GENOTYPE AND ENVIRONMENT IMPACTS ON CANADA WESTERN SPRING WHEAT BREAD-MAKING QUALITY AND DEVELOPMENT OF WEATHER-BASED PREDICTION MODELS

BY

GORDON J. FINLAY

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Department of Soil Science
University of Manitoba
Winnipeg, Manitoba

ABSTRACT

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A study was conducted to quantify weather conditions at specific growth stages of Canadian Western Spring wheat (*Triticum aestivum*) and relate those growing conditions to variations in wheat grade and quality characteristics and to develop pre-harvest prediction models for wheat quality using weather input data. The Canada Western Red Spring (CWRS) genotypes AC Barrie, Superb, Elsa, Neepawa, Canada Prairie Spring-White genotype (CPS-white) Vista and Canada Western White Spring (CWWS) genotype Snowbird were grown in five locations across the Canadian prairies during the 2003 and 2004 growing seasons, which provided a wide range growing conditions. The experimental layout at each location was a randomized complete block design with three replicates. Intensive weather data was collected during the growing season at each location and used to calculate accumulated heat stress, useful heat, moisture demand, moisture supply, moisture use and moisture stress variables for numerous crop development stages. Crop development was observed on a regular basis at each location in order to partition the growing season into several development stages. Grain samples from each plot were subjected to full visual analysis and official grading by the Canadian Grain Commission and were milled into flour using a Buhler Experimental flour mill at the University of Manitoba. Flour samples underwent an extensive analysis of flour, dough, and bread making quality. ANOVA indicated that genotype, environment and their interactions had significant effects on most quality parameters tested. Environmental contribution to wheat quality variance was considerably larger (62 to

89%) than the variance contribution of either genotype (2 to 26%) or GxE interaction (2 to 16%). Regression analysis was completed in order to determine relationships between growing season weather and wheat quality.

Using the weather and crop development stage information, significant regression equations with high regression coefficients were developed for most quality parameters using just a single independent weather variable. Moisture related variables explained the majority of the variation for all the grain properties except yield as well as for most of the flour properties. The farinograph measured dough parameters, except Farinograph stability, were driven by water related variables and the mixograph measured dough properties by useful heat variables and water stress variables. The bread properties were found to be best predicted using useful heat and heat stress variables. Multiple regression equations with even higher R^2 values were developed using three complex weather variables, leading to the opportunity to predict wheat quality 2-5 weeks prior to harvest. R^2 values ranged from 0.29 to 0.95, with the grain and dough properties producing the strongest forecast models. For 13 of the 27 quality properties tested, R^2 values were above 0.80. Equally strong prediction models were developed utilizing basic weather variables which could be obtained from weather stations monitoring only daily maximum and minimum air temperature and precipitation. R^2 values for these models ranged from 0.22 to 0.95.

The development periods of planting to jointing and anthesis to soft dough were the stages most frequently exhibiting the highest correlation to wheat quality indicating weather needs to be monitored during the entire growing season to accurately predict

quality. The level of variance in wheat quality explained by weather variables was improved when more detailed phenological stages were considered.

Grain quality forecast models were validated using 2005 weather and crop data. Prediction models developed from the 2003 and 2004 data required modification in order to accurately and consistently predict the grain properties in 2005. Generally, the best predictive models were developed by using data from a group of genotypes which responded similarly to the environment. Yield was predicted to within 120 to 530 kg/ha, on average, between the three sites using the modified model. The standard error of prediction (SEP) for yield improved from 927 using the original model to 288 using the modified model. Test weight was forecast to within 2.2 to 3.0 kg/hL using the modified model and the original SEP of 6.15 improved to 1.46 using a modified equation. TKW was predicted between 0.4 and 3 g at each location using the modified regression equation. The original TKW model had an SEP value of 13.19, which improved to 0.91 using the best modified model. Protein content results were more varied, with protein content in Regina predicted to within 0.6 %, while at the other two test sites, predicted grain protein content was more than 1.5% from the actual. SEP results reflected protein content variability as SEP values did not improve using modified models.

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1. INTRODUCTION

Wheat is a particularly significant agricultural resource in Canada. The value of this crop originates from the unique ability of the raw material to be made into a diverse array of delicious goods such as bread, pastries, and noodles. The majority of Canadian wheat is produced in Western Canada and this region is known for its ability to produce wheat with high processing quality. The ability to produce high quality wheat gives Canada a strong marketing advantage in the global market. However, wheat processing quality is extremely vulnerable to growing season weather conditions.

The diverse growing conditions experienced in the vast grain crop region of western Canada in a given year can lead to considerable variability in bread making quality characteristics at a regional level. Quality variability is a major concern of wheat customers who require a reliable source of consistent quality wheat, from shipment to shipment and from year to year, in order to produce goods in a consistent, cost effective manner.

Historically, quality variability has been smoothed by the grain handling system. The Canadian grain handling system originally consisted of numerous small grain elevators scattered across the prairies, which effectively blended wheat with various quality characteristics into the bulk grain system. At present, the majority of smaller grain elevators have been replaced by relatively few and much larger facilities which draw from a larger area. The larger facilities have the capability to fill entire shipment cargos, thus reducing geographic quality blending. This results in a shipment of wheat that may have a completely different set of quality characteristics than a shipment sent from another large terminal. The reduction in geographic quality blending emphasizes the importance of local weather effects on quality and the need for improved knowledge of weather impacts on wheat quality.

The development of techniques for pre harvest prediction of wheat quality would be of great value to the Canadian grain industry and to companies such as the Canadian Wheat Board whose business relies on a consistent supply of uniform quality wheat over the long term. An improved ability to predict wheat grade and quality before harvest would lead to an improved capacity to source and market grain to specific wheat customers and more cost effective transportation logistics planning. Improved grain sourcing and marketing would enhance the reputation of Canada as a reliable source of consistent high quality wheat.

This study is one segment of a larger multi-partner research study investigating Canadian spring wheat grade and quality response to growing season weather variation in the Prairie Region. The goals of this particular component were to build on results obtained from a field scale study, which examined the impacts of weather on wheat quality of AC Barrie and Superb genotypes grown in individual producer fields across western Canada (Jarvis, 2006). This study extended the scope of the producer study by increasing the intensity at which weather and crop development data was obtained as well as increasing the number of genotypes utilized in an effort to develop more accurate and reliable wheat quality prediction models.

Each of the following chapters investigates an integral piece of knowledge required to help explain wheat grade and quality response to growing season weather. Chapter 2 was the first step required in order to determine the contribution of the three main factors impacting wheat end-use quality; environment, genotype and genotype by environment interaction. In Chapter 3, relationships between growing season weather conditions and grain, flour, dough, and bread properties were developed. This chapter focused on developing prediction models using high frequency weather data and then compared those results to models developed using simple weather data. In Chapter 4, wheat quality responses to weather during each individual crop development stage were examined in order to determine the most important development stage impacting wheat technological quality. Chapter 5 contains an evaluation of the quality prediction models developed in Chapter 3, utilizing weather and grain property data collected in 2005. In Chapter 5, modified regression equations from Chapter 3 were developed to improve quality forecasting accuracy.

The comprehensive list of quality properties investigated as well as the intensity at which the weather data was measured were unique assets of this study. The extent to which crop development stages were characterized and the very large geographic coverage in the Prairie region in which this study spanned were also unparalleled aspects of this project compared to previous research.

1.1 Objectives

The specific objectives of this study were:

1) to assess the impacts of genotype, environment and genotype by environment interaction on a comprehensive list of technological wheat quality parameters.
2) to quantify the impact of weather on hard spring wheat quality at specific growth stages and relate that weather to variations in grade and bread making quality characteristics.
3) to develop pre-harvest prediction models for wheat grain, flour, dough, and bread properties using detailed, high frequency weather data and to determine the value of high frequency weather data in forecasting wheat quality in comparison to the use of simple weather variables.
4) to identify the most important crop development stage affecting the wheat technological quality properties.
5) to validate the high frequency weather data regression models using weather and grain quality data from the 2005 growing season and to improve the quality prediction ability by developing new forecast models from groupings of similar genotypes or genotype-specific models.

2. GENOTYPE AND ENVIRONMENTAL VARIATION IN GRAIN, FLOUR, DOUGH AND BREAD MAKING CHARACTERISTICS OF CANADIAN HARD SPRING WHEAT

2.1 Abstract

Wheat grain, flour, dough and bread quality characteristics are strongly influenced by the effects of growing season weather conditions. Understanding the impact of genotype, environment, and their interactions on Canadian wheat genotype quality is important for Canada to maintain its high standard for delivery of consistent quality wheat to domestic and international customers. The effects of genotype, environment and genotype by environment interaction on numerous grain, flour, dough and bread characteristics were assessed. The Canada Western Red Spring (CWRS) genotypes AC Barrie, Superb, Elsa, Neepawa, Canada Prairie Spring-white (CPS-white) genotype AC Vista and Canada Western White Spring (CWWS) genotype Snowbird were grown at five locations across the Canadian prairies over two years to provide a total of seven site-years of milling quality wheat for analysis. Analysis of variance (ANOVA) indicated that genotype, environment and their interactions had significant effects on most quality parameters tested. The relative magnitude of the environmental contribution to wheat quality variance was considerably larger (62 to 89%) than the variance contribution of either genotype (2 to 26%) or GxE interaction (2 to 16%). The grain properties had the highest environmental variance values on average. Flour and bread making characteristics had the highest genotypic contribution to variation. The dough properties appeared to have the most GxE interaction contribution to variation. The extent of environmental influences clearly demonstrates the importance of growing season weather

impacts on wheat yield and quality. The relative effect of genotype, environment, and genotype by environment interactions should be characterized for all quality characteristics in order to properly assess new wheat lines. The strong influence of environment on quality also indicates the potential for the development of quality prediction models using growing season weather data, which is the next step of this study.

2.2 Introduction

Wheat kernel development and biomolecule accumulation are strongly influenced by genotype and environmental parameters (Baenziger et al., 1985; Peterson et al., 1992). Environmental parameters such as useful heat accumulation, higher than optimal temperature and water stress are predominant factors influencing grain development. Wheat classes grown in Canada vary significantly in quality and yield. Although the quality response of different classes and genotypes of wheat are expected to vary significantly under differing weather conditions, very little research, especially under field conditions, is conducted to quantify this impact. The vast size of the wheat growing region in western Canada creates an enormous range of temperature and precipitation conditions each year. This environmental variability leads to a wide range in wheat quality being produced each year across western Canada. However, millers and bakers need consistent quality of wheat from shipment to shipment and from year to year to maintain quality of their products.

Several studies have examined the effects of genotype and environmental conditions during grain development (Baker et al., 1971; Fowler and De La Roche, 1975; Baker and Kosmolak, 1977; Lukow and McVetty, 1991; Peterson et al., 1992; Graybosch et al., 1995; Peterson et al., 1998; Ames et al., 1999; Mikhaylenko et al., 2000; Panozzo and Eagles, 2000; Preston et al., 2001; Zhang et al., 2004). The general results of these studies have shown that environment, genotype and GxE interactions are all significant factors contributing to quality variation. However, most of these studies have indicated that environment is the main contributing factor to quality variability while GxE interaction contributes a relatively small portion to quality variability.

Of particular interest to Canadian agriculture are the studies which examined Canadian genotypes and environments. One of the earliest Canadian studies to evaluate the contributions made by genotype and environment to bread quality was by Fowler and de la Roche (1975). They examined winter and spring wheat quality from 15 eastern environments spanning Manitoba to PEI; no western Canadian genotypes or western Prairie locations were used in this study. An extensive list of quality parameters were analyzed, covering grain properties, flour yield, mixograph parameters and loaf volume. A large environmental effect was observed for yield, test weight, protein and protein related parameters. Flour pigment, mixograph peak time, and kernel hardness were found to have the smallest response to environment of the parameters tested. It was also found that genotype-location and genotype-year interactions were relatively insignificant for most quality parameters.

Baker and Kosmolak (1977) examined eight hard red spring wheat quality characteristics from wheat grown at several Manitoba and Saskatchewan sites. Genotypes were pooled into only two environments; however true environmental impact was masked. Genotype by environment interaction was found to be important in determining mixograph development time, falling number, and remix loaf volume, while flour yield, flour protein, farinograph absorption, and grinding time were relatively insensitive to the GxE interaction.

Lukow and McVetty (1991) studied the effect of genotype, environment, and GxE interactions on eight diverse semi-dwarf spring wheat genotypes grown at three sites within central Manitoba over two years. Sixteen quality parameters were analyzed in this study and included grain, flour, dough and loaf characteristics. Genotype, environment, and their interactions were all found to be statistically significant for all quality parameters, except for the environment effect on flour yield and farinograph dough development time. The variation due to environment was pronounced for all quality parameters but the variance component for genotype was greater in all cases, contributing 52 to 93% of total variation. The GxE contribution to variation was considerably smaller in comparison to either E or G, contributing 3.8 to 30% to variation and was considered relatively unimportant in most cases.

In a durum quality study conducted by Ames et al. (1999), ten very diverse genotypes, from USA and Canada, were grown over eight environments in western Canada. Although this study examined durum quality, it can be noted that environment was found to be the main source of variation for grain protein content and mixograph mixing time to peak development, while genotype played a more important role in gluten quality. The GxE interaction was significant for all quality parameters tested but contributed only a small portion to variation in quality.

Preston et al. (2001) analyzed farinograph and Canadian Short process (CSP) baking properties of wheat grown at six locations in Saskatchewan in one year. The study was conducted during the 1995 growing season and thus the cultivars analyzed are no longer current. The variation due to environment was found to be greater than that of genotype for farinograph absorption, CSP absorption and flour protein. However, genotype variation was greater than environment variation for farinograph dough development time and stability, CSP mixing time, mixing energy and kernel hardness. No significant environmental effect was found for farinograph stability. The GxE interaction was also found to be significant for all quality parameters except farinograph stability, flour protein content, and kernel hardness. The overall contribution of the interaction effect to variation was determined to be relatively small in comparison to the other main effects.

