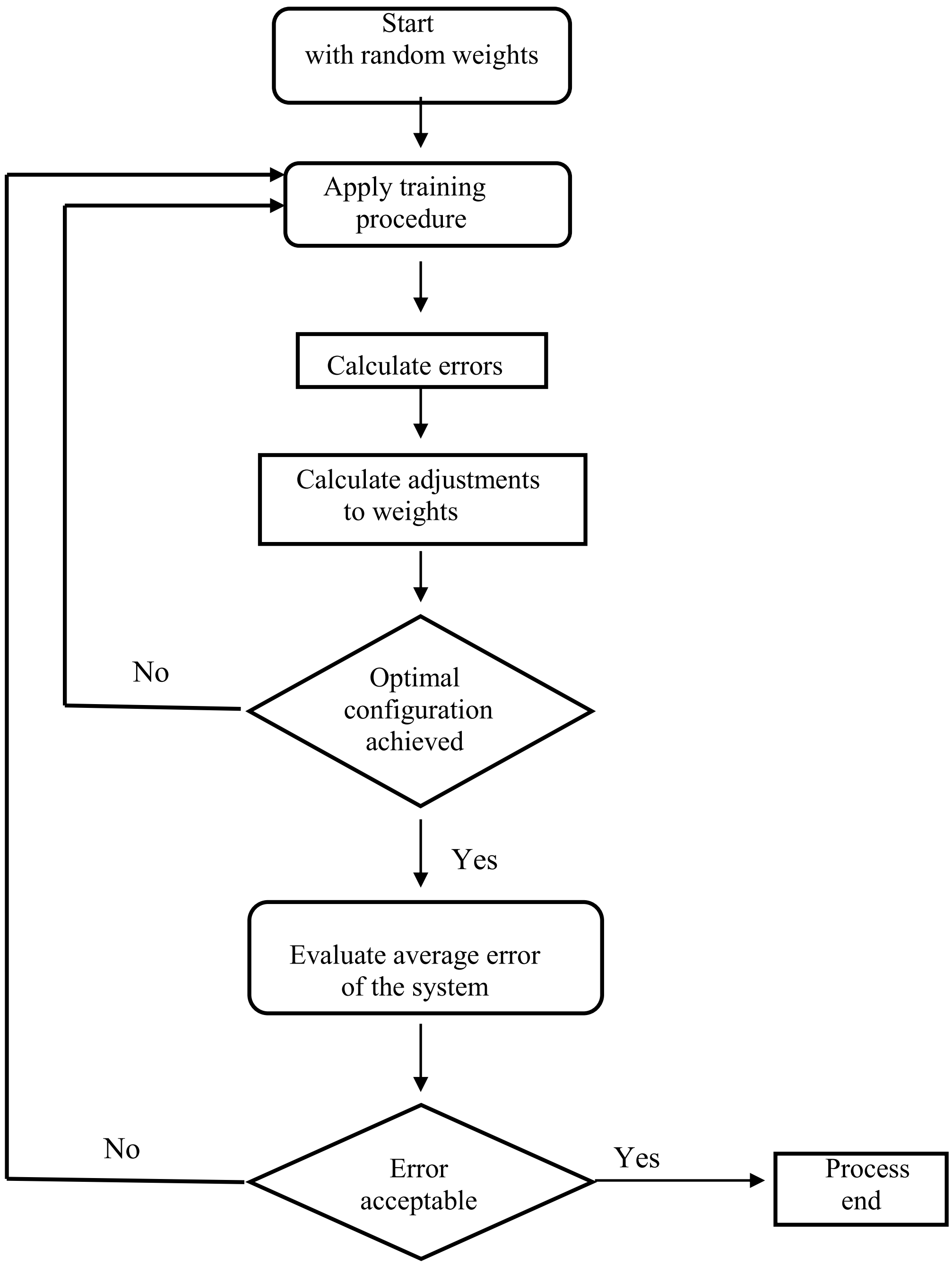


Figure 5-4: Flowchart showing the training protocol of a back propagated artificial neural network model.

5.3 RESULTS AND DISCUSSION

5.3.1 Variability in the Collected Data

The validity of the model assumptions (normal distribution and constant variance of the error terms) was tested by examining the residuals at 5% level of significance. Independence of error terms was assumed to be valid through randomization of treatment combinations. The coefficient of variation (CV) is a first indication of field variability 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%. Results of summary statistics suggested that fruit yield, total losses and slope were highly variable with the CV > 35%, while the plant height and fruit zone were moderately variable for both training and validation datasets (Table 5-1).

Table 5-1. Summary statistics of training and validation datasets.

Training Dataset						
Parameters	Min	Max	Mean	S.D	C.V (%)	Skewness
Speed (km hr^{-1})	1.2	2.0	1.6	0.20	20.43	-0.0
Revolution (rpm)	26.0	30.0	28.0	1.64	5.84	0.0
Fruit Yield (kg ha^{-1})	253	17968.0	4993.0	2950	59.08	0.93
Total Losses (kg ha^{-1})	5.1	2616.0	709.30	569.6	80.30	0.16
Total Losses (%)	0.99	31.0	14.20	5.80	43.42	0.30
Plant Height (cm)	10.6	39.2	23.99	4.25	17.75	0.19
Fruit Zone (cm)	7.40	34.83	19.80	4.20	21.21	0.09
Slope (degrees)	0	23.66	6.30	4.60	72.95	1.28
Validation Dataset						
Parameters	Min	Max	Mean	S.D	C.V (%)	Skewness
Speed (Km hr^{-1})	1.2	2.0	1.60	0.20	20.43	-0.0
Revolution (rpm)	26.0	30.0	28.0	1.64	5.84	0.0
Fruit Yield (kg ha^{-1})	505	15383.0	5341.0	2701.0	50.57	0.59
Total Losses (kg ha^{-1})	80.7	2587.5	813.9	590.0	72.49	0.88
Total Losses (%)	2.94	31.04	15.23	5.89	41.16	0.37
Plant Height (cm)	12.7	32.99	23.57	3.71	15.73	-0.01
Fruit Zone (cm)	10.6	29.03	19.66	3.83	19.50	-0.09
Slope (degrees)	0.77	17.44	5.85	4.22	72.07	1.21

The variability in the crop characteristics, fruit yield and total losses could be due to the intrinsic and extrinsic factors. Intrinsic variability is due to natural variations in soil and extrinsic variability can be caused by the harvester operation, operator skills, field topography, time of harvest, environmental aspects (rain, humidity, degree days, temperature, etc.) and crop management practices. These results also probably reflect the influence of temporal dynamics on the measured parameters due to harvesting at different times during the study period. The validation dataset experienced all kind of variability exhibited in the training dataset suggesting the fitness of the data for external validation.

5.3.2 Selection of Inputs

Correlation matrix was developed for both training and validation datasets in order to identify the significant parameters affecting picking efficiency of the harvester. Correlation matrix revealed significant relationships among the total losses, fruit yield, slope, plant height and fruit zone for both datasets (Table 5-2). Results indicated that the plant height, fruit zone, slope and fruit yield were responsible for the fluctuating fruit losses during harvesting. Significant positive correlation of total losses with the slope (r = 0.21) for training (r = 0.22) and validation dataset suggested that the total losses increased with the steepness of the slope (Table 5-2), revealing that the topography of the ground seems to have an impact on the fruit losses during harvesting. Topography of the field was addressed as one of the challenges during development process of the commercial wild blueberry harvester (Yarborough, 1992; Hall et al., 1983). Significant positive correlation of total losses with fruit yield for training (r = 0.86) and validation (r = 0.85) datasets suggested a linear trend indicating an increase in fruit losses with an increase in fruit yield.

Relationships indicated that the fruit yield, plant height, slope and fruit zone will serve as inputs for the model development and predictions.

Table 5-2. Correlation matrix between fruit yield, berry losses, plant height, fruit zone and slope for training and validation datasets.

Training Data					
	Fruit Yield (kg ha^{-1})	Total Losses (kg ha^{-1})	Plant Height (cm)	Fruit Zone (cm)	Slope (degrees)
Total Losses	0.86***				
Plant Height	-0.29*	-0.28**			
Fruit Zone	-0.12 NS	-0.23**	0.62***		
Slope	-0.10 NS	0.21*	-0.23**	-0.31**	
Validation Data					
	Fruit Yield (kg ha^{-1})	Total Losses (kg ha^{-1})	Plant Height (cm)	Fruit Zone (cm)	Slope (degrees)
Total Losses	0.85***				
Plant Height	-0.21**	-0.26**			
Fruit Zone	-0.29 **	-0.28**	0.80***		
Slope	-0.09 NS	0.22*	-0.15 NS	-0.20 *	

Significance of correlations indicated by *, ** and ***, are equivalent to $p = 0.05$, $p = 0.01$ and $p = 0.001$.Where *NS*, non-significant at $p = 0.05$.

The fitness of ground speed and head revolutions as input for model development was examined through factorial ANOVA (Table 5-3). Results of ANOVA suggested that the main effects of ground speed and header rpm on total losses were non-significant for both training and validation datasets (Table 5-3). Interaction effects were significant for total losses (% and kg ha^{-1}) (Table 5-3). In factorial experiments, when higher order interactions are significant, their main effects can be ignored. In summary, results reported that fruit losses were influenced by the ground speed and header rpm either alone or in combination suggesting that a suitable combination could result in reduced fruit losses during mechanical harvesting. Farooque et al. (2014) also suggested that the picking efficiency of the harvester is influenced by different levels of ground speed and header revolutions. Collectively, the results of correlation matrix and factorial ANOVA suggested that fruit yield, plant height, fruit zone, slope, selected levels of ground speed and header rpm can be used as input variables to model the fruit losses (output) during harvesting. Results of correlation analysis using Peltarion Synapse software were in agreement with the results of Minitab 16 statistical software.

Table 5-3. Factorial analysis of variance using factorial design for training and validation datasets.

Source	Training Dataset		Validation Dataset	
	Total Losses (kg ha^{-1})	Total Losses (%)	Total Losses (kg ha^{-1})	Total Losses (%)
Speed	NS	NS	NS	NS
Revolution	NS	NS	NS	NS
Speed*Revolutions	*	*	*	*

Significance indicated by * and *NS* = non-significant at $p = 0.05$.

5.3.3 Determination of a Mathematical Function

The normalized training dataset according to equation (1) was imported into the Peltarion Synapse software and the input and output variables were defined using software interface. Seven architectures were developed and tested to find a suitable mathematical function for data processing (Table 5-4; Fig. 5-2). The software allowed us to define the mathematical function in order to examine the prediction performance of developed models. All the settings of the developed models were kept constant, the mathematical functions were changed and *RMSE* were recorded (Table 5-4). Results showed that the morlet function resulted in a higher *RMSE* when compared with other functions (Table 5-4) to predict fruit losses. The exponential function resulted in an infinity error for two of the model settings suggesting its non-suitability to process the data. Results indicated that the tanh sigmoid function was able to process the data with a reasonably low *RMSE* (0.089 to 0.16) when compared with other functions for all networks (Table 5-4). Based on the results of *RMSE*, the tanh sigmoid was chosen as the best function for further processing.

Table 5-4. Tested mathematical functions to process the normalized data at an epoch size (iterative steps) of 10,000.

Sr. No	Model Structure	Mathematical Functions				
		Tanh Sigmoid	Exponential	Linear	Logistic Sigmoid	Morlet
		RMSE	*RMSE*	*RMSE*	*RMSE*	*RMSE*
1	1 W (6/6) and 1 F (6/6) layers 6 inputs to 1 output	0.13	0.14	0.16	0.16	0.19
2	1 W (6/6) and 1 F (6/6) layers 3 inputs to 1 output	0.15	0.14	0.17	0.27	0.19
3	2 W (6/6) and 2 F (6/6) layers 6 inputs to 1 output	0.13	∞	0.16	0.14	0.18
4	2 W (6/6 and 6/3) and 2 F (6/6 and 3/3) 3 inputs to 1 output	0.12	0.14	0.15	0.15	0.19
5	2 W (6/12 and 12/6) and 2 F (6/6 and 12/12) layers 6 inputs to 1 output	0.089	0.17	0.16	0.16	0.20
6	2 W (6/12 and 12/6) and 2 F (12/6 and 3/3) 3 inputs to 1 output	0.15	0.18	0.16	0.16	0.20
7	2 W (6/8 and 8/6) and 2 F (8/8 and 6/6) 6 inputs to 1 output	0.16	∞	0.17	0.16	0.21

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

5.3.4 Developing the Optimal Artificial Neural Network Configurations

After determination of a mathematical function, all models were tested and evaluated to configure the optimal settings of network for prediction of fruit losses. The developed networks are shown in Table 5-5 and Figure 5-2. All networks were operated at an epoch of 25,000 with tanh sigmoid mathematical function in order to compare the prediction accuracy. Results suggested that the architecture 5 (2 W and 2 F layers) was able to predict better than the other networks with significantly higher R^2 (0.835), lower *%E* (2.064) and *RMSE* (0.075), and higher *CE* (0.801) suggesting the suitability of network in predicting fruit losses (Table 5-5). Results indicated that the model structure 1, 2 and 4 resulted in lower R^2, higher *% E* and *RMSE*, and lower *CE* suggesting poor performance of these networks in predicting fruit losses (Table 5-5). The variability in performance might be due to the differences in the architecture settings of the developed networks. Results revealed that the actual losses were very close to the predicted losses in all cases, but the *%E*, *RMSE* and *CE* were not promising except model structure 5 (Table 5-5). Results emphasized the need to verify the accuracy of selected model using internal and external validations prior to make any recommendations about prediction accuracy.

Table 5-5. Developed networks using tanh sigmoid function at an epoch size of 25,000.

Sr. No	Model Structure	Actual Losses	Predicted Losses	R^2	*%E*	*RMSE*	*CE*
1	1 W (6/6) and 1 F (6/6) layers	0.401	0.399	0.452	8.281	0.140	-0.209
2	1 W (6/6) and 1 F (6/6) layers	0.401	0.398	0.374	11.293	0.151	-0.683
3	2 W (6/6) and 2 F (6/6) layers	0.401	0.400	0.654	5.806	0.111	0.470
4	2 W (6/6 and 6/3) and 2 F (6/6 and 3/3)	0.401	0.399	0.551	6.740	0.127	0.188
5	2 W (6/12 and 12/6) and 2 F (6/6 and 12/12) layers	0.401	0.393	0.835	2.064	0.075	0.801
6	2 W (6/12 and 12/3) and 2 F (12/6 and 3/3)	0.401	0.408	0.684	4.607	0.107	0.524
7	2 W (6/8 and 8/6) and 2 F (8/8 and 6/6)	0.401	0.405	0.696	4.569	0.105	0.552

Where *W* = Weight layer; *F* = Function layer; *%E* = Percentage variation; *RMSE* = Root mean square error; and *CE* = Coefficient of efficiency.

The *RMSE* were plotted against epoch to find the optimum number of epochs (iterative steps) for the best network to perform efficiently (Fig. 5-5). Results reported that an epoch of 15,000 was enough for the network to perform predictions efficiently, as there was no improvement in error even if the network was trained at 25,000 epochs. Therefore, a value of 15,000 epoch was used for further processing. The proposed settings of the developed BP-ANN network are given in Table 5-6. The architecture of the proposed model is shown in Figure 5-6.

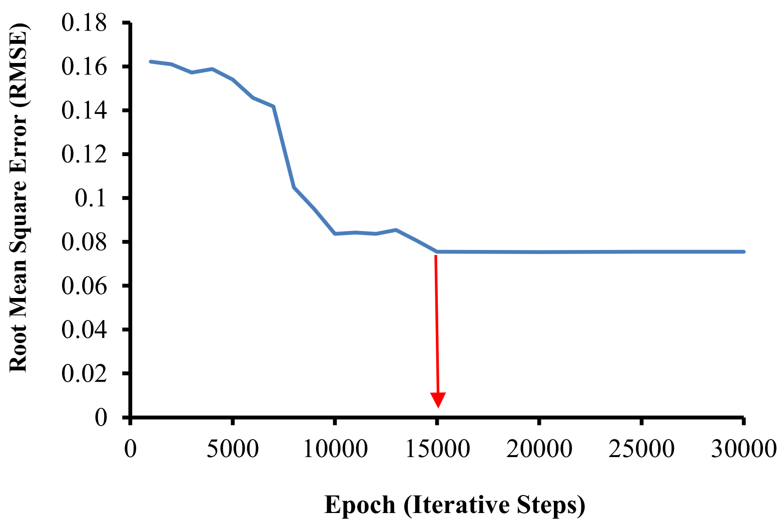


Figure 5-5: Relationship between root mean square errors versus epoch.

Table 5-6. Proposed settings of a back propagated artificial neural network model.

Parameters	**Settings**
Training pattern	70%
Optimum Epoch	15000
Verification pattern	15%
Number of hidden layers	2
Nodes per hidden layer	18
Learning rate	0.10
Momentum	0.70
Mathematical Function	Tanh Sigmoid
External validation	Independent data set (30%)

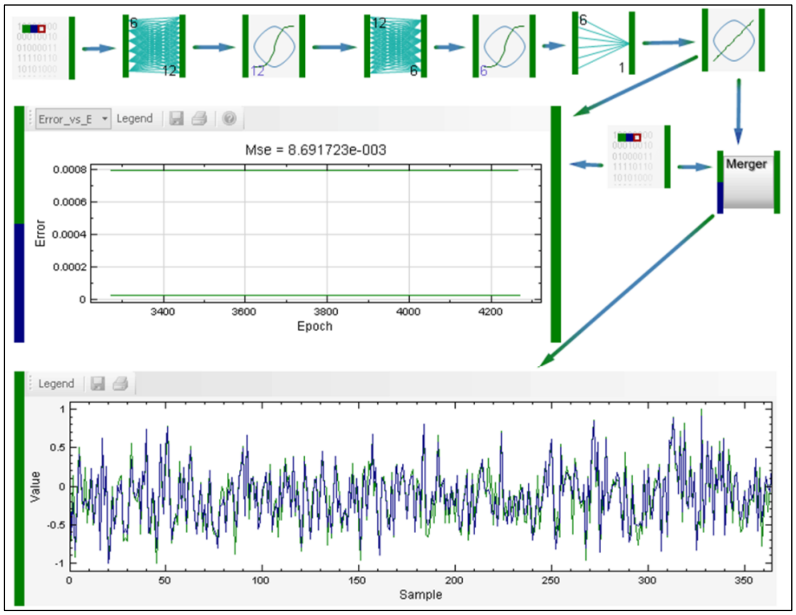


Figure 5-6: Optimal configurations of proposed back propagated artificial neural network model.

5.3.5 Multiple Regression and Artificial Neural Network Models

The prediction performance of MR model was examined using the same criterion as ANN model during development and validation processes (Table 5-7). The MR model with fruit losses (%) as response variable and the ground speed, head revolutions, fruit yield, slope and crop parameters as predictor variables was developed (Eq. 5-5).

Total Losses (%) = 0.137 + 0.0325 Ground Speed + 0.0435 Revolutions + 0.304 Fruit Yield + 0.201 Plant Height - 0.146 Fruit Zone + 0.424 Slope (5-5)

The MR model exhibited higher R^2 for training ($P < 0.001$; $R^2 = 0.461$) and internal validation ($P < 0.001$; $R^2 = 0.594$) when compared with the external validation ($P < 0.001$; $R^2 = 0.372$) datasets. The MR model suggested that the predictor variables contributed about 46 to 59% variability in fruit losses for training and internal validation datasets (Table 5-7). There are a variety of factors other than the selected input variables contributing to fruit losses variability, which have not been addressed. Operator skills, weather fluctuations, winter kill, disease and insect damage, weed coverage, time of harvesting, lodging of crop, pollination, maintenance of the harvester and many uncontrollable factors can also affect fruit losses during harvesting. The MR model experienced poor performance under validation dataset (Table 5-7) indicating its inability to handle non-linear relationship (Park et al., 2005).

The ANN models showed consistently high R^2 values ranging from 0.627 to 0.858 for all datasets. The values of *CE* for training and verification dataset (> 0.80) were approaching to 1 suggesting the accurate predictions using ANN model. Results suggested that the predictor variables explained about 62.7% variability in fruit losses for validation dataset (Table 5-7). In particular, the ANN model showed significant improvement in R^2 (~25%) and substantial decrease in *RMSE* for external validation when compared with MR model. The *%E* was observed to higher for MR model when compared with ANN model for all datasets (Table 5-7). Overall, the R^2 values dropped with both models for external validation dataset when compared with the training and internal validation datasets (Table 5-7).

Although R^2 is a most common measure of explained variance, however, it lacks the ability to discern the shift in predicted values when compared with the actual values, therefore, might be misleading (Comrie, 1997). Therefore, *% E*, *RMSE* and *CE* which uses the actual error value were added to the ranking system to evaluate the performance of developed models.

Table 5-7. Prediction performance comparison of a back propagated artificial neural network and multiple regression models.

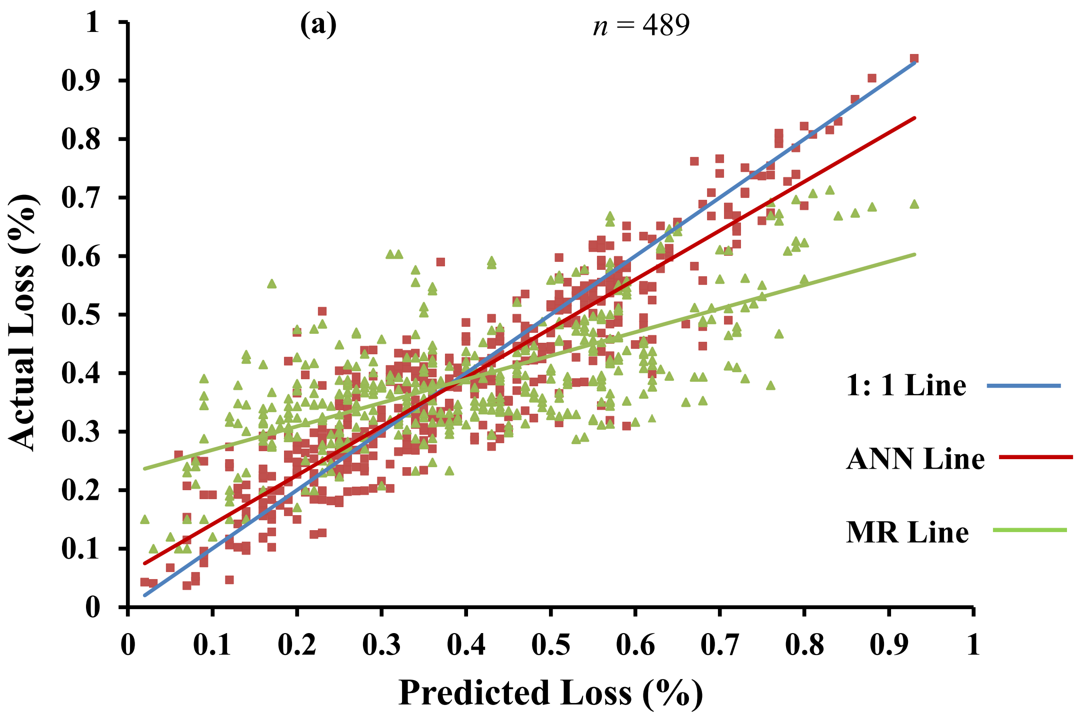
ANN Model					
Dataset	**Model Structure**	R^2	*%E*	*RMSE*	*CE*
Training Dataset	2 W (6/12 and 12/6) and 2 F (6/6 and 12/12) layers	0.835	2.064	0.075	0.801
Internal Validation Dataset		0.858	7.691	0.075	0.811
External Validation Dataset		0.627	15.733	0.114	0.556
MR Model					
Dataset	**Model Structure**	R^2	*%E*	*RMSE*	*CE*
Training Dataset	Total Loss (%) = 0.137 + 0.0325 Ground Speed + 0.0435 Revolutions + 0.304 Fruit Yield + 0.201 Plant Height - 0.146 Fruit Zone + 0.424 Slope	0.461	40.051	0.138	-0.56
Internal Validation Dataset		0.594	29.594	0.126	0.322
External Validation Dataset		0.372	34.916	0.147	-0.130

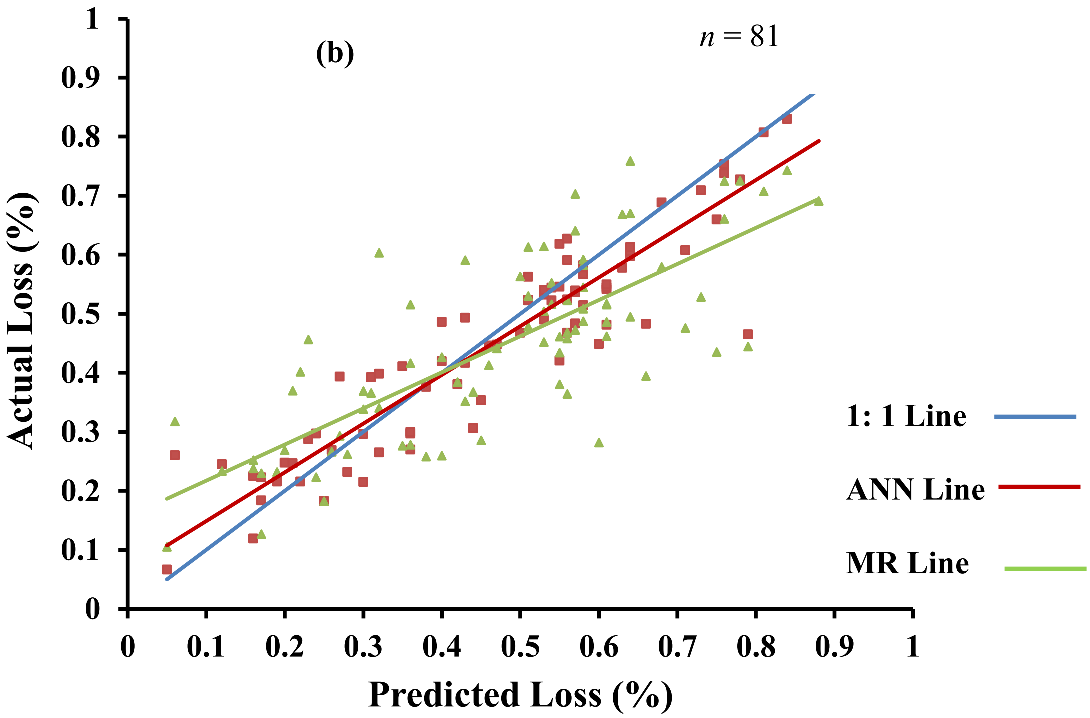
Where R^2 = Coefficient of determination; *%E* = Percentage variation; *RMSE* = Root mean square error; and *CE* = Coefficient of efficiency.