Currently in the Canadian grain system, the evaluation of genotype quality characteristics occurs by pooling genotype samples grown in different trial locations across the Canadian prairies. This has the result of masking the true effect of the environment on a specific genotype. A genotype may perform better in one environment but fail in another, and thus its true quality response to environment is lost. The relative effect of genotype, environment, and genotype by environment interactions should be characterized for all quality characteristics in order to properly assess new wheat lines.

Although several researchers (Fowler and De La Roche, 1975; Baker and Kosmolak, 1977; Lukow and McVetty, 1991; Ames et al., 1999; Preston et al., 2001) have studied the effect of genotype, environment and their interaction on various Canadian spring wheat quality parameters over the past 30 years, the effect of these impacts have not been studied recently using current Canadian genotypes, nor has any recent study completed a comprehensive review of grain, flour, dough, and bread quality characteristics. In addition, none of these GxE studies involving common wheat, spanned an entirely representative growing area of the Prairie provinces.

The major objective of this study was to assess the effects of genotype, environment and GxE interaction on a comprehensive list of technological quality parameters. In addition, the technological quality response of the wheat genotypes to the environment was evaluated in comparison to other studies conducted in different locations and under different testing conditions. This study is unique in that it examined six adapted wheat genotypes, grown under field conditions at widely scattered locations across western Canada. The comprehensive technological quality analysis undertaken is another unique component of this research. The quality analysis covered not only technological quality parameters but also biochemical traits underlying technological quality, which has never been previously examined for Canadian wheat genotypes.

2.3 Materials and Methods

2.3.1 Field Setup

Six spring wheat cultivars from three commercial classes were grown in nine environments on the Canadian prairies during the 2003 and 2004 growing seasons to provide a very diverse range of growing environments. Cultivars included Canada Western Red Spring (CWRS) genotypes AC Barrie, AC Elsa, Neepawa and Superb, Canada Western Hard White Spring (CWHWS) genotype Snowbird, and Canada Prairie Spring (CPS) genotype AC Vista. The genotypes were selected to encompass a wide range in milling and baking quality characteristics for adapted hard spring wheats.

Field sites were established at Regina, Melfort and Swift Current, Saskatchewan and Winnipeg, Manitoba in 2003. In 2004, a fifth site at Carman, Manitoba was added.

The experimental layout in each environment was a randomized complete block design with three replicates. In 2003, Regina, Swift Current and Melfort plots consisted of 16 rows spaced at 23 cm apart, while that at Winnipeg consisted of 20 rows spaced at 20 cm apart. Plot lengths at Regina and Swift Current were 5 m long, at Melfort was 6 m and at Winnipeg were 9 m long. Final harvested lengths were 3 m at Regina and Swift Current, 4.2 m at Melfort and 8.4 m at Winnipeg. The numbers of rows were increased in 2004 to 24 at Swift Current and to 20 at Regina and Melfort. Plot size at Carman was the same as Winnipeg and harvested length was 7 m. All Saskatchewan sites were seeded at a rate of 200 seeds/m^2 and the Manitoba sites were seeded at a rate of 275 seeds/m^2. A low disturbance plot seeder was used at each location. Plots and replicates in Saskatchewan were separated by fall rye and plots in Manitoba were seeded side by side with late seeded spring wheat separating replicates.

Soil tests were conducted prior to seeding at all locations except Melfort where a soil sample was taken the previous fall. Nutrients were then applied as per soil test recommendations at the time of seeding. Broad leaf and grassy weeds were controlled using recommended post emergence herbicides. At the Winnipeg location, Tilt (propiconazole) was applied at the flag leaf stage in 2003 to control leaf disease while in 2004, Folicur (tebuconazole) was applied at anthesis for control of Fusarium Head Blight.

2.3.2 Phenological Development

At each location, phenological observations were recorded every 10 to 15 days for each plot using the Zadoks decimal code (Zadoks, 1974; Tottman, 1987). Observations from emergence to heading were taken from a 1-m row, three or four rows from the edge of the plot, while observations from heading to maturity were taken from 15 random heads. Date of emergence, date of anthesis, and date of maturity observations were made at each site. Date of emergence was defined as the date when 50% of the germinated plants emerged from the soil. Date of anthesis was defined as the date when 50% of the spikes reached anthesis. Date of maturity was defined as the date of maximum dry matter accumulation and the time when kernels reached their maximum weight, usually about 30% moisture.

2.3.3 Agrometeorological Data

Automated weather stations were installed at each location at seeding and air temperature, rainfall, wind speed, relative humidity, solar radiation, soil temperature and soil moisture were collected until harvest on an hourly and daily basis. Hourly and daily average, maximum and minimum values were recorded for each measured weather variable except rainfall, which was hourly and daily totals. Soil moisture was monitored every 10 to 15 days at each location using a neutron probe. Soil water content at the 0-15 cm depth was determined gravimetrically. Soil moisture data was averaged from the 6 plots for each observation date at each location.

2.3.4 Wheat Quality Analysis

Grain samples from each plot at each location were collected and their identity preserved. Replicates at each location were not pooled. The grain was then used for an extensive array of wheat quality analysis. Wheat quality properties examined included grain, flour, dough and bread properties.

2.3.4.1 Grain Properties

A plot combine was used to harvest the center eight rows of the plots, avoiding edge effects. The grain yield was expressed at 13.5% moisture. Moisture was assessed using Labtronics Model 919 Grain Moisture Meter (Labtronics, Winnipeg, MB).

Grain samples from each plot were cleaned on a Carter dockage tester and officially graded by the Canadian Grain Commission (CGC, 2004). Wheat grain protein content (GPC) was determined by AACC Method No. 39-10 using Near-Infrared Reflectance Spectroscopy (NIR) (AACC, 2000). CGC grading also included determination of test weight, fusarium damaged kernels, and level of sprouting damage assessment (CGC, 2004). A minimum of two replications of 250 clean seeds were counted using a seed counter to assess thousand kernel weight (TKW), expressed at 13.5% moisture content. Kernel number per meter square was derived using harvest yield (g m^{-1}) and TKW (g $kernel^{-1}$) data and equation 2.1.

$$\frac{\text{No. of Kernels}}{\text{m}^2} = \frac{\text{Yield (g m}^{-2}\text{)}}{\text{Kernel Weight (g kernel}^{-1}\text{)}} \tag{2.1}$$

2.3.4.2 Flour Properties

Several flour quality parameters were determined to further characterize wheat quality. The following methods were used to analyze the flour quality parameters.

Wheat Milling

Grain samples were tempered to 16.5% moisture content for 24 hr prior to milling. A Buhler Laboratory mill was used to mill approximately 3 kg of wheat to straight grade flour of approximately 14% moisture basis. Flour yield was calculated as (amount of flour recovered from the mill/amount of grain milled)*100. Constant settings were used on the mill which produced different extraction rates for samples. Flour was stored in polyethylene bags and was allowed to mature at room temperature for at least one month before further testing for rheology, baking and biochemical analysis.

Flour Protein

Flour protein content was determined at the Grain Research Laboratory (GRL), Winnipeg, MB, by combustion nitrogen analysis (CNA) (AACC Method 46-30)using a LECO instrument (Model FP-428, LECO Corporation, St. Joseph, MI). Flour protein content was determined by multiplying the measured level of nitrogen by 5.7. Flour protein content was reported on a 14% moisture basis.

Flour protein composition was determined according to the method of Sapirstein and Johnson (2000). This procedure extracted the protein components in three fractions using 50% 1-propanol (v/v) and 50% 1-propanol + 0.1% dithiothreitol (DTT) at 55°C. Initially, the 50% 1-propanol solution was used to extract monomeric proteins (mainly gliadins) and propanol soluble glutenin (low molecular weight glutenin). The insoluble glutenin fraction (high molecular weight glutenin) was then extracted with 50% 1-propanol and 0.1% DTT. Residue protein containing mainly non-gluten protein (Fu and Sapirstein, 1996) was determined by difference. Each protein fraction was reported as a percentage of flour on a 14% moisture basis.

Flour Ash

Flour ash was determined on 3 g of flour according to AACC Method No. 08-01, (AACC, 2000).

Total Flour Pentosans

Total flour pentosans were determined using a rapid and reproducible method as described by Douglas (1981).

Flour Colour

Flour colour was analyzed on each sample using a computerized Minolta spectrophotometer (Model CM-3500d, Minolta Co. Ltd., Osaka, Japan) and Spectramagic software. A flour-water slurry was created by mixing 4 g of flour (14% moisture basis) with 5 ml of water. The flour slurry was then added to an optical glass Petri dish and analyzed. Flour colour characteristics measured included L* (brightness), a* (red-green colour axis with positive = red and negative = green), b* (yellow-blue colour axis with positive = yellow and negative = blue), and percent reflectance across the visible spectrum (400 to 700nm). Reflectance at 546 nm wavelength was determined by extrapolating between the 540 and 550 nm. The 546 nm wavelength was used as this is the standard wavelength used in Agtron Colour measurement according to approved AACC method 14-30 (AACC, 2000).

Starch Damage

Starch damage, a measure of kernel hardness, was analyzed according to approved AACC method 76-31 (AACC, 2000) using the Megazyme procedure. This method used 100 mg of flour sample mixed with 1 ml of fungal α-amylase. Samples were incubated for 10 min at 40^{o}C and then 5ml of H_2SO_4 was added to terminate the reaction. The solution was centrifuged for 5 min and 0.1 ml amyloglucosidase solution was added. Samples were incubated at 40^{o}C for 10 min prior to 4.0 ml of hexokinase enzyme being added. The hexokinase enzyme was substituted in place of the GOPOD reagent for this analysis. Samples were incubated again at 40°C for 20 min. Absorbance at 510 nm was then measured and percent starch damage was calculated.

Falling Number

Approved AACC method 56-81B (AACC, 2000) was used to determine Falling Number for each sample. This method used 7 g of flour mixed with 25 ml of distilled water until all flour was suspended. Sample tube and viscometer-stirrer were placed into a boiling water bath and apparatus was started immediately, recording the time for the viscometer-stirrer to fall.

2.3.4.3 Dough Properties

Farinograph

The farinograph is one of the most widely accepted methods of measuring flour water absorption and dough strength. Optimum flour water absorption (FAB) was determined with a Brabender Farinograph (Brabender Instruments, Inc., South Hackensack, NJ) using Approved Method No. 54-21 (AACC 2000). The farinograph was also used to determine the dough mixing parameters of dough development time (FarDDT), farinograph stability (FarSTAB), and mixing tolerance index (MTI).

10-gram Mixograph

A 10 gram computerized mixograph (National Manufacturing, Lincoln, NE) was used to provide another measure of dough mixing and breakdown characteristics of the flour samples. Ten grams of flour (corrected to 14% mb) was analyzed to a constant dough basis by adding 62% distilled water (25°C) and mixed for 8 min. A constant temperature of 25°C was maintained during mixing by using a water-jacketed mixing bowl. Flours were mixed under the following settings: Mixograph speed 113 rpm; spring setting 12; sampling at 20 points sec^{-1}; top and middle curve smoothing values were set at 499.

Power to Mixing Software (P2M) (RAR Software Systems, Winnipeg, MB) was used to record dough mixing properties. The P2M software created a dough mixing curve based on the measure of torque required to mix the dough in the mixing bowl. Dough mixing parameters generated by the software included mixing time to peak (MTP) (min), peak dough resistance (PDR) (% of full scale torque), peak bandwidth (PBW) (% torque), and work input to peak (WIP) (% torque*min).

2.3.4.4 Bread Properties

The final quality parameters measured were the bread properties, which are considered the most important quality characteristics. Flour samples were prepared and baked using a modified AACC International long fermentation method (AACC Method No. 10-10B) (AACC, 2000). Fleishman's quick rise dry yeast was substituted in place of cake yeast for this bake test. The full formula bake test was performed using 100 g of flour, 6 g of sugar, 1.5 g of salt, 0.75 g of instant active yeast, 4 g of whey, 3 g of shortening, and optimalal water absorption level as determined by the farinograph.

2.3.5 Statistical Analysis

Data for each quality parameter at each location were analyzed by PROC GLM (SAS Institute, 2001) as a randomized complete block design to determine replicate effects within sites. PROC UNIVARIATE was used to check normality and determine outliers using residuals. Homogeneity of variance was tested using Levene's test prior to and after removal of outliers. In order to determine outliers, residuals were plotted and visually examined for outliers. The Proc Univariate procedure provided output of the extreme residual observations for each quality parameter. Outliers were then excluded based on residual values that were obviously higher or lower than the other extreme residual values found. The number of outliers removed ranged from 0 to 4, depending on the quality property. All analysis was completed with the outliers removed.

Error variances across site years were not homogeneous according to Levene's test for the following quality parameters; protein, test weight, soluble protein, total flour protein, residue protein, starch damage, falling number, FarDDT, FarSTAB, MTI, mixograph PBW, and loaf volume. Data were subjected to analysis of variance (ANOVA) using the PROC MIXED procedure, with environment (year by location) and environment by genotype as random effects and genotype as a fixed effect. The statement REPEATED/GROUP=SITEYEAR was added to account for heterogeneous error variances across years. Variance components were estimated using restricted maximum likelihood (REML) and the degrees of freedom method was set to Satterthwaite.

Error variances were found to be homogenous across site years for yield, TKW, kernel number, flour ash, high molecular weight glutenin (HMW), pentosans, farinograph absorption, mixograph mixing time to peak, mixograph peak dough resistance, mixograph work input to peak, and full formula mix time. The PROC MIXED procedure was again used to analyze the data with the estimation method used being REML and the degrees of freedom method set to containment.