5.3.6 Comparisons of Artificial Neural Network and Multiple Regression Models

Figure 5-7a-c shows the modeling performance of ANN model which was almost perfect as opposed to the MR model. Results suggested that the MR and ANN models over- and under predicted fruit losses (ANN: 17%; MR: 55%), with the ANN model slopes relatively closer to 1 for training dataset (Fig. 5-7a). Higher R^2 and lower *RMSE* values provide statistical evidence for this observation (Table 5-7). The ANN estimates were very close to the actual values ($P < 0.001$; $R^2 = 0.86$) when compared with MR model ($P < 0.001$; $R^2 = 0.59$), suggesting better predictions using ANN model (Fig. 5-7b) for internal validation dataset. The ANN model predicted minimum and the maximum fruit losses with high precision; however mid-range predictions suffered slight divergence (Fig. 5-7). On the contrary, scatter plots of MR model showed a high divergence of plots along the ideal regression (Fig. 5-7).

In certain modeling attempts, the MR models can perform equally or even better than ANN models (Clapham and Fedders, 2004), however, in this study the ANN predictions were better than the MR predictions. The MR model exhibited significantly lower R^2 for external validation ($P < 0.001$; $R^2 = 0.372$) when compared with ANN model ($P < 0.001$; $R^2 = 0.627$). Both, the ANN and MR models over predicted up to the desired values of 0.40, and under predicted for the desired values ranging from 0.50 to 1.00 for all datasets. In general, the ANN predictions were very close to the 1:1 line (Fig. 5-7). The possible reason for higher R^2 during training phase could be the large sample size. The external validation presumably resulted in over-and-under fitting of the data and contributed to relatively poor performance when compared with the training dataset. The over-and-under fitting during modeling of an independent dataset had been reported by many authors (Langman et al*.,* 2010; Sha, 2007). The ANN model yielded better predictions for fruit losses with slope values ranging from 0.62 to 0.85 (Table 5-7; Fig. 5-7). The ANN model had lower *RMSE* and *%E* when compared with MR predictions for all datasets. The ANN model was found be better in predicting fruit losses with significantly higher R^2 in comparison with MR model for all datasets. The under predictions through ANN approach yielded relatively consistent and better estimates when compared with MR technique (Fig. 5-7). The ANN has been reported to be a promising tool when modeling processes are complicated and non-linear or unknown (Liu et al., 2009), owing to their capability to model variable relationships.


(a)
n = 489
1: 1 Line
ANN Line
MR Line
Actual Loss (%)
Predicted Loss (%)


(b)
n = 81
1: 1 Line
ANN Line
MR Line
Actual Loss (%)
Predicted Loss (%)

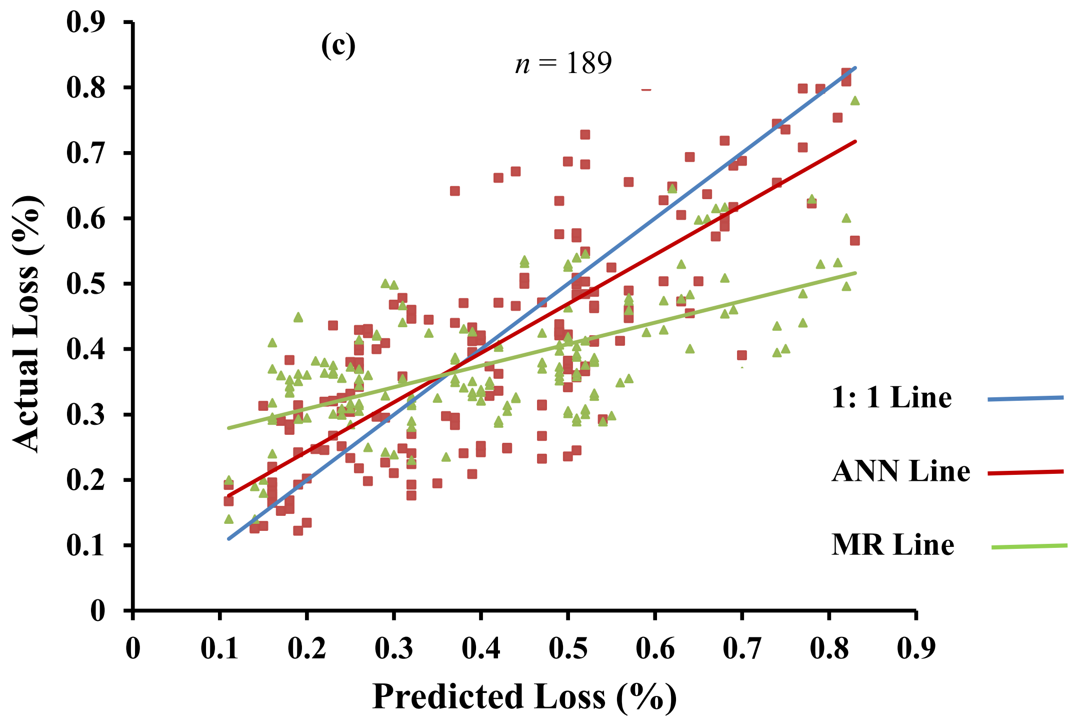


Figure 5-7. Scatter plots of transformed (0 to 1) actual versus predicted losses using ANN and MR approaches, (a) Training dataset, (b) Internal validation dataset and (c) External validation dataset.

Data collected from field conditions are subject to un-controlled factors, often exhibit non-normal distribution, offering flexibility of ANN to avoid any transformations (Coppola et al., 2003) which are required for MR models. The ANN approach offered flexibility with handling of noisy data and ability to model the complex relationships exhibited by sensitive variables having an impact on picking efficiency of the harvester. Tamari et al. (1996) reported that the ANN model leads to less *RMSE*, however, the ANN has not better efficiency than MR models in occasion of highly stable data. The high accuracy of data leads to more efficiency of ANN based on the proper selection of training and verification datasets. More input variables can improve the prediction capabilities of ANN model (Minasny and McBratney, 2002). Overall, the ANN model had the higher R^2

and *CE* values with lower *%E* and *RMSE* when compared with corresponding MR counterpart suggesting that the ANN model predicted fruit losses efficiently and reliably.

5.4 CONCLUSIONS

In this study, MR and ANN models were employed for predicting fruit losses as function of the harvester ground speed, head revolutions, slope, fruit yield, plant height and fruit zone. The optimal ANN network consisted of two hidden layers, a tanh-sigmoid function, a linear activation function in output layer, an epoch size of 15, 000, learning rate of 0.10 and momentum rule of 0.70. The performance of MR and ANN models was evaluated using training, internal and external validation datasets. The ANN model was more suitable for capturing non-linearity of the relationships between variables. Results suggested that ANN can model non-linear relationships and performed better than MR models. With regard to the evaluation criteria, the ANN model had the superiority over the MR model with consistent and better predictions.

The optimal conditions compared favorably with those obtained from experimental observations using ANN model. Results suggested that the ANN model could thus effectively be used for predictive modeling and optimization of fruit losses during mechanical harvesting of wild blueberries. Based on the results of this study, it is suggested to include environmental factors, time of harvest, soil properties, plant densities, fruit diameters and stem thickness to input variables in future studies while modeling the harvesting dynamics of wild blueberry cropping system. In future, inclusion of intensive mechanical, climatic and biological data in the model for multiple years will enable us to develop a robust interface using C# programming language, which will help the farmer's community to make appropriate harvesting recommendations based on spatial variability to reduce fruit losses during harvesting.

CHAPTER 6 CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

The overall goal of this study was to evaluate the performance of a commercial wild blueberry harvester using PA technologies and mathematical modeling procedures, to suggest optimal scenarios for effective berry recovery and quality. An integrated automated system comprising of an ultrasonic sensor, a digital color camera, a slope sensor, a RTK-GPS, custom software and a ruggedized computer was developed. The developed system (hardware and software) was incorporated onto a blueberry harvester for non-destructive mapping of fruit yield, plant height and topographic feature simultaneously while harvesting. Performance of developed system was tested and evaluated in selected blueberry fields. Results of calibrations, validations and mapping in GIS revealed that the developed system was an accurate, reliable and efficient to map plant height, fruit yield, slope and elevation in real-time. Results suggested that the hardware and software of the developed system performed rapidly and reliably to estimate pre-harvest fruit yield. Map comparison and zonal analysis showed substantial variability in measured parameters across the fields.

Results of mapping blueberry fruit yield, plant height and topographic features were valuable for understanding relationships in the monitoring fields. Comparison of actual yield with the estimated yield from a digital color camera suggested that the digital color photography techniques can be used to assess overall fruit losses during harvesting. Non-destructive yield mapping to quantify overall losses during harvesting emphasized the need to evaluate the commercial harvester at different machine operating parameters (ground speed and head rpm). Detailed evaluations of the harvester can suggest optimal operating parameters for the grower's community to increase berry picking efficiency of the harvester. Additionally, the information mapped via developed system could be used to implement site-specific management practices within the blueberry fields to optimize productivity while minimizing environmental impact of farming operations.

In order to validate the overall fruit losses estimated from camera technology, the picking performance of a commercial blueberry harvester was tested and evaluated in selected blueberry fields. Factorial experiments were constructed at each site to examine the joint effect of ground speed and header rpm on picking efficiency of the harvester. The harvester was operated at specific levels of ground speed, *i.e.* 1.2, 1.6 and 2.0 km h^{-1} and header rpm of 26, 28 and 30. Yield plots were constructed randomly within the selected fields. Total fruit yield, un-harvested berries on the plants, berries on the ground, pre-harvest fruit losses and loss through the blower were collected from each plot within the selected fields. The slope, plant height and fruit zone were also recorded manually from each plot. Results suggested that the pre-harvest fruit losses were found to be higher during the late season suggesting that the early season harvesting could be helpful in reducing these losses. Major portion of the fruit losses during harvesting was on the ground when compared with the un-harvested berries on the plants and losses through the blower.

Fruit losses during harvesting were a linear function of the fruit yield, as fruit yield increased the fruit losses increased and vice versa. Results of the harvester evaluation confirmed the accuracy of the camera technology to estimate overall fruit loss during mechanical harvesting. Results of ANOVA reported that the picking efficiency of the blueberry harvester was significantly influenced by the ground speed, header rpm and their interaction. Results of LS means comparison showed that a treatment combination of 1.2

km h^{-1} and 26 rpm can result in significantly lower fruit losses as compare to higher ground speed and header rpm in wild blueberry fields with yield over 3500 kg ha^{-1}. In low yielding fields (< 3000 kg ha^{-1}) a combination of 2.0 km h^{-1} and 26 rpm can do a better job to increase berry picking efficiency of the blueberry harvester. Choosing an ideal combination of ground speed and header rpm based on spatial variations in fruit yield, crop parameters and topographic features can minimize fruit losses to increase farm profitability.

Knowledge of spatial variability in fruit yield, crop characteristics, fruit losses and topographic features is critical for planning and implementing the operational recommendation for mechanical harvesting. Results of CVs, semivariogram parameters, interpolated maps, correlation matrix and zonal analysis confirmed the existence of large spatial variability in fruit yield, plant parameters and topographic features. Results revealed the fruit losses during harvesting were spatially dependent on fruit yield, plant height, fruit zone and slope within the selected sites. In general, fruit losses during harvesting increased with an increase in fruit yield and slope. Zonal analysis suggested that the picking performance of the harvester was inadequate in short and very tall plants. Operational adjustments in machine parameters (ground speed, head rpm, head height, *etc.*) based on spatial variations can enhance picking performance of the blueberry harvester. Variability in fruit losses corresponding with the spatial variations in crop characteristics, fruit yield and slope suggested that these parameters had a significant impact on fruit losses during mechanical harvesting. Results emphasized the need to model these spatial relationships mathematically to propose optimal harvester operating settings to improve berry picking efficiency.

Understanding and predicting the relationships between machine operating parameters, fruit losses, topographic features and crop characteristics can aid in better berry recovery during harvesting. The MR and ANN models were employed for predicting fruit losses as function of the harvester ground speed, head revolutions, slope, fruit yield, plant height and fruit zone. Optimal ANN network consisted of two hidden layers, a tanh-sigmoid function, a linear activation function in output layer, an epoch size of 15, 000, learning rate of 0.10, and momentum rule of 0.70. The ANN model was more suitable for capturing non-linearity of the relationship between variables. Results suggested that the ANN model performed better than MR models in terms of R^2, *%E, RMSE, CE* and scatter plots of actual and predicted values. With regard to the evaluation criteria, the ANN model had the superiority over MR model with consistent and better predictions. Overall, the results of modelling suggested that the ANN model was able to predict fruit losses during harvesting accurately and reliably. The ANN model could thus effectively be used for predictive modeling and optimization of fruit losses during mechanical harvesting.

6.2 Recommendations

Results of this study emphasize the need to characterize and quantify the effect of plant density, stem thickness and fruit diameters on the picking performance of the blueberry harvester in future studies. It is also proposed to examine the harvester's performance in different categories of plant characteristics (low and high density, short and tall plants, thick and thin stem, *etc.*). Additionally, time of harvesting (early, mid and late) and its influence on fruit losses and berry quality need to be evaluated in detail. Harvesting of the wild blueberry crop at proper ripening can enhance berry recovery and quality. Based on the existence of large spatial variability in fruit yield, berry losses, crop characteristics and topographic features within the selected fields, it is proposed to investigate the potential of using sensing and control systems for automation of the blueberry harvester. Automation of the blueberry harvester can aid in real-time decision making to minimize fruit loss during harvesting. Real-time adjustments in the harvester (ground speed, head rpm, bin handling, head height, *etc.*) based on spatial variations can also lower the operator's stress during harvesting.

Based on the results of this study, it is suggested to include environmental factors, time of harvest, soil properties, plant densities, fruit diameters and stem thickness to input variables in future studies while modeling the harvesting dynamics of wild blueberry cropping system. In future, inclusion of intensive mechanical, climatic and biological data in the model for multiple years will enable us to develop a robust interface using C# programming language, which will help the farmer community to make appropriate harvesting recommendations to reduce fruit losses during harvesting. Improved berry picking efficiency can enhance farm profitability with no additional cost and contribute millions of dollars to Canada's economy every year.

CONTRIBUTIONS TO KNOWLEDGE

This PhD thesis presents detailed evaluation of a commercial wild blueberry harvester using innovative precision agriculture technologies and mathematical modeling. An integrated sensing and control system equipped with custom software was developed and incorporated into a commercial wild blueberry harvester to sense multiple attributes. Individual sensors have been installed onto various machines to sense targets for different cropping systems. However, the integration of multiple sensors and control systems onto one platform to sense plant height, fruit yield, slope and elevation on-the-go during mechanical harvesting is an original, worthwhile, and substantial contribution to knowledge. Non-destructive estimation of fruit yield prior to harvesting was utilized to quantify overall fruit losses during mechanical harvesting. The intensive data collected by multiple sensors provided an opportunity to study the relationships among the mapped parameters, which can be used to identify the factors responsible for fluctuating trends during harvesting. Additionally, the mapped information can be used to implement site-specific management practices to improve crop productivity, reduce cost of production and mitigate environmental risks.

Non-destructive estimation of fruit losses served as a basis for the physical evaluation of a commercial blueberry harvester to quantify actual losses during harvesting. The wild blueberry harvester was designed in early 1980's. Improved management practices (fertilizers, selective herbicides, fungicides, insecticides, pollination and pruning) in last two decades have resulted in healthy crop conditions and significantly higher yield in blueberry fields. These situations also demanded for evaluation of the harvester to suggest optimal machine operating parameters to enhance berry picking efficiency. Fruit losses on the ground were significantly higher when compared with un-harvested berries on the plants and loss through the blower. Fruit losses during harvesting were linear function of yield and were greatly influenced by the ground speed and header rpm either alone or in combination. This research presented a scientific approach and developed procedures for data collection to evaluate the blueberry harvester, which is a unique contribution towards academic community as well as the blueberry industry. Findings of this research suggested an ideal combination of ground speed and header rpm based on variations in fruit yield, crop parameters and topographic features to improve berry picking efficiency.

Knowledge of spatial variability is very valuable to plan operational recommendations for the mechanical harvester. This dissertation investigated the response of fruit losses in relation to spatial variation in crop characteristics, slope and yield. Fruit yield, losses, plant parameters and ground slope were highly variable within the selected fields. Spatial variability in fruit losses corresponding with the variability in yield, plant height, fruit zone and slope provided a strong evidence that the picking performance of a blueberry harvester was significantly influenced by the spatial variations. Investigation of spatial picking response of the blueberry harvester using classical and geo-statistical tools, correlation analysis, mapping in GIS and zonal analysis is a significant contribution to the scientific community. Findings of spatial trends emphasized the need to model these relationships mathematically.

Application of mathematical modeling (ANN and MR) to explore and understand the non-linear relationships between fruit yield, plant characteristics, machine operating parameters, fruit losses and ground slope is a valuable contribution to the wild blueberry industry. Modeling of harvesting dynamics revealed that the predictive capabilities of the ANN to estimate fruit losses were significantly better than the MR models. Modeling of spatial relationships confirmed that the fruit losses during harvesting were significantly influenced by the variations in fruit yield, crop characteristics, machine operating parameters and ground slope. Selection of an ideal combination of ground speed and header rpm by considering these spatial variations can reduce fruit losses during mechanical harvesting, which can generate more revenue for growers at no additional cost.

The wild blueberry industry is facing increased harvesting losses with their existing harvesters due to changes in crop conditions caused by improved management practices. This PhD project is unique, as it addresses the current industrial problem. This research recommended an operational combination of 1.2 km h^{-1} and 26 rpm, by considering spatial variations to improve berry picking efficiency by 3 to 5% in high yielding fields. Increased harvesting efficiency (3 to 5%) can contribute 4 to 7 million dollars annually to Nova Scotia's provincial economy and 20 to 30 million dollars to Canada's economy every year. Furthermore, this dissertation provided future research directions to address the problems associated with the mechanical harvesting of wild blueberries.

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APPENDIX A: EXPERIMENTAL RESULTS OF MULTIPLE SENSORS TO MAP FRUIT YIELD, PLANT HEIGHT AND TOPOGRAPHIC FEATURES

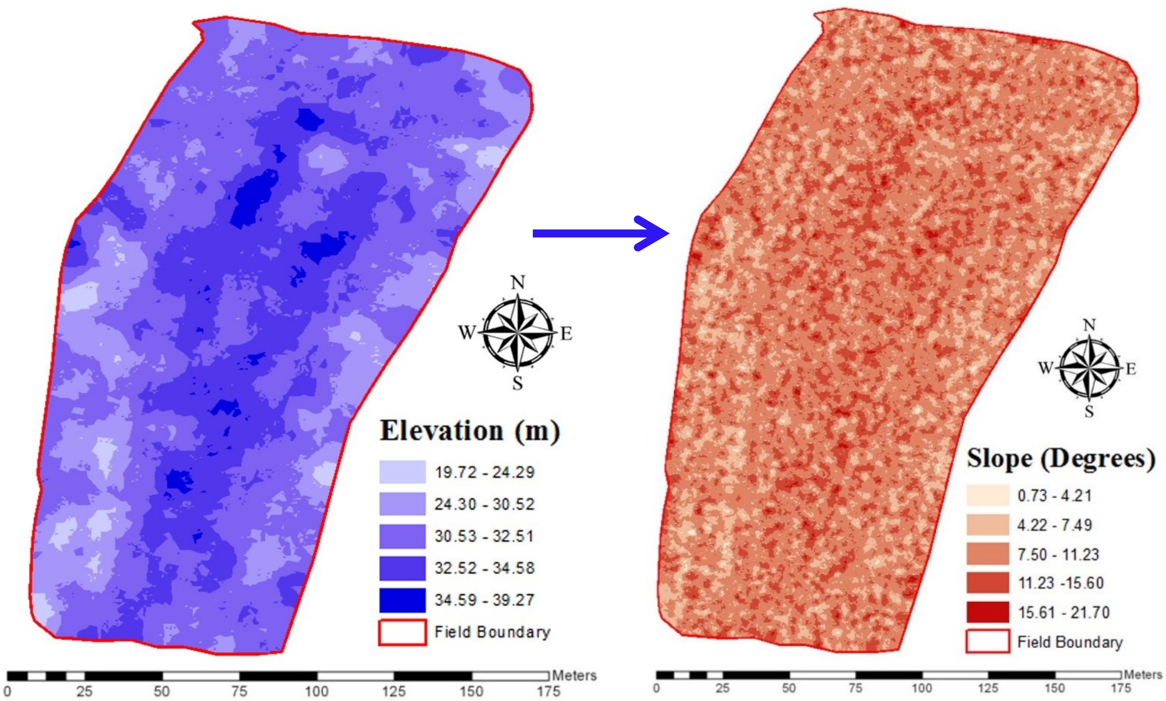


Figure A-1: Derived slope from elevation data using Slope Protocol of Spatial Analyst extension of ArcGIS 10 software for Frankweb site.

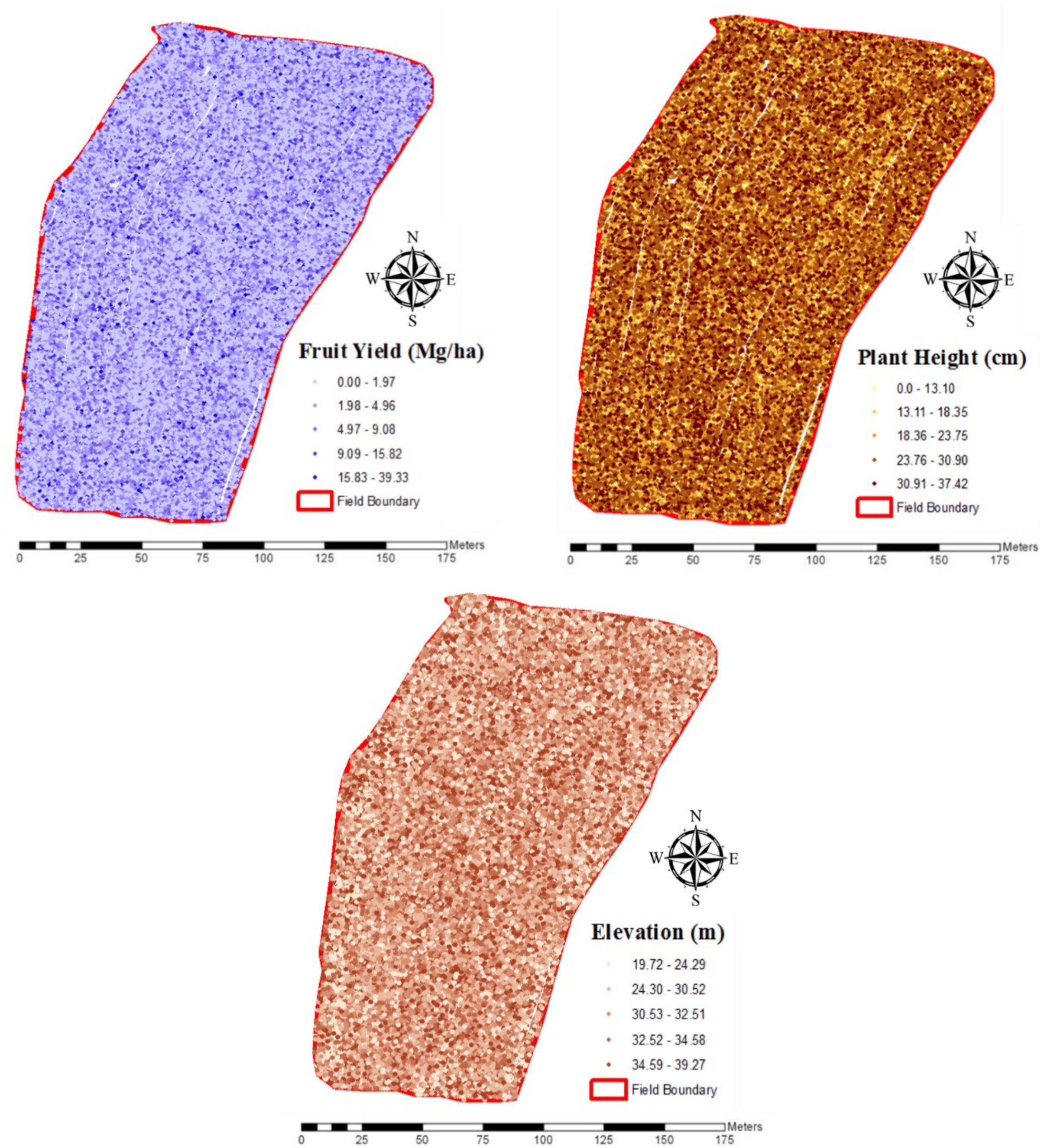


Figure A-2: Survey dot maps of fruit yield, plant height and elevation for Frankweb site using multiple sensors.