The LSMEANS statement was added to determine the least significant difference (LSD) among genotypes at the 5% significance level.

Grade, flour yield and FarSTAB data were found not to be normally distributed and accordingly were not included in the statistical analysis in this chapter. Non-normal variables were removed from ANOVA analysis only but are included in the analysis and results of subsequent chapters.

2.4 Results and Discussion

The 2003 and 2004 growing seasons provided a wide range of growing conditions across the study sites, leading to a very diverse set of wheat quality characteristics. Mean growing season weather conditions are summarized in Table 2.1. The 2003 season provided warmer, dryer conditions for crop growth, with an average growing season temperature range across the sites from 16.5 to 19.2°C and growing season precipitation range from 81 to 200 mm. The 2004 season was much cooler and wetter, with an average growing season temperature range across the sites of 12.9 to 16°C and growing season precipitation from 225 to 370 mm. Due to a severe frost event in parts of Saskatchewan during the grain filling stage in 2004, quality data from Regina 2004, and Melfort 2004 were excluded from analysis. The purpose of this study was to examine the growing season weather impacts on wheat quality. The effects of a severe frost event would mask other growing season weather impacts on wheat quality and thus frost samples were removed.

Table 2.1. Growing season weather conditions at the western Canada study site locations

				------ Growing Season Mean^{z} ------				
Location	Year	Coordinates		Temp^{y}	RH^{x}	Rad^{w}	Wind^{v}	Prec^{u}
Carman	2004	49.50°N	98.03°W	15.5	72.9	209.3	2.6	224.7
Melfort	2003	52.82°N	104.61°W	16.5	62.8	240.0	2.3	136.3
Regina	2003	50.41°N	104.57°W	19.2	58.3	262.4	2.4	87.7
Swift Current	2003	50.27°N	107.73°W	17.6	56.1	267.7	4.3	82.6
Swift Current	2004	50.27°N	107.73°W	13.3	76.5	232.7	5.1	233.6
Winnipeg	2003	49.81°N	97.12°W	18.5	69.3	201.7	1.7	199.6
Winnipeg	2004	49.81°N	97.12°W	16.0	72.8	160.7	2.0	328.9

^{z} Mean daily value between planting and maturity
^{y} Air temperature (°C) at 1.8 m
^{x} Relative humidity (%) at 1.8 m
^{w} Incoming solar radiation (Watts m^{-2} d^{-1}) at 2.3 m
^{v} Wind speed (m s^{-1}) at 2.5 m
^{u} Total precipitation (mm) from planting through maturity

2.4.1 Genotype and Environment Comparisons

Genotype means for all quality parameters averaged across replicates and environments are summarized in Table 2.2. All quality parameters experienced a wide range in means among genotypes. The CPS genotype AC Vista produced the highest yield and kernel weight and the lowest protein content among the six genotypes tested. The lower average grade for AC Vista was also indicative of its lower tolerance to disease and weathering generally found in CPS genotypes. The oldest CWRS genotype, Neepawa (registered in 1969), had the lowest yield and kernel weight with a GPC similar to the newer genotypes. This was also not unexpected as wheat breeding has consistently improved CWRS yields while maintaining grain protein content. It was also apparent in the dough properties (Table 2.2), that Neepawa had a tendency towards weaker dough with significantly lower FarDDT, MTP, PDR and WIP than most or all of the other genotypes. The mean grain protein level was strongly reflected in the flour protein level for each genotype as would be expected.

Table 2.2. Mean[z] grain, flour, dough and bread quality variables of six wheat genotypes grown in 2003 and 2004[y]

Genotype	AC Barrie	AC Elsa	Neepawa	AC Snowbird	Superb	AC Vista	Mean[x]	SD
Grain Property								
Yield (kg ha^{-1})	3849.5*bc*	3965.9*b*	3561.2*c*	4059.7*b*	4069.6*b*	4712.5*a*	4036.4	380.7
1000-Kernel Weight (g)	32.02*c*	30.46*cd*	29.38*d*	30.67*cd*	34.32*b*	37.56*a*	32.40	3.04
Kernel Number m^{-2}	11609.6*c*	12556.4*ab*	11527.9*bc*	12760.9*a*	11409.4*c*	12317.1*abc*	12030.2	584.4
Test Weight (kg hL^{-1})	81.57*a*	80.89*ab*	80.40*b*	81.16*ab*	80.91*ab*	79.00*c*	80.65	0.90
Grade[w,v]	1.33	1.71	1.67	1.38	1.90	2.52	1.75	0.43
Grain Protein Content (%)	14.44*a*	14.74*a*	14.66*ab*	14.31*bc*	14.21*c*	13.12*d*	14.25	0.59
Flour Property								
Flour Yield[v] (%)	74.86	73.68	71.21	73.08	74.09	72.51	73.24	1.28
Flour Ash (%)	0.380*bc*	0.396*ab*	0.383*abc*	0.363*c*	0.407*a*	0.398*ab*	0.388	0.02
Flour Protein (%)	13.94*a*	13.79*a*	13.77*a*	13.57*ab*	13.36*b*	12.16*c*	13.43	0.65
Soluble Protein (%)	9.54*a*	9.39*ab*	9.60*a*	9.13*bc*	9.15*c*	7.77*d*	9.10	0.68
HMW-Glutenin (%)	3.62*a*	3.57*a*	3.34*c*	3.53*ab*	3.65*a*	3.41*bc*	3.52	0.12
Residue Protein (%)	0.78*ab*	0.78*ab*	0.83*ab*	0.89*ab*	0.71*b*	0.94*a*	0.82	0.08
Pentosans (%)	1.65*c*	2.04*a*	1.99*ab*	1.97*ab*	1.90*b*	2.08*a*	1.94	0.15
Starch Damage (%)	5.52*cd*	5.54*cd*	5.68*bc*	5.37*d*	5.87*b*	6.74*a*	5.79	0.49
Flour Colour[u] (%)	85.04*c*	86.41*a*	85.05*c*	85.62*b*	85.30*bc*	86.19*a*	85.60	0.59
Falling Number (sec)	557.90*a*	556.74*ab*	514.17*c*	557.76*a*	490.67*c*	502.64*bc*	529.98	31.02
Dough Property								
Farinograph Absorption (%)	61.50*d*	63.45*ab*	62.96*bc*	62.46*c*	63.13*bc*	64.15*a*	62.94	0.90
Dough Dev. Time (min)	5.77*ab*	6.43*a*	5.08*c*	5.85*ab*	6.30*a*	5.96*bc*	5.90	0.48
Farinograph Stability (min)	10.97*b*	13.27*ab*	11.30*ab*	11.55*ab*	13.88*ab*	14.85*a*	12.64	1.59
Mixing Tolerance Index (BU)	37.95*a*	40.00*a*	37.23*a*	36.00*a*	32.85*a*	36.66*a*	36.79	2.36
Mixing Time to Peak (min)	2.88*a*	2.49*bc*	2.36*c*	2.72*ab*	2.81*a*	3.00*a*	2.72	0.24

Table 2.2 Cont'd	AC Barrie	AC Elsa	Neepawa	AC Snowbird	Superb	AC Vista	Mean[x]	SD
Peak Dough Resistance (% torque)	58.14*b*	61.79*a*	54.30*d*	56.75*c*	58.13*bc*	58.89*b*	58.00	2.47
Peak Bandwidth (% torque)	25.11*a*	24.20*a*	21.15*b*	24.13*a*	25.07*a*	24.53*a*	24.03	1.47
Work Input to Peak (% torque*min)	111.18*ab*	104.58*b*	88.63*c*	108.29*ab*	109.82*ab*	117.31*a*	106.64	9.76
Bread Property								
Full Formula Mix Time (min)	4.36*a*	3.44*b*	3.57*b*	4.46*a*	4.31*a*	4.51*b*	4.11	0.47
Loaf Volume (cc)	965.50*b*	1023.93*a*	927.62*c*	938.63*c*	1002.02*ab*	855.00*d*	952.12	60.07

[z] Means of three reps and seven environments
[y] Within rows, means followed by the same letter are not significantly different according to LSD (P<0.05)
[x] Mean of six genotypes and seven environments
[w] Grade based on Canadian Grain Commission scale: 1 = No. 1, 2 = No. 2, 3 = No.3, 4 = No. 4, 5 = CW Feed
[v] Non-normal data
[u] Agtron equivalent % reflectance at 546 nm

AC Vista, with the lowest flour protein content, had the lowest loaf volume, another relationship that would be expected. The link between flour protein and loaf volume was not entirely consistent. For example, Neepawa had a significantly lower loaf volume than Barrie and Elsa, despite the fact that the flour protein level among these three genotypes was not significantly different.

Very wide ranges in quality parameter means were also detected among environments. Environment means for all quality parameters averaged across replicates and genotypes are summarized in Table 2.3.

2.4.2 Genotype Effect

The effect of genotype on the quality parameters was investigated by analysis of variance. ANOVA indicated a highly significant difference ($p<0.0001$) among the six genotypes for yield, GPC, TKW weight, test weight, starch damage, soluble protein, total flour protein, pentosans, flour colour, FAB, PDR, WIP, and loaf volume at each environment as well as across all environments. A significant difference at $p<0.01$ was found among the six genotypes for HMW Glutenin, Falling Number, and FarDDT. For kernel number and flour ash a significant difference at the $p<0.05$ level was indicated and for FarSTAB, MTI, and residue protein there was not a significant difference among genotypes (Table 2.4). Most of these results are in agreement with previous studies (Fowler and De La Roche, 1975; Lukow and McVetty, 1991; Ames et al., 1999; Preston et al., 2001) which also found significant genotype differences for all quality parameters tested. The reason why a significant difference was not found among genotypes for the parameters of FarSTAB, MTI, and residue protein is unknown. The lack of difference between genotypes could be attributed to the high standards within the Canadian wheat breeding system, which ensures very high quality wheat being produced. LSD mean separations for all quality parameters are summarized in Table 2.2.

The coefficients of variation for all quality properties were determined for each genotype across growing locations (Table 2.5). Superb had the highest CV of the six genotypes for yield, protein, TKW, kernel number, total flour protein, HMW-Glutenin, and FAB (CV=42, 14, 22, 33, 16, 18, and 4%, respectively). The higher CV indicated that Superb tended towards being less stable and more variable across growing locations for these quality traits. Conversely, Superb was the most uniform in regards to starch damage, farinograph dough development time, full formula mix time and had the second lowest CV for flour colour and loaf volume (CV=39, 12, 1.1, 8.8%, respectively). In general, Superb appeared to be more variable in its grain characteristics but not as variable in its dough and bread characteristics in comparison to the other genotypes. These characteristics would make this genotype less predictable for western Canadian producers because of the grain yield, and grain protein content variability but more predictable for millers and bakers due to more consistent bread making characteristics. Snowbird had the most stable flour properties of all the genotypes with the most stable grain protein content, flour protein content, and protein composition. AC Barrie seemed to be more environmentally stable compared to Superb with only two quality parameters CVs (residue protein and full formula mix time) ranked highest among the six genotypes. In general, AC Barrie and Snowbird were the least variable genotypes and AC Elsa and Superb were the most variable.

Table 2.3. Mean[z] grain, flour, dough and bread quality variables of spring wheat grown at seven environments in 2003 and 2004

Environment	Carman 2004	Melfort 2003	Regina 2003	Swift Current 2003	Swift Current 2004	Winnipeg 2003	Winnipeg 2004	Mean[y]	SD
Grain Property									
Yield (kg ha^{-1})	4997.7	5857.3	3119.8	1237.3	4196.9	4474.6	4371.3	4036.4	1485.8
1000-Kernel Weight (g)	34.72	39.93	33.14	20.80	32.92	35.71	30.09	32.47	5.97
Kernel Number m^{-2}	14399.7	14762.6	9419.3	5947.5	12713.3	12481.4	14487.6	12030.2	3255.9
Test Weight (kg hL^{-1})	81.21	83.91	82.93	74.11	81.25	82.53	78.94	80.69	3.31
Grade[x, w]	2.39	1.11	1.00	2.17	1.00	2.44	2.17	1.75	0.68
Grain Protein Content (%)	14.34	14.49	14.56	16.75	15.44	10.71	13.71	14.29	1.86
Flour Property									
Flour Yield (%)	73.36	74.90	74.06	72.98	74.84	72.93	69.61	73.24	1.80
Flour Ash (%)	0.37	0.38	0.40	0.39	0.37	0.42	0.39	0.39	0.02
Flour Protein (%)	13.72	13.26	13.29	15.97	14.89	9.86	12.99	13.43	1.90
Soluble Protein (%)	9.08	9.22	9.05	10.55	9.91	6.85	8.87	9.08	1.15
HMW-Glutenin (%)	3.63	3.41	3.61	4.09	3.93	2.58	3.40	3.52	0.49
Residue Protein (%)	1.00	0.63	0.62	1.33	1.02	0.39	0.72	0.82	0.32
Pentosans (%)	1.78	2.25	2.06	1.84	1.82	1.94	1.86	1.94	0.17
Starch Damage (%)	5.86	6.09	5.95	4.67	5.48	6.57	5.90	5.79	0.59
Flour Colour[v] (%)	85.05	86.31	85.94	84.59	85.43	87.01	84.87	85.60	0.87
Falling Number (sec)	509.19	537.61	504.11	607.33	636.08	487.17	428.36	529.98	71.37
Dough Property									
Farinograph Absorption (%)	62.31	66.64	63.80	62.58	62.43	61.72	61.11	62.94	1.83
Dough Development Time (min)	4.29	6.59	8.07	9.09	6.86	1.95	4.15	5.86	2.50
Farinograph Stability[w] (min)	6.86	10.81	22.76	24.91	11.65	5.31	8.21	12.93	7.79
Mixing Tolerance Index (BU)	65.28	28.61	18.61	18.72	32.22	44.82	49.72	36.86	17.26