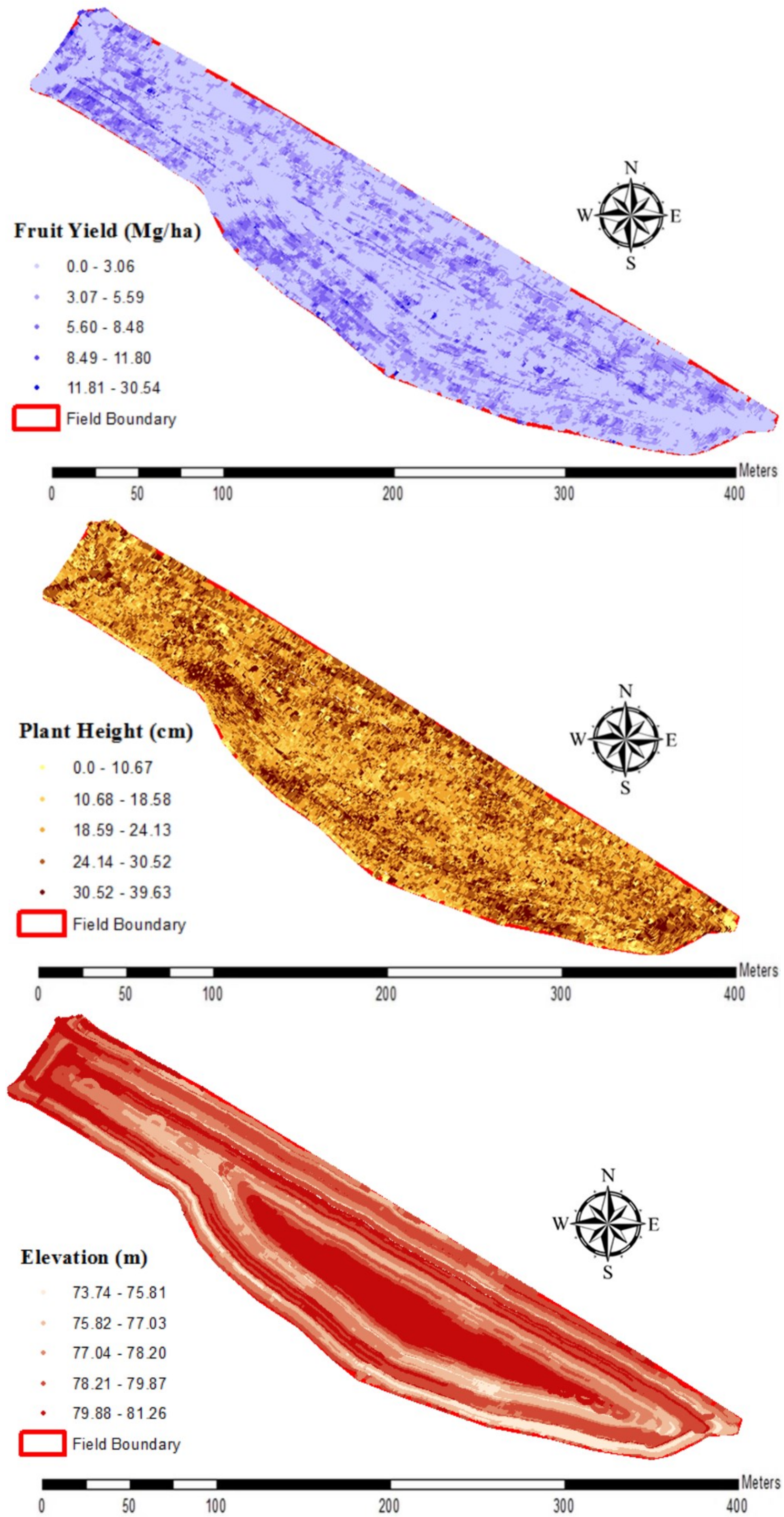


Figure A-3: Survey dot maps of fruit yield, plant height and elevation for Tracadie site using multiple sensors.

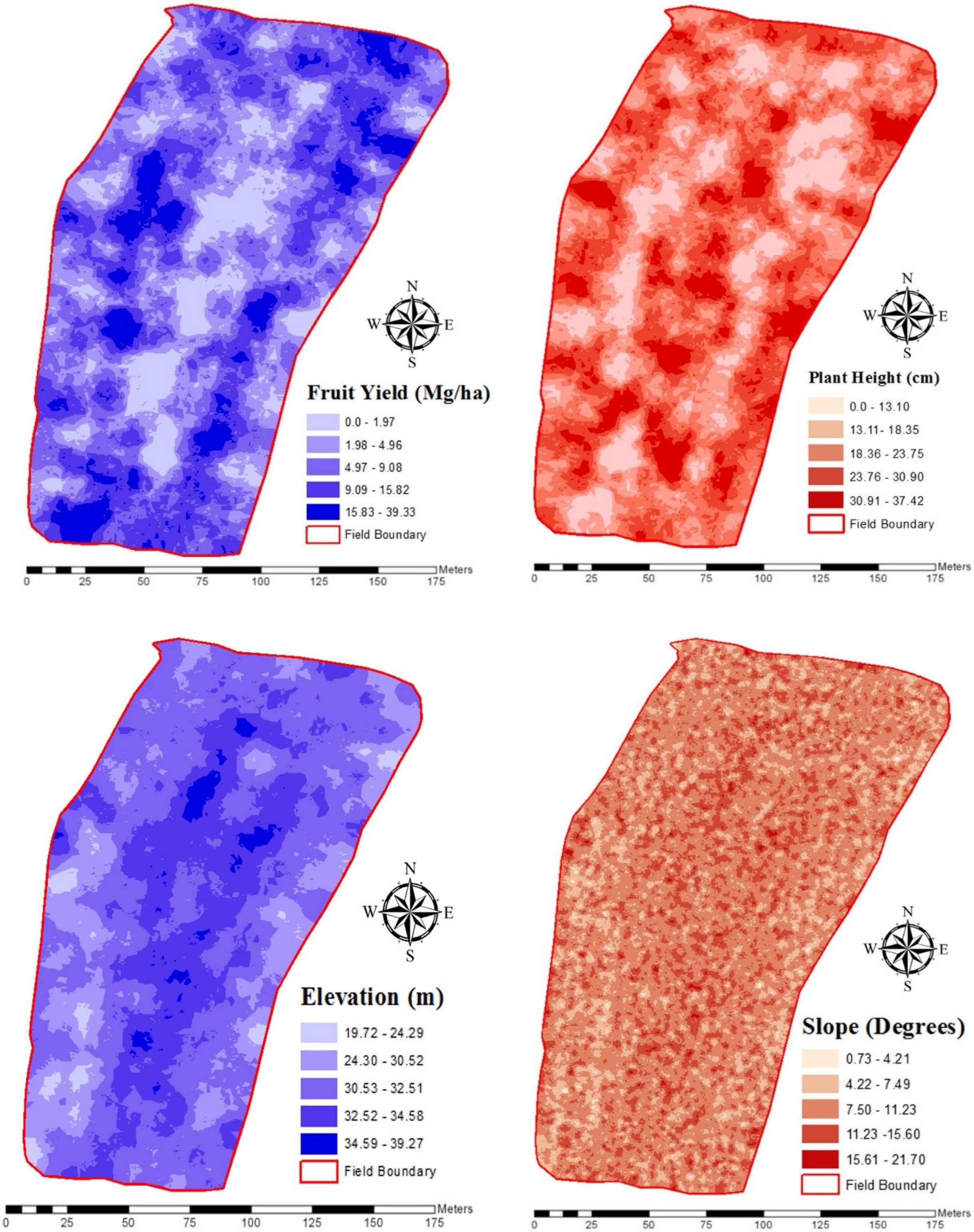


Figure A-4: Kriged maps of fruit yield, plant height, elevation and slope for Frankweb site.

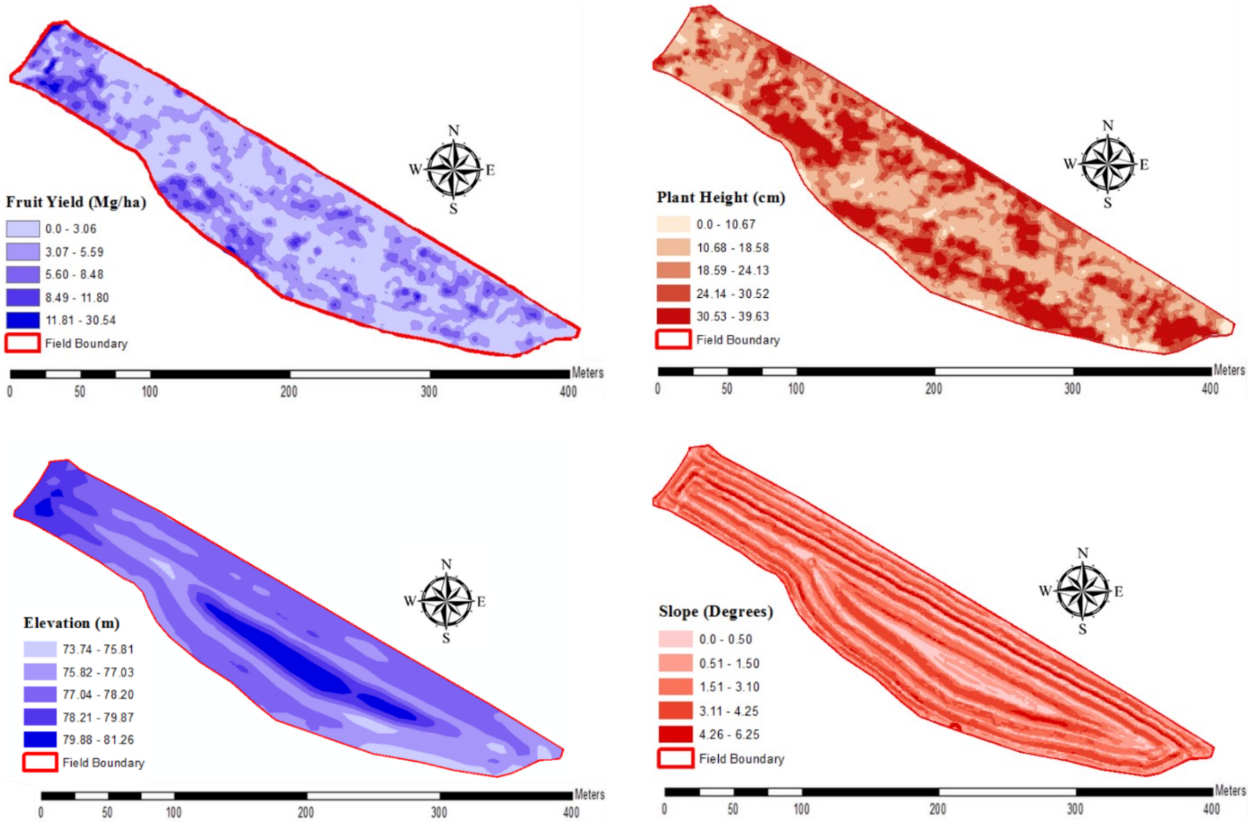
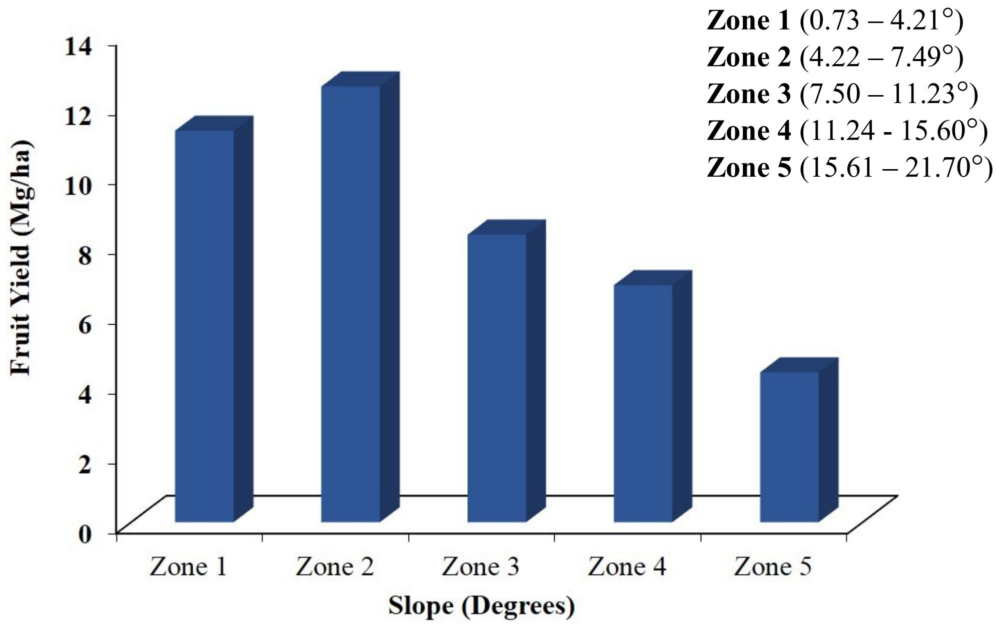
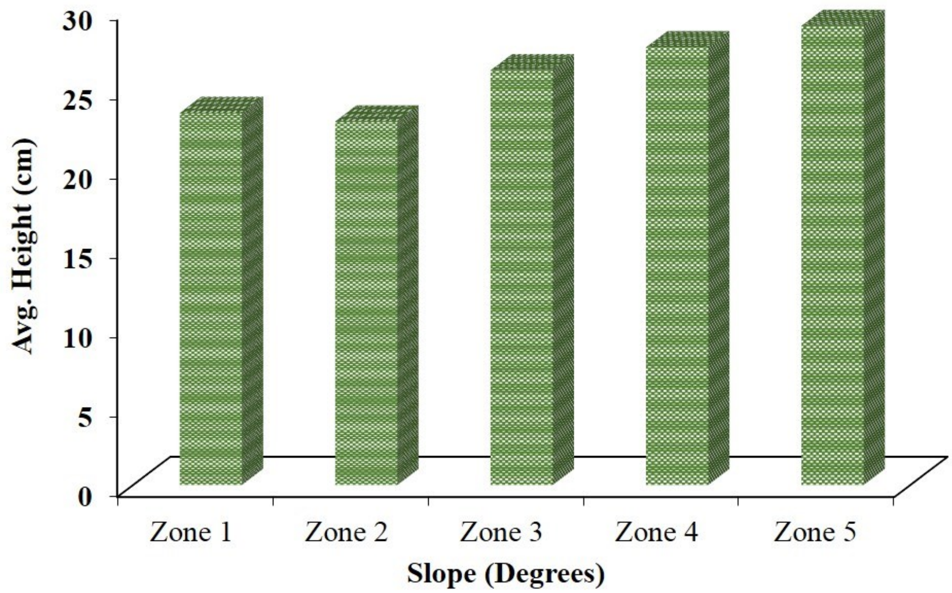


Figure A-5: Kriged maps of fruit yield, plant height, elevation and slope for Tracadie site.