Table 2.3 cont'd	Carman 2004	Melfort 2003	Regina 2003	Swift Current 2003	Swift Current 2004	Winnipeg 2003	Winnipeg 2004	Mean[y]	SD
Mixing Time to Peak (min)	2.02	2.23	2.98	3.11	2.44	4.03	2.25	2.73	0.70
Peak Dough Resistance (% torque)	63.17	57.98	56.41	62.81	66.14	39.09	58.53	57.73	8.91
Peak Bandwidth (% torque)	28.66	21.71	21.99	26.89	29.24	14.00	25.99	24.07	5.33
Work Input to Peak (% torque*min)	89.30	87.18	114.27	126.29	110.66	121.66	96.68	106.58	15.62
Bread Property									
Full Formula Mix Time (min)	3.38	3.38	4.23	4.68	4.10	5.34	3.65	4.11	0.72
Loaf Volume (cc)	997.78	952.06	919.17	1044.86	1026.53	744.85	968.06	950.47	100.42

[z] Means of three reps and six genotypes
[y] Mean of seven environments and six genotypes
[x] Grade based on Canadian Grain Commission scale: 1 = No. 1, 2 = No. 2, 3 = No.3, 4 = No. 4, 5 = CW Feed
[w] Non-normal data
[v] Agtron equivalent % reflectance at 546 nm

Table 2.4. Variance components contribution to variation (percent of total estimate) for environment (E), genotype (G), and G x E interaction effects for grain, flour, dough and bread quality variables of six wheat genotypes grown at seven locations[z]

Variance Component	E	G	G*E	Rep(E)	Error
Grain Property					
Yield	88.56*	5.46****	2.43***	1.81**	1.74****
1000-Kernel Weight	74.71*	18.54****	4.70***	0.01	2.03****
Kernel Number m^{-2}	86.33*	1.78*	5.48***	3.39**	3.00****
Test Weight	88.78*	6.26****	2.73***	0.51*	1.72
Grain Protein Content	78.65*	8.29****	2.53**	6.98*	42.71
Grain Property Average	83.41	8.07	3.58	2.54	10.24
Flour Property					
Flour Ash	13.91NS	9.81*	4.60NS	5.27NS	66.40****
Flour Protein	78.40*	8.97****	3.11*	5.12NS	4.40
Soluble Protein	63.13*	22.58****	4.37*	5.73NS	4.19
HMW-Glutenin	81.69*	4.41**	5.37**	2.82*	5.72****
Residue Protein	48.59NS	0.00NS	9.33NS	5.33NS	36.74
Pentosans	31.08NS	26.97****	0.00NS	0.88NS	41.06****
Starch Damage	45.37NS	32.80****	9.98*	5.39**	6.46
Flour Colour	51.31NS	25.54****	8.92*	7.17*	7.07
Falling Number	59.36*	10.73***	12.43NS	7.49NS	10.00
Flour Property Average	52.69	14.53	6.15	4.75	21.87
Dough Property					
Farinograph Absorption	63.40*	14.46****	7.51**	2.03NS	12.59****
Dough Development Time	87.38*	2.84**	2.68**	1.69NS	5.41
Farinograph Stability[y]	84.22*	0.85NS	9.95**	1.02NS	3.96
Mixing Tolerance Index	68.55*	0.00NS	9.74*	10.94NS	10.77
Mixing Time to Peak	68.89NS	6.98**	10.17***	7.76*	6.19****
Peak Dough Resistance	81.85*	8.07****	2.72**	4.00*	3.36****
Peak Bandwidth	73.75*	4.82****	0.61NS	1.92NS	18.90
Work Input to Peak	45.06NS	18.82****	10.74**	7.14*	18.24****
Dough Property Average	69.84	8.00	6.31	5.07	10.78
Bread Property					
Full Formula Mix Time	48.90NS	20.50****	16.88***	7.11*	6.61****
Loaf Volume	62.79*	22.87****	1.94*	4.14NS	8.25
Bread Property Average	55.85	21.69	9.41	5.63	7.43
Total Average[x]	66.29	11.46	7.12		

*, **, ***, **** Significance at the 0.05, 0.01, 0.001, and 0.0001 probability levels, respectively; NS is non-significant at 0.05 probability level

[z] Grade, flour yield, and farinograph stability data are non-normally distributed

[y] Non-normal data

[x] Mean % contribution to variation for all quality parameters

Table 2.5. Coefficients of variation (CV) due to environment effect for grain, flour, dough and bread quality variables of six spring wheat genotypes grown in 2003 and 2004[z]

Genotype	AC Barrie	AC Elsa	Neepawa	Snowbird	Superb	AC Vista	Environment CV[y]
Grain Property							
Yield	37.87	36.34	36.89	36.83	42.12	33.64	37.28
1000-Kernel Weight	17.85	16.02	17.72	18.72	21.68	19.38	18.56
Kernel Number m^{-2}	27.23	27.89	26.02	24.88	33.05	27.59	27.78
Test Weight	4.05	4.14	4.53	3.84	4.33	4.10	4.16
Grade[x]	25.00	45.50	32.66	32.47	55.99	66.41	43.01
Grain Protein Content	13.55	14.12	13.33	10.73	14.15	13.64	13.25
Grain Property Average	20.92	24.00	21.86	21.25	28.55	27.46	24.01
Flour Property							
Flour Yield	2.94	2.14	3.66	2.44	1.63	2.85	2.61
Flour Ash	8.00	6.88	8.52	9.44	3.50	5.50	6.97
Flour Protein	14.51	15.71	13.87	12.39	15.84	14.29	14.44
Soluble Protein	12.87	15.07	12.54	11.21	13.70	12.86	13.04
HMW-Glutenin	12.13	13.81	12.12	12.32	17.80	16.46	14.11
Residue Protein	54.70	45.79	50.44	30.48	45.87	39.63	44.48
Pentosans	7.13	10.33	9.42	9.52	10.17	11.43	9.67
Starch Damage	13.02	10.53	12.80	11.65	9.37	9.87	11.21
Flour Colour	1.20	1.27	1.12	1.09	1.08	0.71	1.08
Falling Number	13.43	12.16	12.78	11.05	13.68	23.29	14.40
Flour Property Average	13.99	13.37	13.73	11.16	13.27	13.69	13.20
Dough Property							
Farinograph Absorption	2.92	2.67	2.60	3.27	4.15	2.79	3.07
Dough Development Time	43.12	46.66	40.07	40.26	39.67	50.23	43.33
Farinograph Stability	50.80	68.95	73.56	53.04	53.11	71.81	61.88
Mixing Tolerance Index	40.50	50.63	46.06	59.04	49.15	58.80	50.70
Mixing Time to Peak	32.82	35.53	31.96	25.93	21.80	15.63	27.28
Peak Dough Resistance	16.37	16.22	18.74	16.12	14.70	14.31	16.08
Peak Bandwidth	22.59	25.65	25.17	22.62	21.54	20.87	23.07
Work Input to Peak	16.46	17.68	16.45	20.96	15.61	13.07	16.70
Dough Property Average	28.20	33.00	31.82	30.16	27.46	30.94	30.26
Bread Property							
Full Formula Mix Time	24.68	19.73	23.27	21.92	12.05	16.13	19.63
Loaf Volume	11.08	8.35	11.09	12.78	8.88	14.20	11.06
Bread Property Average	17.88	14.04	17.18	17.35	10.47	15.17	15.35

[z] Mean CV of three reps and seven environments
[y] Mean CV of six genotypes
[x] Grade based on Canadian Grain Commission scale: 1 = No. 1, 2 = No. 2, 3 = No.3, 4 = No. 4, 5 = CW Feed

2.4.3 Environment Effect

ANOVA showed that there were significant differences ($p<0.05$) among the seven site years when genotype means were combined for all quality parameters except for starch damage, flour ash, residue protein, pentosans, flour colour, MTP, WIP, and full formula mix time (Table 2.4). In the Fowler and De La Roche (1975) and Lukow and McVetty (1991) studies, the environment effect was significant for all of the grain, flour, dough, and loaf properties tested. Mikhaylenko et al. (2000) reported that environment significantly influenced protein content, ash content, mixograph absorption and mixing time for soft and hard wheat flours. Preston et al. (2001) also found a significant environment effect on all farinograph and CPS bake test parameters except for farinograph stability. The farinograph stability data in our study was found to be non-normal, but the effect of environment was found to be significant. The reasons why starch damage, flour ash, residue protein, pentosans, flour colour, MTP, WIP, and full formula mix time did not have a significant response to environmental variation in our study is not known. The strong environment contribution to variance and environment CV (Table 2.4 and 2.5) indicated that environment played an important role in determining these quality traits, however it did not appear to be a significant role.

2.4.4 Genotype by Environment Interaction Effect

Analysis of variance indicated that GxE interactions were also significant for all quality parameters except for flour ash, residue protein, falling number and pentosans (Table 2.4). Interactions effects on yield, TKW, kernel number, test weight, MTP and full formula mix time were significant at $p<0.001$, while interactions effects on GPC, FAB, FarDDT, FarSTAB, PDR, WIP, and HMW-Glutenin were significant at the $p<0.01$ level. Interactions effects on soluble proteins, total flour protein, starch damage, flour colour, MTI, and loaf volume were all significant at the $p<0.05$ level. Even though there were significant GxE interactions, the relative GxE contribution to variance was considerably smaller (2 - 17% of variance total) than that of genotype or environment (Table 2.4). Our results are in general agreement with previous studies. Fowler and De La Roche (1975), Baker and Kosmolak (1977), Lukow and McVetty (1991), Ames et al. (1999), Mikhaylenko et al. (2000), and Preston (2001) all found significant yet relatively small GxE interactions for most quality parameters tested. Some conflicting results came from Baker and Kosmolak (1977) who claimed the GxE interaction was important in determining MTP, falling number, and loaf volume. Their field study differed compared to ours in that composite samples from two to four environments were used. Our dough and loaf characteristic results are also supported by findings from Panozzo and Eagles (2000) and Mikhaylenko et al. (2000) who found that there was a significant GxE interaction for farinograph measured parameters and loaf volume.

2.4.5 Relative Influence of Genotype, Environment and GxE Interactions

The relative importance of the growing environment on quality parameters can be clearly seen by comparing the CV across genotypes versus the CV across environments (e.g. Yield genotype CV= 11% versus environment CV = 37%, respectively). For all quality parameters, except flour pentosans and flour ash, the environmental variation was found to be 1.3 to 3.5 times greater than the corresponding variation due to genotype (Table 2.5 compared to Table 2.6). The environmental variation for pentosans and flour ash was only 1.04 and 1.1 times greater than that of genotype variation. This indicates that the environment and genotype were equally important in determining the outcome of flour ash and flour pentosans. For the remainder of the quality parameters, environment played a more important role in determining technological quality as compared to genotype. These results agree with numerous other studies which have shown that environment was the major source of variation for most of the quality parameters tested (Baker et al., 1971; Fowler and De La Roche, 1975; Baker and Kosmolak, 1977; Lukow and McVetty, 1991; Peterson et al., 1992; Gaines et al., 1996; Graybosch et al., 1996; Ames et al., 1999; Mikhaylenko et al., 2000; Panozzo and Eagles, 2000; Preston et al., 2001).

Each variance component estimate (genotype, environment, and GxE interaction) was compared to the total variance components estimate (Table 2.4). The relative magnitude of the environmental contribution to wheat quality variance was considerably larger (62 to 89%) than the variance contribution of either genotype (2 to 26%) or GxE interaction (2 to 16%). Fowler and De La Roche (1975) also found yield, GPC, and test weight to have a large variation response to environment, while flour pigment, MTP, and kernel hardness had a smaller response to environment. Our results indicated a non-significant relationship to environment for starch damage, flour colour and MTP. These differences may have resulted from genotypes grown or environments used. Ames et al. (1999) also found that environment effect was important in determining GPC and MPT, while for gluten quality, genotype effect was greater than environment effect. The Ames et al. (1999) study examined ten very diverse American and Canadian durum genotypes thus leading to the greater genotype effect in certain cases. Preston et al. (2001) found the environment variation to be greater than genotype variation for flour protein, farinograph absorption and CSP water absorption, which is in agreement with our results. However, for kernel hardness, FarDDT and FarSTAB they found the genotype effect was greater than the environment effect. Preston et al. (2001) used fourteen genotypes in their study, potentially representing more genetic diversity compared to this thesis research study. Also, only six growing sites were studied over one year in Preston et al. (2001), spanning a much smaller land area and therefore a smaller range in environments in comparison to our study. Lukow and McVetty (1991) reported that the environment effect was pronounced for all quality parameters but the genotype variance component was greater in all cases. This may be due to the fact that their study covered only three sites over two years in Manitoba, resulting in less environmental variability compared to this study. Eight genetically diverse genotypes were used in the Lukow and McVetty (1991) study. Several other genotype x environment studies on wheat quality have shown similar results to this thesis research with the relative magnitude of the genotype x environment interaction effect being considerably smaller than either genotype or environment (Busch et al., 1969; McGuire and McNeal, 1974; Fowler and De La Roche, 1975; Baker and Kosmolak, 1977; Baenziger et al., 1985; Lukow and McVetty, 1991; Peterson et al., 1992; Ames et al., 1999; Mikhaylenko et al., 2000; Preston et al., 2001).

The relative importance of genotype and environment on wheat quality can be seen by comparing the standard deviation for genotype means (Table 2.1) to the standard deviation for environment means (Table 2.2). The standard deviations for environment means were much greater than the standard deviation for genotype means for all quality parameters tested. The larger environment standard deviation indicated that the

Table 2.6. Coefficient of variation (CV) due to genotype effect for grain, flour, dough, and bread quality variables of wheat grown at seven locations[z]

Environment	Carman 2004	Melfort 2003	Regina 2003	Swift Current 2003	Swift Current 2004	Winnipeg 2003	Winnipeg 2004	Genotype CV[y]
Grain Property								
Yield	11.87	5.16	14.14	15.00	13.83	8.10	12.90	11.57
1000-Kernel Weight	10.49	11.53	13.32	9.05	7.39	9.95	5.48	9.60
Kernel Number m^{-2}	6.70	7.10	12.38	11.28	8.30	4.38	8.02	8.31
Test Weight	1.90	0.70	1.00	1.07	1.70	1.54	1.05	1.28
Grade[x]	32.32	15.49	0.00	65.09	0.00	47.76	21.21	25.98
Grain Protein Content	5.78	4.50	4.93	3.50	4.87	2.95	7.08	4.80
Grain Property Average	11.51	7.41	7.63	17.50	6.02	12.45	9.29	10.26
Flour Property								
Flour Yield	2.59	1.31	1.97	1.31	1.79	2.02	2.99	2.00
Flour Ash	9.68	4.23	4.83	3.43	7.54	5.83	8.43	6.28
Flour Protein	6.82	5.62	5.83	3.60	5.72	3.72	7.86	5.60
Soluble Protein	8.42	8.81	7.90	6.56	8.34	6.10	10.32	8.06
HMW-Glutenin	5.16	5.01	5.69	4.43	4.98	5.26	5.50	5.15
Residue Protein	29.03	32.84	26.06	13.71	20.18	32.90	28.12	26.12
Pentosans	8.34	8.48	11.25	7.77	8.92	11.58	8.42	9.25
Starch Damage	10.49	10.14	11.27	7.93	10.94	5.89	10.38	9.58
Flour Colour	0.81	0.69	0.91	0.99	0.82	0.67	0.67	0.79
Falling Number	8.69	4.78	5.36	6.14	5.85	5.60	19.56	8.00
Flour Property Average	9.00	8.19	8.11	5.59	7.51	7.95	10.23	8.08
Dough Property								
Farinograph Absorption	1.41	1.53	2.13	1.94	1.76	1.84	2.10	1.82
Dough Development Time	13.04	9.44	14.14	7.33	10.54	13.12	19.76	12.48
Farinograph Stability	19.92	9.53	19.91	21.32	21.15	22.18	9.92	17.71
Mixing Tolerance Index	15.44	21.30	15.42	9.45	32.00	28.20	11.50	19.04
Mixing Time to Peak	16.49	7.41	14.14	15.65	15.27	9.44	15.18	13.37
Peak Dough Resistance	6.76	5.41	4.71	5.40	4.61	9.69	6.68	6.18
Peak Bandwidth	6.88	13.21	7.33	10.87	6.28	8.07	7.22	8.55

Table 2.6 cont'd	Carman 2004	Melfort 2003	Regina 2003	Swift Current 2003	Swift Current 2004	Winnipeg 2003	Winnipeg 2004	Genotype CV[y]
Work Input to Peak	15.19	12.39	12.15	13.34	13.35	9.14	11.73	12.47
Dough Property Average	11.89	10.03	11.24	10.66	13.12	12.71	10.51	11.45
Bread Property								
Full Formula Mix Time	11.87	10.35	14.93	17.66	15.01	14.03	17.12	14.43
Loaf Volume	6.14	4.94	8.06	5.46	5.38	12.85	6.26	7.01
Bread Property Average	9.01	7.65	11.50	11.56	10.19	13.44	11.69	10.72

[z] Mean CV of three reps and six genotypes
[y] Mean CV of seven environments
[x] Grade based on Canadian Grain Commission scale: 1 = No. 1, 2 = No. 2, 3 = No.3, 4 = No. 4, 5 = CW Feed

environment is more important for creating variability in wheat quality than that of genotype.

Quality parameters which appeared the most sensitive to environment included yield, test weight, kernel number, FarDDT, and FarSTAB, which all had environmental variation more than three times larger than genotypic variation (Table 2.5 compared to Table 2.6). The dough properties, excluding farinograph absorption, appeared to be more sensitive to environment than grain, flour, or loaf properties (Table 2.5). The average environment CV for the dough properties was 30% compared to 24% for grain and 15% for flour properties respectively.

Quality properties such as test weight, farinograph absorption, and flour yield had much lower CVs in comparison to all other quality parameters (Tables 2.5 and 2.6). However, even though the CV was lower for these characteristics overall, environment CV was much greater than genotype CV (1.3 to 3.25 times greater).

In comparison to the other quality parameter classes, the grain properties had the greatest environmental contribution to variation on average (Table 2.4). On the other hand, the bread making and flour characteristics had the most genotypic contribution to variation. The dough properties appeared to have the highest GxE interaction contribution to variation.

2.5 Conclusions

For all of the quality parameters tested, the environment related variation was larger than the genotype related variation. This clearly demonstrates the importance of growing season weather impacts on wheat yield and technological quality characteristics. There were significant environmental effects for all quality parameters tested except starch damage, flour ash, residue protein, pentosans, flour colour, MTP, WIP, and full formula mix time. This was generally in agreement with earlier work; however, others have found significant environmental effects on flour ash and mixing time. Significant genotype effects were noted for all quality parameters except FarSTAB, MTI, and residue protein. Significant genotype by environment interactions were also found for all quality parameters except flour ash, residue protein, falling number and total flour pentosans. The contribution of the GxE interaction to total variation was considerably less than either genotype or environment.

During the development of new wheat lines, quality characteristics are analyzed based on a pooled sample from across the Prairies. This fact combined with the results from this study, which showed significant environment effects on most quality characteristics, indicates that experimental line samples should not be pooled across environments. Knowledge of environment, genotype and GxE interaction effects on end-use quality may facilitate improved experimental line selection ability. The relative effect of genotype, environment, and genotype by environment interactions should be characterized for all quality characteristics in order to properly assess new wheat lines.

This study has provided a comprehensive assessment of Prairie wide regional variation in bread making characteristics. The determination of the significance of the genotype, environment and genotype by environment interactions effect on wheat technological quality was an initial step in this overall project. Quantification of the growing season weather impacts on wheat quality using the comprehensive weather data collected at each location was performed in the next study (Chapter 3) to determine which components of growing season weather were affecting each quality characteristic.

This facilitated development of predictive models for wheat quality based on growing season weather (Chapter 3).

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3. GROWING SEASON WEATHER IMPACTS ON BREAD-MAKING QUALITY OF SIX CANADIAN HARD SPRING WHEAT GENOTYPES

3.1 Abstract

Wheat technological quality traits are extremely vulnerable to growing season weather conditions. Environmental conditions have been found to contribute significantly more to quality variation compared to genotype or genotype by environment interactions contribution to variation. The large contribution by environment to quality variation suggests the potential to predict quality using weather data. The objectives of this study were to quantify the weather impacts on wheat quality, relate the growing season weather conditions to technological wheat quality and to develop pre-harvest wheat quality prediction models using both complex weather variables as well as simple weather variables. The genotypes (CWRS) AC Barrie, Superb, Elsa, Neepawa, (CPS-white) Vista and (CWWS) Snowbird were grown in five locations across the Canadian prairies over two years to provide a total of seven site-years for analysis. Intensive weather data was collected during the growing season at each location and used to calculate accumulated heat stress, useful heat, moisture demand, moisture supply, moisture use and moisture stress variables for numerous crop development stages. Grain, flour, dough and bread properties were examined. The growing season weather conditions experienced in 2003 and 2004 provided a wide range of growing environments for wheat production.

Using the weather and crop development stage information, significant regression equations with high regression coefficients were developed for most quality parameters

using just a single independent weather variable. Moisture related variables explained the majority of the variation for all the grain properties except yield as well as for most of the flour properties. The farinograph measured dough parameters, except FarSTAB, were driven by water related variables and the mixograph measured dough properties by useful heat variables and water stress variables. The bread properties were found to be best predicted using useful heat and heat stress variables. Using the three complex weather variable models, the grain properties R^2 values ranged from 0.57 to 0.95. The flour property regression equations produced R^2 values that ranged from 0.29 to 0.89. R^2 values ranged from 0.65 to 0.92 for the dough properties, while R^2 values ranged between 0.57 and 0.76 for the bread properties. For 13 of the 27 quality parameters studied, R^2 values were above 0.8.

The development of models that use weather variables derived only from daily temperature and precipitation data produced regression equations with R^2 values similar to those from the regression equations developed using complex weather variables. Grain property R^2 values ranged from 0.55 to 0.95. The flour property models produced R^2 values that ranged between 0.22 to 0.87, while the dough and bread properties that ranged from 0.62 to 0.92 and 0.57 and 0.75, respectively. These equations have potential as prediction models for technological wheat quality parameters several weeks prior to harvest.

3.2 Introduction

Wheat is Canada's most important grain crop. Over the past 10 years, Canada's average annual wheat production has ranged from 16.2 to 29.8 million tonnes (FAOSTAT data, 2006), which provided, on average, over $2 billion dollars to western

Canadian wheat producers (CWB, 2005). The economic value of this crop is provided by the excellent processing quality of the grain, which makes it a very important commodity world-wide. The processing quality traits consist of numerous grain, flour, dough, and loaf properties, which are extremely vulnerable to growing season weather conditions. An enormous range of temperature and precipitation conditions occur each year across the vast area of the grain crop region in western Canada. This environmental variability leads to a wide range in wheat quality being produced each year across Western Canada. Wheat quality variability directly affects millers and commercial bakers who require a consistent quality of wheat from shipment to shipment and from year to year to produce uniform high quality products.

Protein content is one of the most important factors influencing bread-making quality of wheat. In situations where end-use quality differs significantly among samples with similar protein content, the differences are generally attributable to variation in protein quality or composition. Genetics and the environment contribute to the variation in protein content and composition. However, studies have shown that environmental contribution to variation is generally greater than genotypic variation (Baker and Kosmolak, 1977; Graybosch et al., 1996; Lukow and McVetty, 1991; Mikhaylenko et al., 2000; Peterson et al., 1992).

The accumulation of the protein fractions is highly ordered in the grain, however it is also asynchronous. Genotype contributes to the amount and size distribution of the polymeric protein in the grain, while environmental factors have been found to significantly alter the rate of individual protein fraction accumulation. Depending on environmental conditions and the duration of the filling period, growth and development can be dramatically affected. This in turn will affect the rate and quantity of each protein fraction synthesized. The environmental variables which affect protein composition include temperature stress, moisture stress, and fertility stress.

Wheat protein is generally classified as albumins, globulins, gliadins, and glutenins. The albumin/globulin fraction composes 15 to 20 per cent of total grain protein (Panozzo et al., 2001; Stone and Savin, 1999; Triboi and Triboi-Blondel, 2001b). However, these protein components do not play a critical role in protein functionality and may only contribute indirectly to bread making quality due to their enzyme content. Albumins and globulins are synthesized mainly within the first 10 days after anthesis (daa) and then synthesis slows significantly for the duration of the filling period (Daniel and Triboi, 2002; Jamieson et al., 2001; Panozzo et al., 2001; Stone and Nicolas, 1996).

The gliadin fraction has been found to represent 30 to 40 per cent of total grain protein (Panozzo et al., 2001; Stone and Nicolas, 1996). Gliadin synthesis begins within the first 10 daa and synthesis continues until mid kernel development (Panozzo et al., 2001; Stone and Nicolas, 1996). The gliadin fraction is typically responsible for dough viscosity when producing bread.

Several studies have shown that glutenin synthesis initially proceeds at a slower rate than that of gliadin. Glutenin synthesis begins within the first 7 to 10 daa and continues at a slow rate until the point where gliadin synthesis decreases (Huebner et al., 1990; Panozzo et al., 2001; Stone and Nicolas, 1996). At this point, glutenin synthesis increases, becoming present in large quantities in the latter half of the grain filling period (Panozzo et al., 2001; Stone and Nicolas, 1996). The glutenin fraction makes up approximately 40% of the protein content in mature wheat. The glutenin polymer is made up of low molecular weight glutenin sub units (LMW-GS) and high molecular weight glutenin sub units (HMW-GS) (Gupta et al., 1996; Panozzo et al., 2001; Zhu and Khan, 1999). LMW-GS and HMW-GS are synthesized concurrently with HMW-GS commencing a few days earlier than LMW-GS (Gupta et al., 1996; Panozzo et al., 2001; Zhu and Khan, 1999). LMW-GS accumulation is greater in the first half of the glutenin synthesis period compared to HMW-GS accumulation, which results in a lower HMW-GS to LMW-GS ratio at this stage. HMW-GS synthesis increases considerably 28 daa and by the time synthesis is completed, the ratio of HMW-GS to LMW-GS is increased significantly (Gupta et al., 1996; Panozzo et al., 2001; Zhu and Khan, 1999). Glutenin polymerization begins at the same time glutenin synthesis begins but the majority of the polymerization process occurs late in kernel development (Gupta et al., 1996; Zhu and Khan, 1999). The glutenin fraction, more specifically HMW polymeric glutenin, is responsible for dough strength and bread quality.

The asynchronous nature of protein accumulation in the developing kernel indicates that the stage at which a stress event occurs will affect the protein fraction accumulating at that stage (Jamieson et al., 2001; Panozzo et al., 2001). There may also be detrimental affects on proteins that have already accumulated and on future protein synthesis. Several studies have shown that each protein fraction reacts differently to an inflicted heat stress (Blumenthal et al., 1993; Ciaffi et al., 1996; Corbellini, 1997; Daniel and Triboi, 2002; Graybosch et al., 1995; Johansson et al., 2005; Johansson et al., 2002; Majoul, 2004; Panozzo and Eagles, 1999; Panozzo and Eagles, 2000; Panozzo et al., 2001; Stone, 1998; Stone and Nicolas, 1996; Triboi and Triboi-Blondel, 2001b; Triboi et al., 2003).