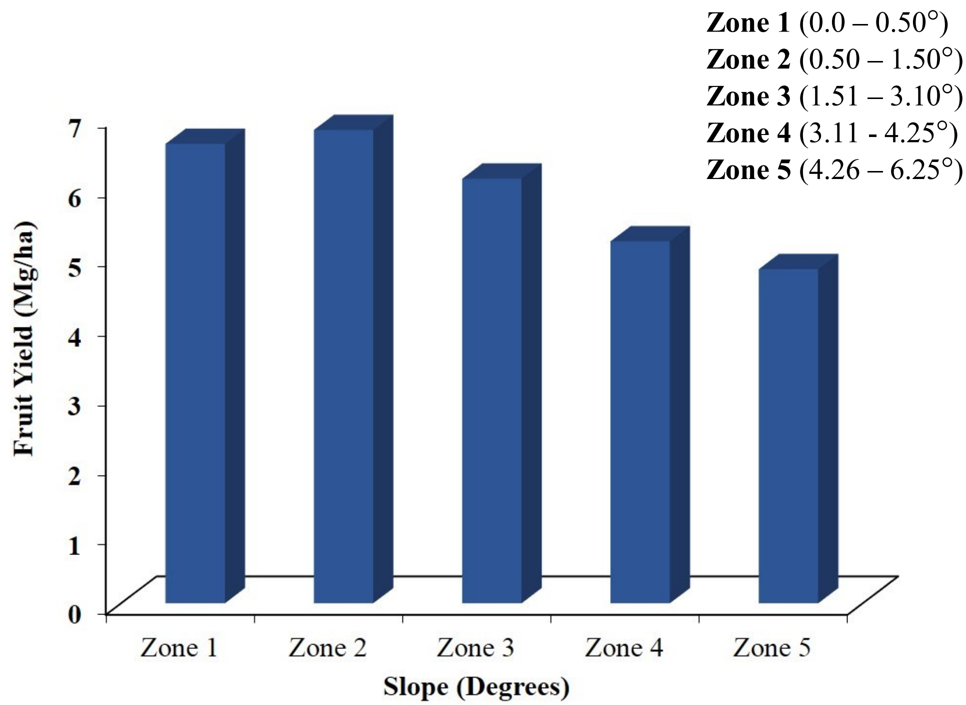


(a)

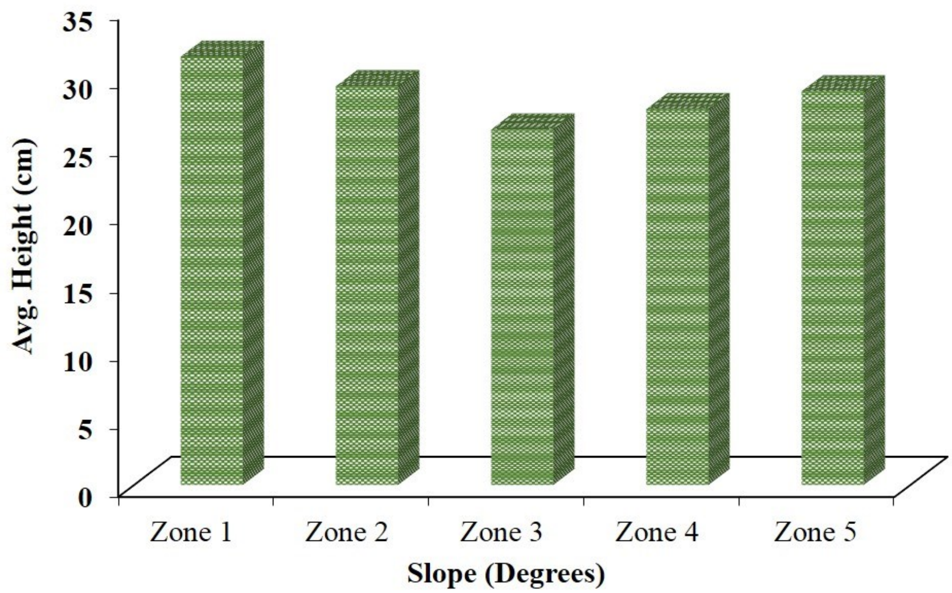


(b)

Figure A-6: Bar graphs showing the variation of fruit yield and plant height within different slope zones for Frankweb site.



(a)



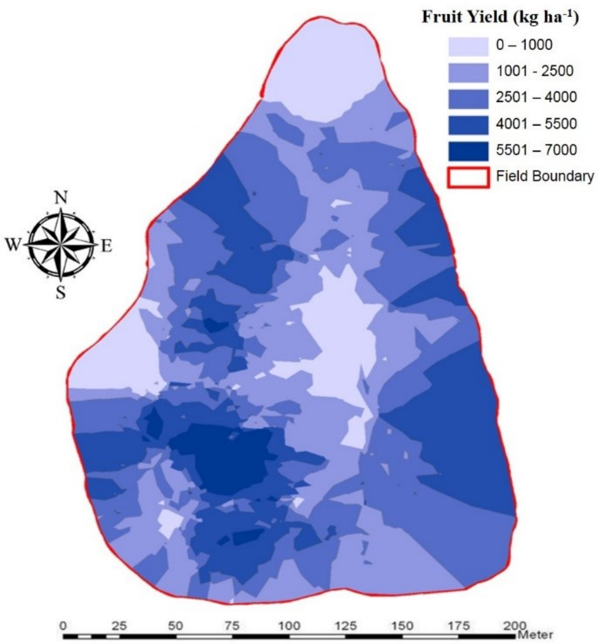
(b)

Figure A-7: Bar graphs showing the variation of fruit yield and plant height within different slope zones for Tracadie site.

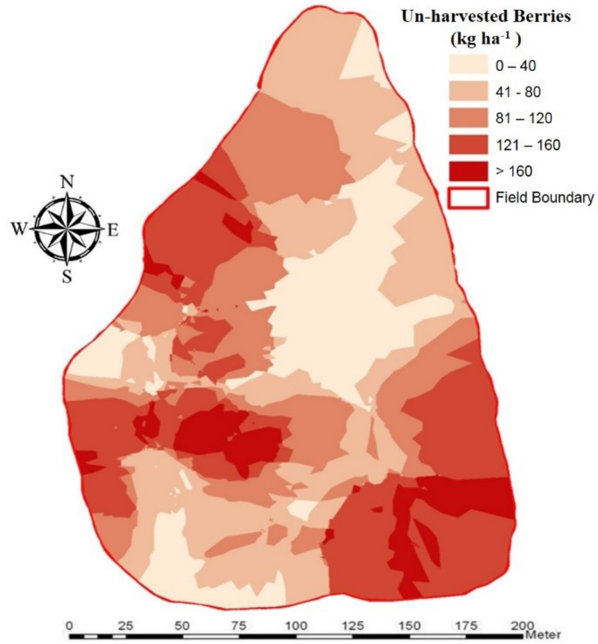
Table A-1. Semivarigram parameters of fruit yield, plant height, slope and elevation for Frankweb and Tracadie sites.

Parameters	Nugget	Sill	Range (m)	Nugget Sill ratio (%)	R^2	Model
Frankweb Site						
Fruit Yield (Mg ha^{-1})	3.22	23.21	15.90	13.87	0.79	Exponential
Plant Height (cm)	6.11	42.67	11.56	14.31	0.71	Spherical
Slope (Degrees)	10.89	33.20	25.66	32.80	0.87	Exponential
Elevation (m)	15.33	41.20	30.34	37.20	0.82	Exponential
Tracadie Site						
Parameters	Nugget	Sill	Range (m)	Nugget Sill ratio (%)	R^2	Model
Fruit Yield (Mg ha^{-1})	5.23	29.61	23.10	17.66	0.67	Spherical
Plant Height (cm)	10.20	49.81	11.66	20.47	0.83	Gaussian
Slope (Degrees)	0.30	15.88	20.13	1.88	0.88	Gaussian
Elevation (m)	6.99	48.75	29.88	14.33	0.73	Exponential

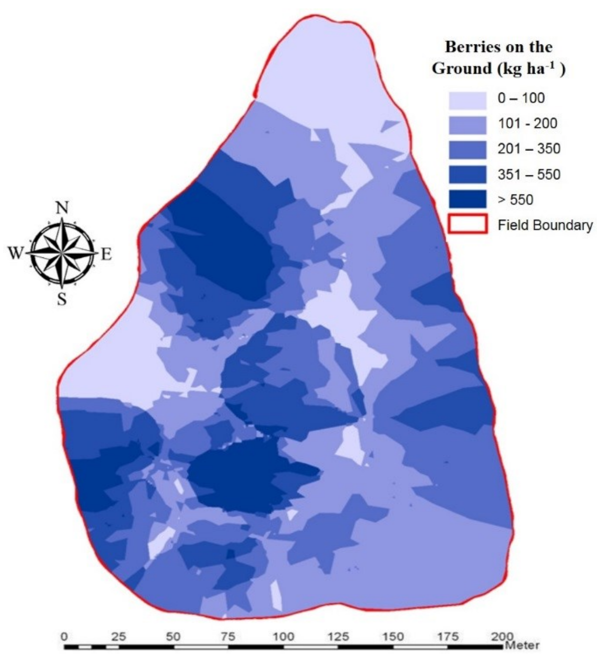
APPENDIX B: EXPERIMENTAL RESULTS OF RESPONSE OF FRUIT LOSSES TO SPATIAL VARIABILITY



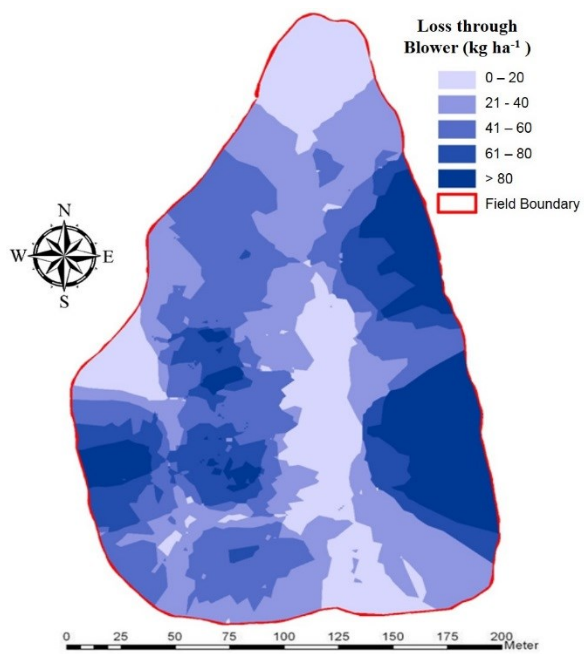
(a)



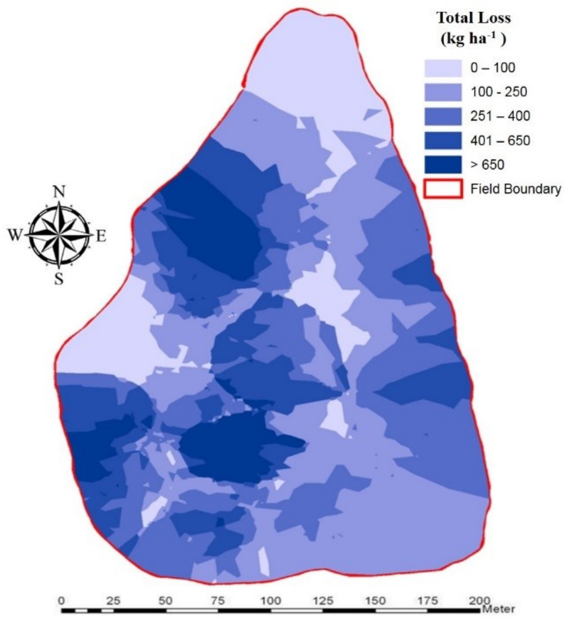
(b)