Many studies have examined the impacts of genotype (G), environment (E) and their interactions on various wheat quality parameters. The general conclusion of these studies is that G, E, and GxE are all significant in contributing to quality variation. However, in most cases environment is the main contributor to quality variation (Ames et al., 1999; Baker and Kosmolak, 1977; Baker et al., 1971; Fowler and De La Roche, 1975; Graybosch et al., 1995; Lukow and McVetty, 1991; Mikhaylenko et al., 2000; Panozzo and Eagles, 2000; Peterson et al., 1992; Peterson et al., 1998; Preston et al., 2001; Zhang et al., 2004). Due to the strong environmental impact, several studies have looked at the impacts of some specific environmental parameters, such as heat and water stress, on wheat yield and quality.

3.2.1 Temperature Effect on Protein

Of the protein fractions, the gliadin proportion has been found to be the most significantly affected by high temperature stress (Blumenthal et al., 1993; Ciaffi et al., 1996; Corbellini, 1997; Daniel and Triboi, 2000; Daniel and Triboi, 2001; Panozzo and Eagles, 2000; Panozzo et al., 2001; Stone and Nicolas, 1996). There are two main viewpoints regarding gliadin synthesis. In the first, the rate of gliadin synthesis has been found to increase in response to heat stress, but the total quantity of gliadin in the grain decreases overall due to a shortening of the filling period (Blumenthal et al., 1993; Borghi, 1995; Ciaffi et al., 1996; Daniel and Triboi, 2000; Daniel and Triboi, 2001; Daniel and Triboi, 2002; Stone and Nicolas, 1996). Other research has indicated that the rate of gliadin synthesis is not increased with increasing temperature; it is simply less negatively affected by heat stress compared to glutenin synthesis and therefore decreases less than glutenin synthesis (Altenbach et al., 2002; Jamieson et al., 2001; Perrotta et al., 1998; Stone and Nicolas, 1996). In either case, the result is an increase in the gliadin to glutenin ratio, which ultimately leads to decreased dough strength (Blumenthal et al., 1993; Daniel and Triboi, 2000; Daniel and Triboi, 2001).

The glutenin fraction has been found to decrease in quantity in the kernel with temperature stress during filling. A reduction in the proportion of SDS-insoluble polymer relative to SDS-soluble polymer has also been observed by a number of researchers (Ciaffi et al., 1996; Corbellini, 1997; Stone and Nicolas, 1996; Stone et al., 1997), which indicates a reduction in glutenin polymerization. Since polymerization does not occur on a large scale until later during the filling period the most notable reduction in polymerization occurs when a heat stress event occurs late during the filling period (Corbellini, 1997). Generally, stresses which shorten the duration of the filling period will negatively affect the accumulation of individual protein fractions, especially those that are laid down late in the filling period. The potential for glutenin synthesis is decreased with temperature stress due to the shortening of the filling period as glutenin synthesis begins later in the filling period. This indicates that the gliadin to glutenin ratio will increase with increased temperature stress. The reduction in polymerization mentioned above would lead to decreased HMW glutenin. However, recent studies have shown that heat stress was found to decrease protein biosynthesis, rather than protein aggregation (Don et al., 2005; Spiertz et al., 2006). These studies found that under heat stress conditions a smaller amount of HMW glutenin was found but larger particles were formed.

3.2.2 Water Stress Effect on Protein

Several studies have shown that water stress during the grain filling period increases grain protein content (Entz and Fowler, 1988; Simpson et al., 1983; Xu et al., 2006; Xu et al., 2005; Yang and Zhang, 2006; Yang et al., 2000; Yang et al., 2001a). Due to the importance of the accumulation and distribution of N reserves in vegetative organs, moisture stress plays an important role during grain filling. Moisture stress during grain filling has been found to increase protein content by enhancing the remobilization of N to the kernel, decreasing photosynthesis, inhibiting starch synthesis and increasing protein synthesis (Campbell et al., 1997; Guttieri et al., 2001; Jamieson et al., 2001; Xu et al., 2006; Xu et al., 2005; Yang and Zhang, 2006; Yang et al., 2000; Yang et al., 2001a). Generally, under conditions where a plant stayed green longer, an increase in starch accumulation would occur along with a dilution of protein, thus decreasing protein content.

There has been relatively little research investigating water stress effects on protein composition and as a result there is little to report. A drought event results in a shortened grain filling period, which would lead to a reduction of the time available for the accumulation of the larger proteins. A water stress event at a given stage would result in a decrease of the protein fraction that would have developed at that stage and there may be no effect on the previously accumulated proteins or proteins yet to accumulate. Jamieson et al. (2001) speculated that some protein fractions may be more tolerant to water stress compared to other protein fractions, which would again alter the mature grain protein composition. Bunker et al. (1989) found that the gliadin fraction increased when evapotranspiration increased. Evapotranspiration increases when water is not limiting, so conversely, when there is a water stress, gliadin synthesis would be hindered. Daniel and Triboi (2002) reported that the rapid rate of protein polymerization occurred earlier than normal in the kernel when a moisture stress occurred during grain filling.

3.2.3 Starch

Starch comprises the majority of the mass of the wheat kernel, typically making up 60-75% of the total dry kernel weight (Morrell et al., 1995; Triboi and Triboi-Blondel, 2001a). Starch accumulation in the kernel occurs very shortly after fertilization. The filling process is considered to be made up of three phases. During the first phase, the initial lag phase immediately following anthesis, rapid cell division occurs in the endosperm resulting in an accumulation of starch and protein bodies. The kernel size potential is set during this phase depending on the number of cells created. The second phase consists of a constant rate of grain filling, which is determined by genotype as well as environmental conditions during that phase. The third phase occurs when the flow of assimilates to the grain is ceased and is known as physiological maturity (Panozzo and Eagles, 1999). Starch accumulation is also very dependant on assimilate storage in the vegetative tissue and the translocation of assimilates from the vegetative tissue to the kernel. Environmental conditions, moisture stress and heat stress, have been found to affect the remobilization of assimilates to the grain and thus affects grain yield, or starch accumulation (Asseng and Milroy, 2006; Blum, 1998; Campbell et al., 1997; Xu et al., 2005; Yang and Zhang, 2006).

3.2.4 Environment Effect on Starch

Due to the specific stages of starch accumulation, the timing of environmental stresses affect the accumulation and type of starch granules developed. Temperature stress during grain filling has also been found to negatively affect starch synthesis due its impact on the soluble starch synthase enzyme, which appears to be sensitive to heat stress (Blum, 1998; Chinnusamy and Khanna-Chopra, 2003). Water stress which occurs during early grain development curtails the kernel sink potential by reducing the number of endosperm cells and amyloplasts formed. This has the effect of reducing grain weight as a result of a reduction in the capacity of the endosperm to accumulate starch, in rate and duration (Yang and Zhang, 2006).

3.2.5 Objectives

Due to the obvious importance of environment on wheat yield and quality a detailed analysis of the impacts and timing of various weather conditions needs to be addressed. Currently in Canada, forecast models are being used effectively to predict wheat yields. Knowledge of which weather parameters are affecting each of the various quality parameters would allow prediction models to be developed for other technological quality parameters such as protein content or loaf volume. This would have a very significant impact on the grain marketing system in Canada. An early forecast of wheat quality would lead to improved grain sourcing, logistical planning and improved marketing strategies. In order to develop such forecast models, a quantification of weather impacts on wheat quality is needed. Very few studies have analyzed a comprehensive list of quality variables in relation to weather conditions nor has any previous research attempted to relate such a comprehensive list of weather variables to end use quality.

The major objective of this study was to quantify the impact of weather on hard spring wheat and relate those weather conditions to variations in grade and bread making quality characteristics. This study was also conducted to develop pre-harvest prediction models for wheat grain, flour, dough, and bread properties using detailed, high frequency weather data. In addition, we examined the utility of simple weather variables to predict wheat quality characteristics prior to harvest.

3.3 Materials and Methods

3.3.1 Field Setup

Six hard spring wheat genotypes, from three commercial classes, were grown in seven sites during the 2003 and 2004 growing season. Each site consisted of three replicates organized in a randomized complete block design. Details are provided in Chapter 2.

3.3.2 Agrometeorological Data

Automated weather stations were installed at each location at seeding and air temperature, rainfall, wind speed, relative humidity, solar radiation, soil temperature and soil moisture were collected until harvest on an hourly and daily basis. Air temperature and relative humidity were measured at 1.8 m height with a radiation shielded probe (CS 500, Campbell Sci., Logan, Utah). Incoming solar radiation was measured at 2.0 m with a silicon pyranometer (Model SP-LITE, Kipp & Zonen, Netherlands). Wind at 2.5 m (Cup Anemometer, Model 3102, RM-Young Co. Traverse City, MI) and rainfall (Tipping

Bucket Rain Gauge, Model TE-525mm, Texas Electronics, Houston, TX) were also measured. The data loggers were programmed to log each sensor every 10 s and to output both hourly and daily averages, sums, and maximum and minimum values.

3.3.3 Soil Moisture Measurements

Prior to planting, six random soil samples were collected at depths of 0-15 cm, 15-30 cm, 30-45 cm, 45-60 cm, 60-90 cm, and 90-120 cm to determine initial soil moisture. Immediately following harvest each plot was sampled at depths of 0-15 cm, 15-30 cm, 30-45 cm, 45-60 cm, 60-90 cm, and 90-120 cm to determine final soil moisture content.

Soil moisture was monitored every 10 to 15 days at each growing location using a neutron probe (Troxler Laboratories, Triangle Park, NC). Neutron access tubes were installed to a depth of 150 cm into each Barrie and Superb plot between the 3rd and 4th rows, 1m meter within the plot. Neutron readings were taken at 12.5 cm, 22.5 cm, 37.5 cm, 52.5 cm, 75 cm, and 105 cm to provide a neutron count for the corresponding horizons of 0-15 cm, 15-30 cm, 30-45 cm, 45-60 cm, 60-90 cm, 90-120 cm. A calibration curve was developed for each site using gravimetric soil samples collected near access tubes. The calibration equation was used to produce volumetric moisture content data from the neutron counts from the six access tubes. Soil water content at the 0-15cm depth was determined gravimetrically. Soil moisture data was averaged from the 6 plots for each date at each location.

Soil characteristics were determined for each site, including particle size analysis, bulk density, field capacity and permanent wilting point.

The soil types were as follows: Regina, silty clay (0-15 cm), clay (15-120 cm); Swift Current, silty loam (0-120 cm); Melfort, silty clay loam (0-30 cm), clay (30-120 cm); Winnipeg, silty clay (0-120 cm); Carman, sandy loam (0-30 cm), clay (30-120 cm).

3.3.4 Environmental Parameters

Several environmental parameters were examined in order to quantify the weather impacts on wheat quality. Using the high frequency weather station data along with the soil moisture measurements collected at each location numerous weather variables were derived. These environmental parameters ranged from very simple (eg. cumulated rainfall) to more complex derived variables. They can be broken down into four main groups; useful heat, heat stress, moisture variables and non-temperature/moisture related variables.

3.3.4.1 Useful Heat

Useful heat, or the required heat to grow and mature a crop, was quantified using two methods in this study. The simplest useful heat parameter calculated was growing degree days (GDD) with base temperatures ranging from 3 through 10^{o}C (Equation 3.1). The GDD concept is simply the accumulation of heat in a day, above a minimum, that is available for plant growth.

$$GDD_{3-10} = \sum_{Stage1}^{Stage2} \frac{T_{\max} + T_{\min}}{2} - T_{base} \qquad (3.1)$$

The other useful heat variable investigated was physiological days (Pdays) (Sands et al., 1979). Pdays incorporate a minimum, maximum and optimum temperature into an equation, where the optimum temperature is weighted more than the minimum and maximum, creating a bell shaped crop growth curve (Equation 3.2). For this study, 46 different combinations of minimum, optimum, and maximum temperatures were calculated with minimum temperatures from 4 to 6°C, optimum temperatures from 17 to 25°C and maximum temperatures from 30 to 35°C.

$$Pdays = \frac{1}{24}(5 \times P(T_1) + 8 \times P(T_2) + 8 \times P(T_3) + 3 \times P(T_4)) \qquad (3.2)$$

Where:

$$T_1 = T_{\min}$$

$$T_2 = \frac{(2 \times T_{\min}) + T_{\max}}{3}$$

$$T_3 = \frac{T_{\min} + (2 \times T_{\max})}{3}$$

$$T_4 = T_{\max}$$

$P = 0$	*when* $T <= Tmin$
$P = k * \{1-[(T-Topt)^2 / (Topt-Tmin)^2]\}$	*when* $Tmin <= T < Topt$
$P = k * \{1-[(T-Topt)^2 / (Tmax-Topt)^2]\}$	*when* $Topt <= T < Tmax$
$P = 0$	*when* $T >= Tmax$

3.3.4.2 Heat Stress

The temperature influence on wheat quality was also examined by calculating heat stress variables. Using daily max and min temperatures, a daily temperature range was calculated. The daily temperature range was summed over each development stage to provide temperature stress variables. Two other heat stress parameters were calculated, degree days above a threshold temperature and degree hours above a threshold temperature. Degree days and hours above a threshold were calculated using [time*(T-T_B)], where time is the amount of time the temperature was above the threshold, T is the mean hourly or daily temperature, and T_B is the threshold temperature. Degree hours and days were accumulated over each development period. The threshold values examined for degree days ranged from 15 to 30^{o}C while the threshold values set for degree hours ranged from 25 to 30^{o}C.

3.3.4.3 Moisture Variables

Several soil moisture parameters were calculated to quantify moisture impacts on wheat quality. The moisture variables can be classified into several categories, which include moisture supply, moisture demand, moisture use, and moisture stress.

3.3.4.3.1 Moisture Supply

The most basic moisture variable investigated was the supply variable of accumulated precipitation. Moisture supply was also quantified using monthly percent of normal and monthly Standardized Precipitation Index (SPI).

Monthly percent of normal precipitation values were calculated as the monthly precipitation divided by the monthly normal value. The monthly normal values were obtained from Environment Canada and taken from a station near each field site (Swift Current CDA, Regina CDA, Melfort CDA, Winnipeg A and Elm Creek).

SPI was calculated by the transformation of non-normal precipitation data to a normal distribution. A program developed by the National Drought Monitoring program (Lincoln, Nebraska) was utilized for the transformation calculation. The transformed precipitation data have a distribution with a mean of zero and standard deviation of one. The SPI is the difference of the precipitation from the mean, divided by the standard deviation. Therefore, an SPI value of 1 indicates rainfall for that particular period is higher than the mean by 1 standard deviation (McKee et al. 1995). SPI was calculated for a single month, 2 months in a row, 3 months in a row, and 4 months in a row for May through August.

3.3.4.3.2 Moisture Demand

A number of empirical methods were used to estimate potential evapotranspiration (ETp). These included Baier and Robertson (1965) three parameter model, Baier and Robertson six parameter model, Hargreaves et al. (1985) model, ASCE Penman Monteith model and the FAO 56 model. The REF-ET reference evapotranspiration software program (version 2.0) developed at the University of Idaho (Allen, 2000) was used to calculate Hargreaves ETp, ASCE Penman Monteith ETp and FAO56 ETp. Crop water demand, water use, water use/demand ratio, and water deficit were later calculated using ETp derived from each model.

The Baier and Robertson (1965) three parameter method used daily maximum temperature, daily temperature range along with solar radiation at the top of the atmosphere. Another simple means of ETp estimation used was the Hargreaves et al. (1985) method which used daily mean temperature, daily temperature range and extraterrestrial solar radiation.

Three more rigorous ETp determination methods included the Baier and Robertson six parameter method (Baier and Robertson, 1965), ASCE Penman-Monteith method, and FAO56 Penman-Monteith method. The Baier and Robertson six parameter method requires daily maximum temperature, temperature range, solar radiation at the earth's surface, daily wind run, vapour pressure deficit, and solar radiation at the top of the atmosphere. The ASCE Penman-Monteith equation uses similar inputs to the Baier and Robertson six parameter method, except it uses standard aerodynamic resistance, leaf area index and surface relationships for a grass reference crop, as reported by Allen et al. (1998). The FAO 56 Penman-Monteith method, which also uses the same weather inputs as above, is a simplified version of the ASCE Penman-Monteith method that is applied to a 0.12m tall grass reference crop. The differences include simplifications involving latent heat of vaporization, air density and aerodynamic resistance (Allen et al., 1998). Solar radiation at the top of the atmosphere was calculated using the latitude at each study site, which was obtained using a hand held Global Positioning System.

Daily crop water demand was then calculated as daily ETp * daily crop coefficient. The crop coefficient was calculated using neutron probe measured soil moisture and precipitation data to determine actual evapotranspiration (ETa) on a bi-weekly basis for each site. The crop coefficient value was calculated as ETa / FAO 56 reference evapotranspiration (ETo). Calculated crop coefficients were then related to GDD_5 and a model was developed to estimate daily crop coefficient values based on GDD_5 (Appendix A).

3.3.4.3.3 Moisture Use

A water balance method was then used to determine crop water use. Initial soil moisture to 120 cm was determined gravimetrically at the time of seeding. Root growth was simulated using a temperature-based root function, which assumed the root zone to be 5 cm at the time of seeding and increased in depth to a maximum of 120cm halfway between the heading and soft dough stage (Rasmussen and Hanks, 1978). Crop water use was then calculated as the lesser of crop water demand or water supply remaining in the root zone each day.

The Second Generation Prairie Agrimeteorological Model (PAM2), developed at Environment Canada (Raddatz, 1993; Raddatz et al., 1996), was used as another means of estimating daily potential evapotranspiration and actual evapotranspiration. PAM2 simulates crop development and uses fractional leaf area to divide ET into evaporation and transpiration components. Crop water use is determined using a bulk canopy resistance, soil resistance and skin humidity, and a stability adjusted aerodynamic resistance. The available soil moisture is a function of the infiltration of precipitation, rooting depth, top zone moisture (10cm depth) and root zone moisture. PAM2 requires daily temperature extremes, daily precipitation and incidental solar radiation. Upper air data is also used to measure the capacity of the air to vertically transport water through the atmosphere. The parameters produced by PAM2 and used as independent wheat quality explanatory variables were a water demand variable of potential evapotranspiration (PE) and a water use variable of actual evapotranspiration (AE).

3.3.4.3.4 Moisture Stress

Daily moisture deficit was determined as daily crop water use minus daily crop water demand. The final moisture parameter calculated was a daily water use ratio, which was crop water use/crop water demand.

3.3.4.4 Non-Temperature/Moisture Variables

Several non temperature or moisture variables were also investigated for their impacts on wheat quality. The simplest weather variable calculated was calendar days, which is the number of days each development period spanned. Total wind run was the accumulated daily wind run during each development period. Total incoming solar radiation was also accumulated for each development period. The final weather variable calculated was cumulated vapour pressure deficit. This variable was calculated using mean temperature and mean relative humidity (RH) using Equation 3.3.

$$\textit{Vapour Pressure Deficit} = (0.61078\wedge\{[17.269*(\textit{Mean Temp.})] / [(\textit{Mean Temp.})+237.3]\})-(\{0.61078\wedge [(17.269*(\textit{Mean Temp.})] / [(\textit{Mean Temp.})+237.3)]\}*[(\textit{Mean Relative Humidity})/100]) \tag{3.3}$$

A list of all weather variables in the analysis and their abbreviations are presented in Table 3.1.

Table 3.1. Weather variable codes and explanations.

Weather Variable Code	**Description**
Other	
CDays [z]	Calendar days
CumVaporPresDef	Cumulative vapour pressure deficit
TotalWRunKm	Total wind run (km/hr)
TotalGlobRad	Total incoming solar radiation (W m^{-2})
Useful Heat	
GDD3 [z]	Growing degree days, base temperature 3^{o}C (Range of base temperatures utilized was 3 to 10^{o}C)
P5_17_31 [z]	Pdays with min temp. of 5^{o}C, optimum temp. of 17^{o}C and max temp. of 31^{o}C (Range of temperatures utilized were min temp 4 to 6^{o}C, opt temp 17 to 25^{o}C, max temp 28 to 33^{o}C)
Heat Stress	
TempRange [z]	Accumulated daily temperature range (^{o}C)
TmpDegDay30 [z]	Degree days with a max temperature threshold set at 30^{o}C (Range of threshold values utilized was 15 to 30^{o}C)
DegHr30	Degree hours with a max temperature threshold set at 30^{o}C (Range of threshold values utilized was 25 to 30^{o}C)
Moisture Variables	
Moisture Supply	
Precip [z]	Precipitation (mm)
May_Pnor [z]	Percent of normal precipitation for May (Months included were May, Jun, Jul, Aug)
June_SPI [z]	SPI for June (Time periods included were May, Jun, Jul, Aug, May-Jun, Jun-Jul, Jul-Aug, May-Jul, Jun-Aug and May-Aug)
Moisture Demand	
BRET3 [z]	Baier & Robertson three parameter model derived ETp (mm)
HarET [z]	Hargreaves method derived ETp (mm)

Table 3.1 cont'd

Weather Variable Code	Description
BRET6	Baier & Robertson six parameter model derived ETp (mm)
ASCEET	ASCE Penman Monteith derived ETp (mm)
FAOET	FAO 56 Penman Monteith derived ETp (mm)
PE	PAM2nd derived potential evapotranspiration (mm)
BRDem3 [z]	Baier & Robertson three parameter model derived water demand (mm)
HarDem [z]	Hargreaves method derived water demand (mm)
BRDem6	Baier & Robertson six parameter model derived water demand (mm)
ASCEdem	ASCE Penman Monteith method derived water demand (mm)
FAOdem	FAO56 Penman Monteith method derived water demand (mm)
Moisture Use	
BRWU3 [z]	Baier & Robertson three parameter model derived water use (mm)
HarWU [z]	Hargreaves method derived water use (mm)
BRWU6	Baier & Robertson six parameter model derived water use (mm)
ASCEWU	ASCE Penman Monteith method derived water use (mm)
FAOWU	FAO56 Penman Monteith method derived water use (mm)
AE	PAM2nd derived actual evapotranspiration (mm)
Moisture Stress	
BRWUR3 [z]	Baier & Robertson three parameter model derived water use ratio
HarWUR [z]	Hargreaves method derived water use ratio
BRWUR6	Baier & Robertson six parameter model derived water use ratio
ASCEWUR	ASCE Penman Monteith method derived water use ratio
FAOWUR	FAO56 Penman Monteith method derived water use ratio
BRDef3 [z]	Baier & Robertson three parameter model derived water deficit (mm)
HarDef [z]	Hargreaves method derived water deficit (mm)
BRDef6	Baier & Robertson six parameter model derived water deficit (mm)
ASCEdef	ASCE Penman Monteith method derived water deficit (mm)
FAOdef	FAO56 Penman Monteith method derived water deficit (mm)

[z] Variables which can be calculated using only daily maximum-minimum temperature and precipitation data

3.3.5 Phenological Development

At each location, phenological observations were recorded every 10 to 15 days for each plot using the Zadoks decimal code (Tottman, 1987; Zadoks, 1974). Observations from emergence to heading were taken from a 1-m row, three or four rows from the edge of the plot, while observations from heading to maturity were taken from 15 random heads. Date of emergence, date of anthesis, and date of maturity observations were made at each site. Date of emergence was defined as the date when 50% of the germinated plants emerged from the soil. Date of anthesis was defined as the date when 50% of the spikes reached anthesis. Date of maturity was defined as the date of maximum dry matter accumulation and the time when kernels reached their maximum weight, usually about 30% moisture.

3.3.6 Growing Season Partitioning

Each of the weather variables explained above were accumulated for 18 different crop development stage combinations. The stages analyzed are listed in Table 3.2 along with the abbreviated development stage code.

Table 3.2. Crop development stage combinations with stage code

Stage	Stage Code
Planting to Maturity	Plt_Mat
Planting to Jointing	Plt_Jnt
Planting to Inflorescence	Plt_Infl
Planting to Start of Anthesis	Plt_An
Planting to 50% Anthesis	Plt_An50
Planting to Milk	Plt_Mlk
Planting to Soft Dough	Plt_Dgh
Jointing to Inflorescence	Jnt_Infl
Inflorescence to Start of Anthesis	Infl_An
Inflorescence to 50% Anthesis	Infl_An50
Inflorescence to Milk	Infl_Mlk
Start of Anthesis to Milk	An_Mlk
Start of Anthesis to Dough	An_Dgh
Start of Anthesis to Maturity	An_Mat
50% Anthesis to Milk	An50_Mlk
50% Anthesis to Soft Dough	An50_Dgh
50% Anthesis to Maturity	An50_Mat
Soft Dough to Maturity	Dgh_Mat

Each final weather variable code consists of a weather variable code plus a development stage code (eg. Precip_Plt_Mat is the accumulated precipitation from planting to maturity). There were 54 useful heat variables, 46 of which were different P-day combinations, 23 heat stress variables, 21 moisture supply variables, 11 moisture demand variables, six moisture use variables, 10 moisture stress variables, and four non-temperature/moisture related variables.

3.3.7 Wheat Quality Analysis

Grain samples from each plot at each location were collected and their identity preserved. Replicates at each location were not pooled. The grain was then used for an extensive array of wheat quality analysis. Wheat quality properties examined included grain, flour, dough and bread properties.

Analysis of grain properties included an official grade, grain yield, grain protein content, test weight, thousand kernel weight, and kernel number. Flour properties examined included flour yield, total flour protein, soluble protein fraction (monomeric and low molecular weight (LMW) glutenin), high molecular weight (HMW) glutenin fraction, residue protein fraction, flour ash, total flour pentosans, starch damage, falling number and flour colour. Dough property analysis was completed using the farinograph and 10-gram mixograph. Farinograph parameters measured included farinograph absorption (FAB), farinograph dough development time (FarDDT), farinograph stability (FarSTAB), and mixing tolerance index (MTI). Mixograph analysis included mixing time to peak (MTP), peak dough resistance (PDR), peak bandwidth (PBW), and work input to peak (WIP). Samples were also baked to determine full formula mix time and loaf volume. The detailed methods for all quality parameter determinations are described in Chapter 2.

3.3.8 Statistical Analysis

All statistical analysis was completed using the SAS Institute, Inc. Software, version 9.1 (SAS Institute, 2001). The weather and quality data analyzed were the average of three replicates at each site year. Even though genotypes were found to be significantly different for most quality parameters (Chapter 2), genotypes were not separated in the regression analysis. The PROC REG procedure with the MAXR option was used to determine the best explanatory weather variable for each quality parameter based on the highest R^2 value produced. A single explanatory variable model and a three parameter model were generated for each quality characteristic. Additional models using more independent variables were not reported because there was very little improvement in R^2 and a lack of significance if more explanatory variables were entered into the models. A significance level of 5% or a R^2 increase of 2% was required for a variable entry into the model (Appendix B).

Variables were tested for normality once a relationship model was developed. Non-normally distributed variables were transformed using the box-cox method to find the most appropriate exponent for data transformation. Transformed variables were analyzed again using MAXR to determine if the transformed variable still yielded the highest R^2 value.

This regression process was initially completed using all of the developed weather variables (1982 weather variables in total) to determine the best explanatory variables and models using high frequency weather data. The weather variable data set was then reduced to simpler variables that could be derived with only daily maximum and minimum air temperature and precipitation data (1478 simple weather variables in total). The regression procedure was then repeated using only the simple weather variables.