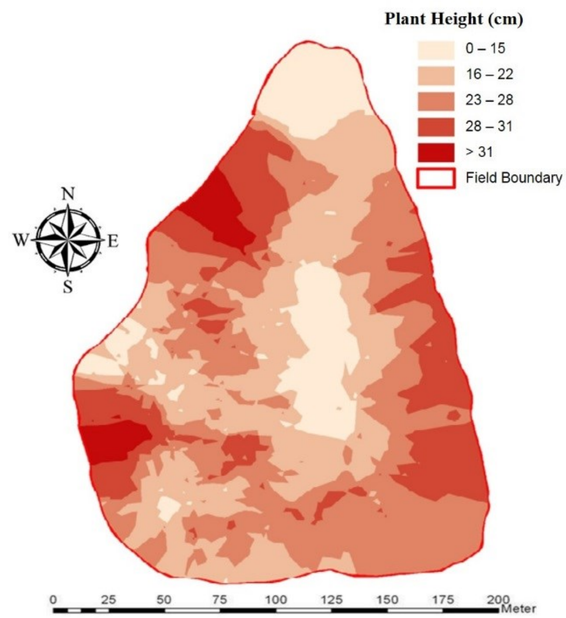
(c)



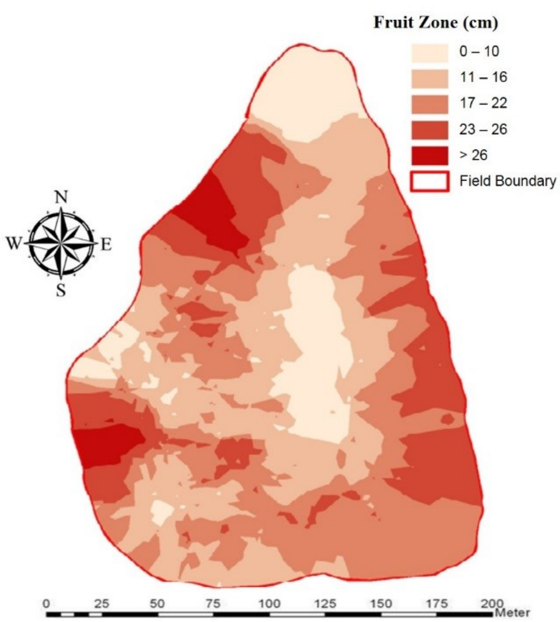
(d)



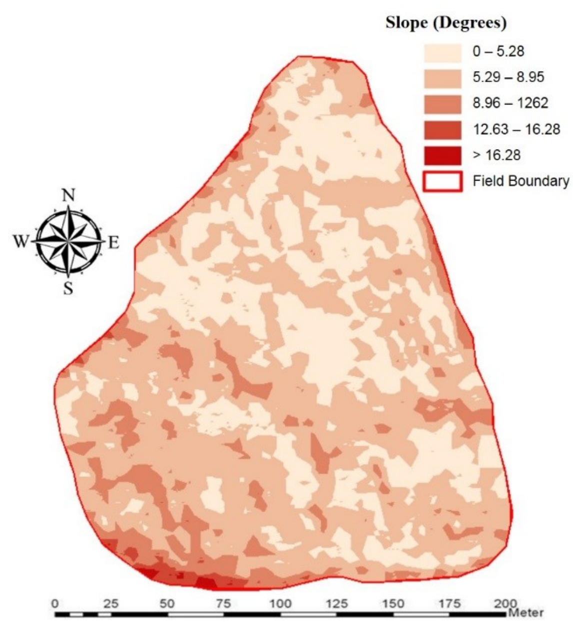
(e)



(f)

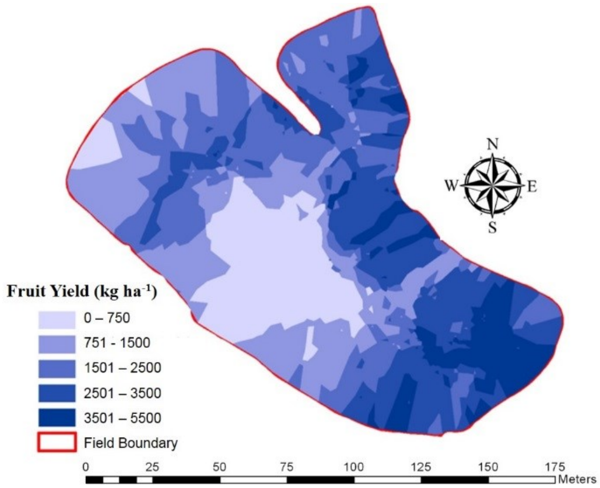


(g)

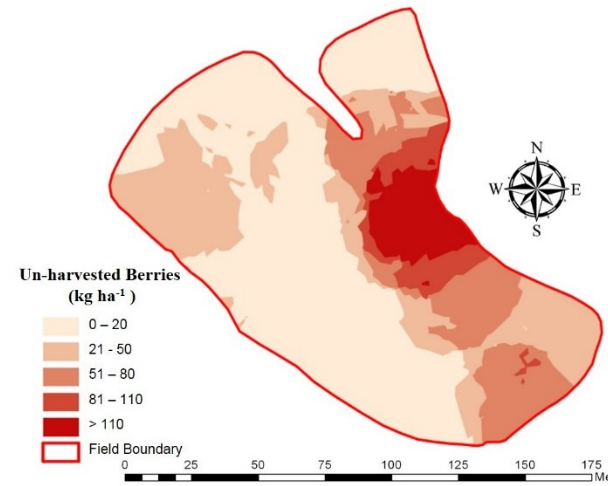


(h)

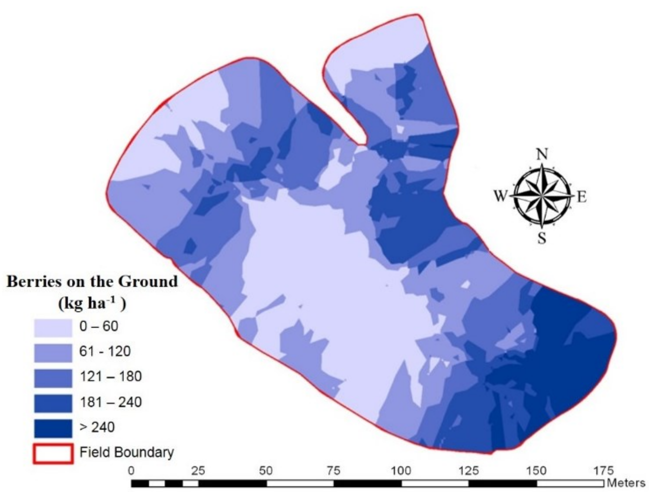
Figure B-1: Interpolated maps, (a) Fruit Yield, (b) Un-harvested berries, (c) Berries on the ground, (d) Loss through blower, (e) Total Loss, (f) Plant height, (g) Fruit zone and (h) Slope for Cooper site.


N
W
E
S
Fruit Yield (kg ha^{-1})
0 – 750
751 - 1500
1501 – 2500
2501 – 3500
3501 – 5500
Field Boundary
0 25 50 75 100 125 150 175
Meters

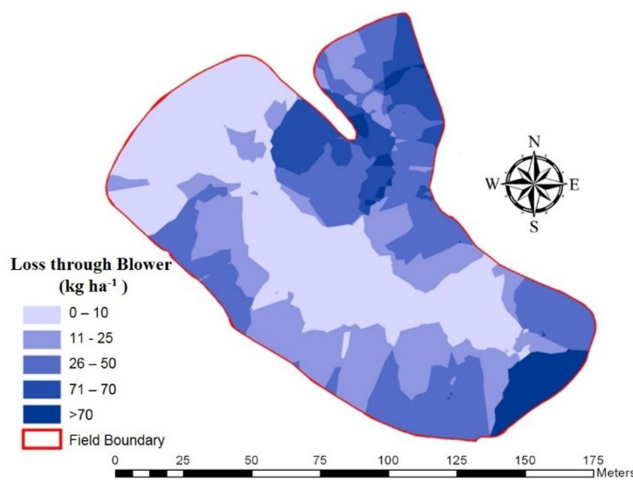
(a)


N
W
E
S
Un-harvested Berries
(kg ha^{-1})
0 – 20
21 - 50
51 – 80
81 – 110
> 110
Field Boundary
0 25 50 75 100 125 150 175
Meters

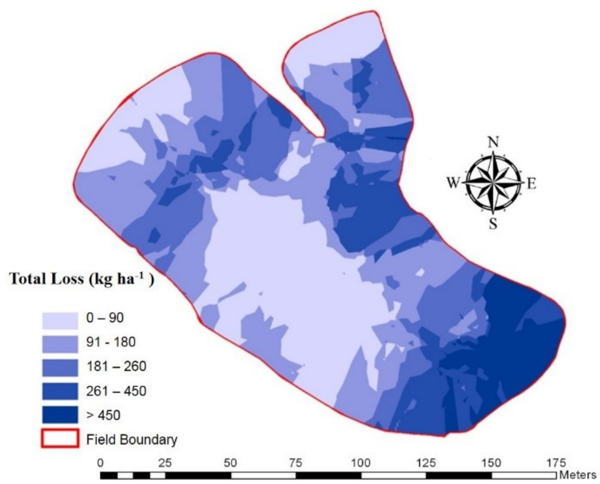
(b)


N
W
E
S
Berries on the Ground
(kg ha^{-1})
0 – 60
61 - 120
121 – 180
181 – 240
> 240
Field Boundary
0 25 50 75 100 125 150 175
Meters

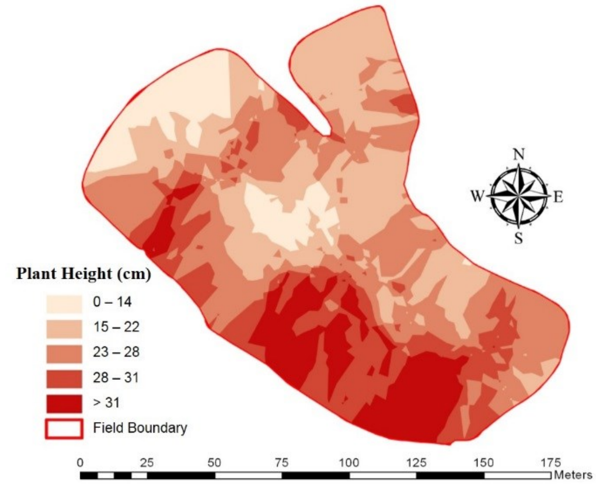
(c)


N
W
E
S
Loss through Blower
(kg ha^{-1})
0 – 10
11 - 25
26 – 50
71 – 70
>70
Field Boundary
0 25 50 75 100 125 150 175
Meters

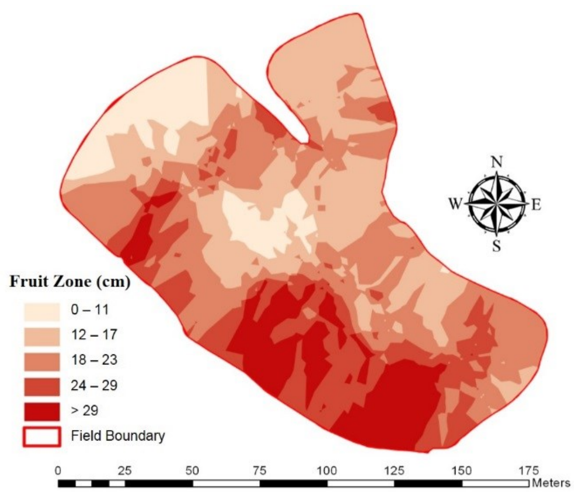
(d)



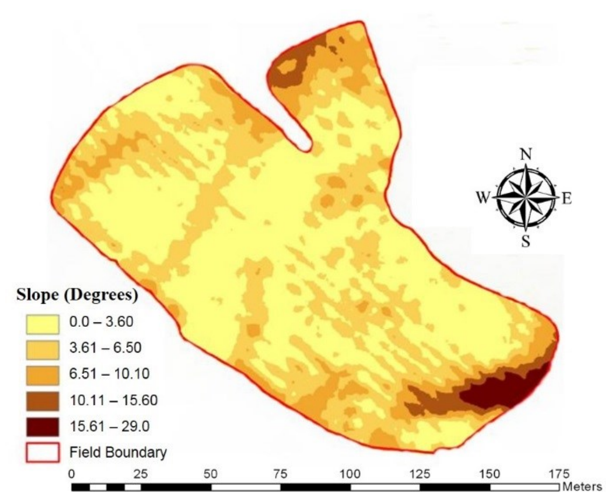
(e)



(f)

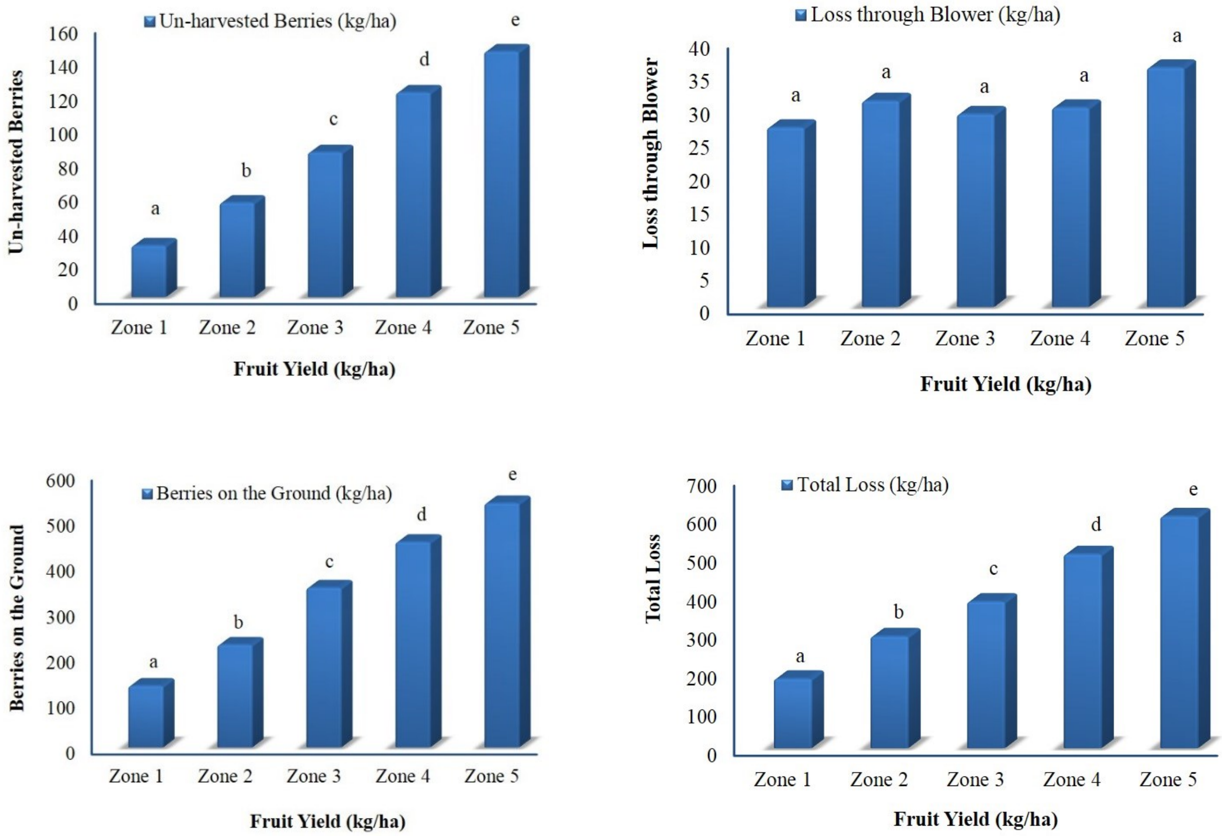


(g)



(h)

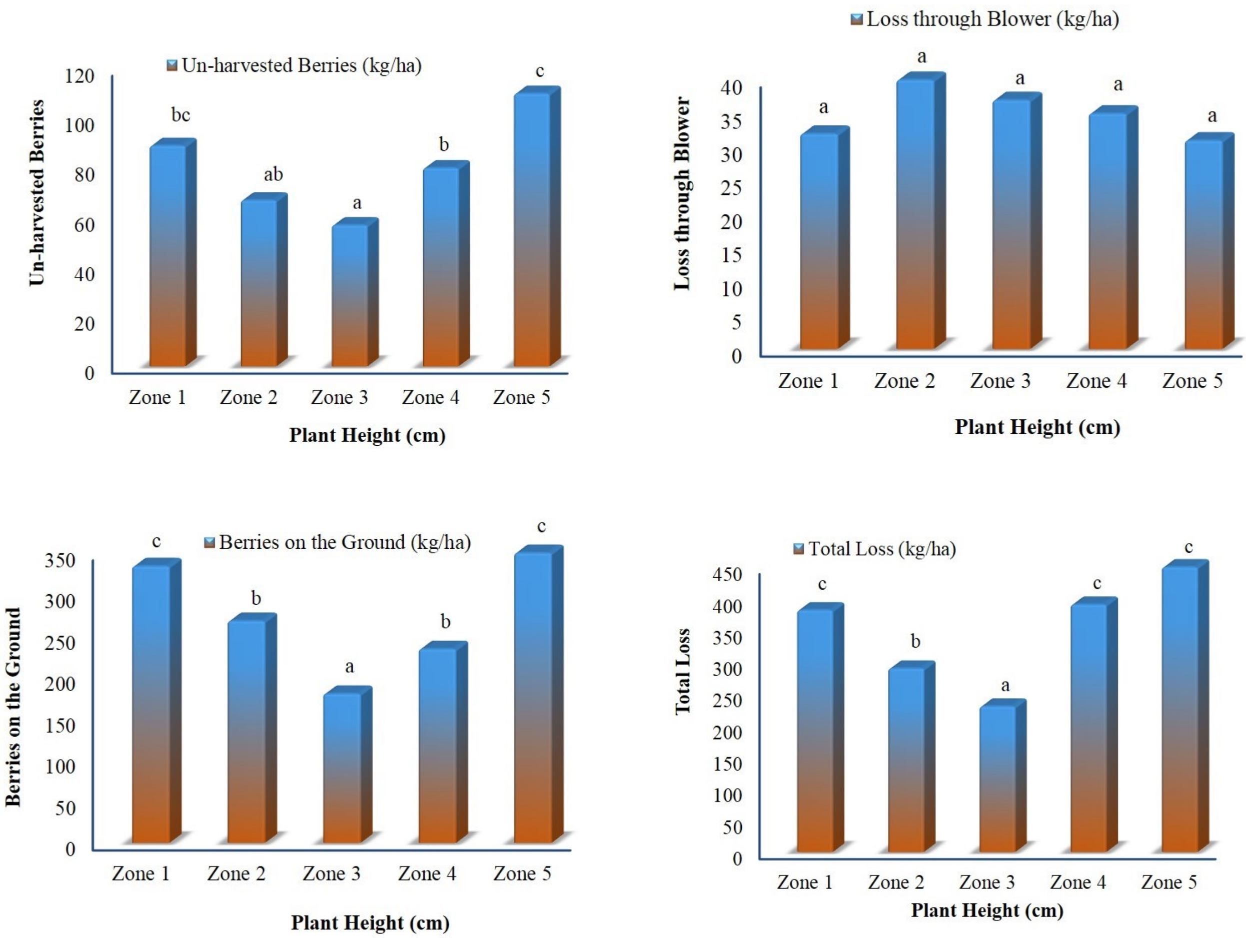
Figure B-2: Interpolated maps, (a) Fruit Yield, (b) Un-harvested berries, (c) Berries on the ground, (d) Loss through blower, (e) Total Loss, (f) Plant height, (g) Fruit zone and (h) Slope for Small Scott site.



Fruit Yield (kg/ha) Zones

Zone 1 (0 – 1000)
Zone 2 (1001 – 2500)
Zone 3 (2501 – 4000)
Zone 4 (4001 – 55000)
Zone 5 (> 5500)

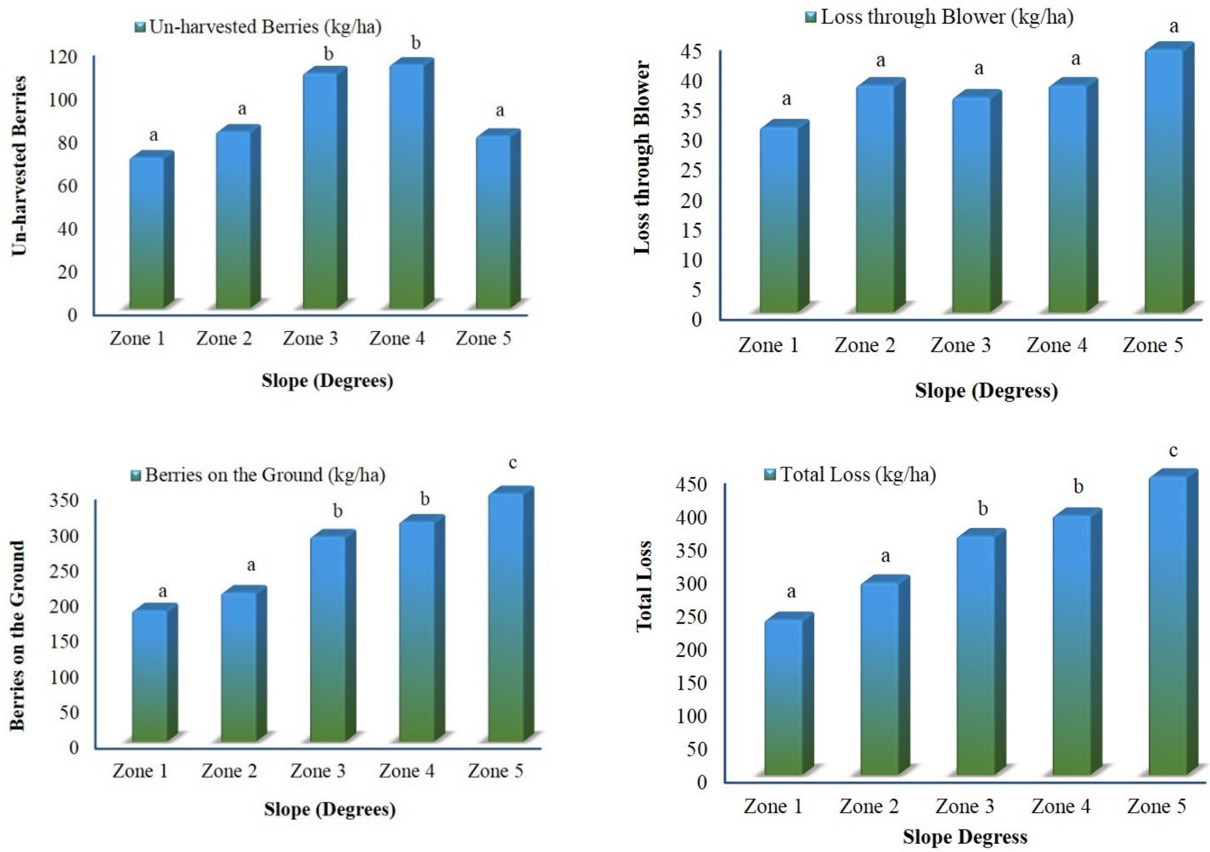
Figure B-3: Multiple means comparison of fruit losses in relation to different zones of fruit yield for Cooper site.



Plant Height (cm) Zones

Zone 1 (0 – 15)
Zone 2 (16 – 22)
Zone 3 (23 - 27)
Zone 4 (28 – 30)
Zone 5 (> 30)

Figure B-4: Multiple means comparison of fruit losses in relation to different zones of plant height for Cooper site.



Slope (Degrees) Zones

Zone 1 (0 – 5.28)
Zone 2 (5.29 – 8.95)
Zone 3 (8.96 – 12.62)
Zone 4 (12.63 – 16.28)
Zone 5 (> 16.28)

Figure B-5: Multiple means comparison of fruit losses in relation to different zones of slope for Cooper site.

Table B-1. Multiple means comparison of fruit losses in relation to different zones of fruit yield, plant height and slope for Small Scott site.

	Fruit Yield (Kg ha^{-1}) Zones				
Parameters	Zone 1 0 to 750	Zone 2 751 to 1500	Zone 3 1501 to 2500	Zone 4 2501 to 3500	Zone 5 3500 to 5500
Un-harvested Berries	20.3 a	36.7 ab	67.9 b	93.4 bc	110.1 c
Berries on the Ground	41.2 a	93.2 b	135.6 c	190 d	240 e
Loss through Blower	13.1 a	21.5 a	9.8 a	10.3 a	26.8 a
Total Losses	75.3 a	148.7 b	210.4 c	270.8 d	336.1 e
	Plant Height (cm) Zones				
Parameters	Zone 1 0 to 14	Zone 2 15 to 22	Zone 3 23 to 28	Zone 4 29 to 31	Zone 5 > 31
Un-harvested Berries	48.9 bc	38.7 ab	21.6 a	46.3 bc	57.6 c
Berries on the Ground	170.6 c	136.4 b	83.5 a	113.6 b	185.6 c
Loss through Blower	20.1 a	15.3 a	17.4 a	23.6 a	19.8 a
Total Losses	220.4 c	173.8 b	130.5 a	183.7 b	250.6 d
	Slope (Degrees) Zones				
Parameters	Zone 1 0 to 3.60°	Zone 2 3.61 to 6.50°	Zone 3 6.51 to 10.10°	Zone 4 10.11 to 15.60°	Zone 5 > 15.60°
Un-harvested Berries	17.3 a	25.6 ab	38.9 bc	49.6 c	59.3 c
Berries on the Ground	45.8 a	98.6 b	143.5 c	190.3 d	237.6 e
Loss through Blower	14.6 a	23.8 a	21.5 a	16.8 a	20.1 a
Total Losses	77.4 a	143.6 b	198.5 c	256.8 d	265.6 d

Means followed by different letters are significantly different at $p = 0.05$.
Fruit losses were recorded in kg ha^{-1}.

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Journal Article

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PhD Candidate, Mechanical Engineering Department
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"Effect of Ground Speed and Header Revolutions on the Picking Efficiency of a Commercial Wild Blueberry Harvester." Applied Engineering in Agriculture 30(4): 535-546.

"Development of a Predictive Model for Wild Blueberry Harvester Fruit Losses during Harvesting Using Artificial Neural Network" (ASABE manuscript PM 10872, in review).

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