3.4 Results and Discussion

3.4.1 Growing Season Weather Summary

The 2003 and 2004 growing seasons provided a wide range of growing conditions across the study sites, leading to a very diverse set of wheat quality characteristics. Mean growing season weather conditions are summarized over six development stages in Table 3.3. Clearly, each location experienced a very different set of growing conditions. For example both Regina in 2003 and Swift Current in 2003 received 81 mm of precipitation during the growing season. However, the distribution of the precipitation during the growing season was very different in each case. In 2003, Swift Current received the majority of its rainfall very early in growing season while Regina in 2003 had its rainfall more evenly distributed until the soft dough stage. The timing and duration of heat and moisture stress was also obviously different between locations. Swift Current 2003 received the majority of its heat stress during the anthesis 50% to soft dough stage, while heat stress in Winnipeg 2004 occurred mainly prior to anthesis. Moisture deficit was greatest at Swift Current 2003 (-143 mm) and least at Winnipeg 2003 and 2004 (-15 and -20 mm, respectively).

In general, the 2003 season provided warmer, drier conditions for crop growth, with an average growing season temperature across the sites from 16.5 to 19.2°C and growing season precipitation range from 81 to 200 mm. The 2004 season was much cooler and wetter, with an average growing season temperature range across the sites of

12.9 to 16°C and growing season precipitation from 194 to 329 mm. Due to a severe frost event in parts of Saskatchewan during the grain filling stage in 2004, quality data from Regina 2004, and Melfort 2004 were excluded from analysis. The purpose of this study was to examine the growing season weather impacts on wheat quality. The effects of a severe frost event will mask growing season weather impacts on wheat quality and thus frost samples were removed.

Table 3.3. Summary of weather variables at seven sites over six development stages

	Carman 2004	**Melfort 2003**	**Regina 2003**	**Swift Current 2003**	**Swift Current 2004**	**Winnipeg 2003**	**Winnipeg 2004**
Precipitation							
Plt_Jnt	78	58	32	69	149	131	158
Jnt_Infl	0	34	4	4	23	9	11
Infl_An50	1	17	10	1	1	10	0
An50_Dgh	65	27	35	1	59	45	159
Dgh_Mat	50	4	0	7	13	7	0
Plt_Mat	194	138	81	81	245	200	329
Total Wind Run							
Plt_Jnt	13411	10431	7580	19097	27184	5465	11571
Jnt_Infl	1465	2072	2307	3125	4745	1047	1120
Infl_An50	1074	1703	1693	2068	3186	960	994
An50_Dgh	2103	4735	4187	5944	12348	3817	7311
Dgh_Mat	2103	845	1079	1562	3524	587	2538
Plt_Mat	23033	19529	16686	31499	50702	11670	23408
GDD5							
Plt_Jnt	398	402	409	471	303	461	474
Jnt_Infl	98	111	148	104	130	97	115
Infl_An50	105	99	109	104	102	75	81
An50_Dgh	415	420	365	311	393	437	415
Dgh_Mat	92	92	89	71	83	109	152
Plt_Mat	1095	1115	1104	1045	995	1168	1228
P5_17_31							
Plt_Jnt	333	307	282	351	305	333	381
Jnt_Infl	74	80	86	73	103	60	60
Infl_An50	56	65	67	49	72	46	44
An50_Dgh	285	253	173	137	264	244	331
Dgh_Mat	83	49	36	30	62	47	126
Plt_Mat	822	747	637	633	797	722	934
Degree hours > 28^{o}C							
Plt_Jnt	13	6	56	31	0	3	14
Jnt_Infl	1	22	54	15	0	4	7
Infl_An50	2	2	38	61	2	0	10

Table 3.3 cont'd	Carman 2004	Melfort 2003	Regina 2003	Swift Current 2003	Swift Current 2004	Winnipeg 2003	Winnipeg 2004
An50_Dgh	21	39	166	209	42	28	4
Dgh_Mat	0	9	52	42	0	24	3
Plt_Mat	38	79	359	349	44	59	38
FAOETp							
Plt_Jnt	172	208	165	243	208	143	164
Jnt_Infl	29	43	63	47	51	25	30
Infl_An50	32	38	39	44	42	20	21
An50_Dgh	117	131	124	123	136	100	112
Dgh_Mat	27	23	24	26	30	17	29
Plt_Mat	373	439	409	476	462	303	352
FAO56Demand							
Plt_Jnt	103	120	108	165	99	90	103
Jnt_Infl	26	39	57	42	43	23	28
Infl_An50	30	34	34	36	38	18	18
An50_Dgh	77	80	65	62	103	54	57
Dgh_Mat	4	1	0	1	10	0	0
Plt_Mat	237	271	259	301	290	183	202
FAO56def							
Plt_Jnt	-4	-10	-13	-36	-10	-11	-8
Jnt_Infl	-9	-5	-4	-28	-7	0	-1
Infl_An50	-17	-11	-5	-28	-5	0	-1
An50_Dgh	-43	-34	-18	-54	-33	-4	-10
Dgh_Mat	-1	0	0	-1	-3	0	0
Plt_Mat	-71	-59	-39	-143	-58	-15	-20
Duration of Stage							
Plt_Jnt	45	44	34	48	57	41	48
Jnt_Infl	9	10	11	9	12	7	7
Infl_An50	7	8	8	6	8	5	6
An50_Dgh	35	30	22	18	31	29	39
Dgh_Mat	11	6	5	4	8	6	15
Plt_Mat	105	97	80	84	116	87	114

3.4.2 Wheat Quality Summary

A very wide range in quality parameter means were found among environments. A summary of quality parameter means and the significance of environment, genotype, and GxE interaction to quality variation can be found in Chapter 2.

3.4.3 Prediction of Quality Using High Frequency Weather Data Variables

3.4.3.1 One Variable Model

The initial regression analysis was carried out to develop a single variable model to predict wheat quality using a comprehensive list of explanatory variables. The extensive list of weather variables from the detailed weather data provided the opportunity to see what aspect of growing season weather (useful heat, heat stress, moisture supply, moisture demand, moisture use, moisture stress, or non-temperature/moisture related variables) was explaining the majority of the variation in each quality parameter.

Grain Properties

The grain properties were most highly correlated to growing season weather. Kernel number, test weight, yield and grain protein content (GPC) had very high R^2 values of 0.86, 0.85, 0.80, and 0.74, respectively using only one explanatory variable (Table 3.4).

Moisture related variables explained the majority of the variation for all the grain properties except yield, which was explained best by a heat stress variable. Kernel number was related strongest to a water stress variable, while protein, grade, test weight and 1000-kernel weight were best related to moisture demand, use and supply variables. High temperatures have been found to reduce grain yield due to a reduction in grain weight. The soluble starch synthase enzyme is extremely sensitive to high temperatures and thus starch accumulation would be hindered (Chinnusamy and Khanna-Chopra, 2003; Fokar et al., 1998). Yang and Zhang (2006) found that water stress occurring during early grain development curtails the kernel sink potential by reducing the number of endosperm cells and amyloplasts formed, thus reducing grain weight. Xu et al. (2005) found that irrigation during grain filling enhanced the translocation of assimilates from the leaf to the grain which may explain the positive relationship we found between water supply and test weight and TKW. The positive relationship found between kernel number/m^2 and water deficit early in the growing season does not agree with previous research. Kernel number has previously been found to be determined by growth conditions during spike growth, 30 days prior to anthesis. A water shortage at this time has been found to reduce the kernel number per area (Asseng and Milroy, 2006). Zhang et al. (2005) found that the number of kernels per spike increased when a water deficit occurred during the jointing to booting stage. They stated that a water deficit increased root growth thus improving water and nutrient extraction from the soil. Our results are in closer agreement with this study and indicate that kernel number may be determined earlier than currently thought.

Table 3.4. Grain, flour, dough, and bread properties explained using a single complex weather variable explanatory model.

Quality Parameter	Explanatory Variable	R^2	Equation
Grain Properties			
Yield	TmpDegDay30_Infl_Mlk	0.80***	Yield = -190.64*TmpDegDay30_Infl_Mlk + 5009.194
Protein	FAOET_Plt_Mat	0.74***	Protein = 0.02711*FAOET_Plt_Mat + 3.37801
Grade[z]	BRWU6_Plt_Mlk	0.44***	Grade = -0.02747*BRWU6_Plt_Mlk + 6.35667
Test Weight	Precip_Infl_Mlk	0.85***	Test Weight = 0.27451*Precip_Infl_Mlk+73.8457
TKW	Precip_Infl_Mlk	0.63***	TKW = 0.46539*Precip_Infl_Mlk + 20.93278
Kernel No/m^2	BRDef3_Plt_Infl	0.86***	Kernel Number = 298.6505*BRDef3_Plt_Infl + 17690
Flour Properties			
Flour Yield	AE_Plt_Jnt	0.52***	Flour Yield = -0.08077*AE_Plt_Jnt +81.32717
Flour Ash	TempRange_Plt_Mat	0.27**	Flour Ash = -0.00013*TempRange_Plt_Mat + 0.54609
Pentosans	Aug_SPI	0.31***	Pentosans = -0.1211*Aug_SPI + 1.93636
Starch Damage	BRDef6_Jnt_Infl	0.45***	$(\text{Starch Damage})^{-1.25}$ = -0.00226*BRDef6_Jnt_Infl + 0.10159
Falling Number	GDD5_Plt_Mat	0.66***	Falling Number = -0.87857*GDD5_Plt_Mat + 1502.5966
Flour Colour	GDD10_an50_Dgh	0.60***	Flour Colour = 0.02801*GDD10_an50_Dgh + 78.66341
Soluble Protein	FAOET_Plt_Mat	0.60***	Soluble Protein = 0.01697*FAOET_Plt_Mat + 2.24603
HMW-Glutenin	PE_Infl_Mlk	0.66***	HMW-Glutenin = 0.02463*PE_Infl_Mlk + 0.88173
HMW-G/Sol Ratio	PE_An_Mlk	0.13*	HMW-G/Sol Ratio = 0.000966*PE_An_Mlk + 0.31702
Flour Protein	FAOET_Plt_Mat	0.68***	Flour Protein = 0.02696*FAOET_Plt_Mat + 2.60441
Residue Protein	FAOWUR_An_Mlk	0.51***	Residue Protein = -0.06806*FAOWUR_An_Mlk + 1.44287
Dough Properties			
FAB	Aug_SPI	0.50***	FAB = -1.35449*Aug_SPI + 62.95015
FarDDT	BRDem6_Plt_Mlk	0.81***	FarDDT = 0.08301*BRDem6_Plt_Mlk -10.69597
FarSTAB	TmpDegDay29_An_Dgh	0.85***	FarSTAB = 0.50513*TmpDegDay29_An_Dgh + 5.71533
MTI	BRET3_Plt_Infl	0.63***	MTI = -0.76947*BRET3_Plt_Infl + 215.1818
MTP	BRDef3_Plt_Jnt	0.58***	MTP = -0.09884*BRDef3_Plt_Jnt + 1.60149
PDR	GDD10_An50_Mat	0.60***	PDR = -0.1783*GDD10_An50_Mat + 112.6424
PBW	GDD10_An_Mat	0.64***	PBW = -0.11863*GDD10_An_Mat + 61.86821
WIP	BRDef3_Plt_Jnt	0.45***	WIP = -2.14395*BRDef3_Plt_Jnt + 81.96606
Bread Properties			
Full Formula Mix Time	TempRange_An_Dgh	0.42***	Full Formula Mix Time = -0.01087*TempRange_An_Dgh + 8.40397
Loaf Volume	GDD10_An50_Mat	0.56***	Loaf Volume = -2.15663*GDD10_An50_Mat + 1614.236

[z] Data did not transform to normal

Flour Properties

The flour properties were not as well explained using one explanatory variable compared to the grain and dough properties. The highest R^2 values obtained were 0.68 for flour protein and 0.66 for both Falling Number and HMW Glutenin content (Table 3.4).

Most of the flour properties were also found to be best explained by moisture related variables. Flour protein content and kernel composition parameters were found to be best explained by the non-stress related moisture variables. All protein related variables, except residue protein, were explained by either the FAO56 or PAM2 calculation of potential ET, a water demand variable. These models use several weather parameters (temperature, humidity, wind, and solar radiation) to calculate ETp, indicating that a combination of weather variables affecting atmospheric water demand are driving protein content and protein composition.

Grain protein content, flour protein content, and soluble protein content were driven by ETp from planting to maturity. Blum et al. (1998) stated that reserve accumulation and storage capacity in the stem strongly depended on the growing conditions before anthesis. When a stress occurred during stem elongation, carbon assimilation was limited and therefore storage in stems was reduced. Another study also found that protein content was mainly driven by ETp accumulated over the growing season agreeing with our results (Entz and Fowler, 1988).

ETp increases as growing season weather becomes warmer, windier and sunnier. A high ET rate early in the growing season indicates the plant would be actively growing, photosynthesizing and producing assimilates, therefore increasing the amount of N and C stored in the stem and leading to an increased amount of N available for remobilization to the kernel. High ETp over the entire growing season indicates water demand was high for the crop and thus a water deficit likely occurred. A recent study has shown that a quadratic relationship exists between ETp and wheat yield (Zhang et al., 2005). Yield increased as ETp increased up to a point, then as ET increased past that point a negative relationship resulted. Generally as yield decreases, protein content increases, which would lead to the positive relationship we found between protein and ETp. Another study indicated that the gliadin fraction (soluble protein) increased as ET increased (Bunker et al., 1989), supporting our soluble protein fraction results. ETp during the inflorescence to milk stage explained the majority of the variation in HMW glutenin fraction. A water deficit occurring around heading and initial kernel development has been found to improve remobilization of N to the grain and decrease starch production (Xu et al., 2006; Yang and Zhang, 2006; Yang et al., 2001a; Yang et al., 2001b), resulting in increased protein content in the grain. However, there has not been any research indicating the effect of high atmospheric demand of moisture on protein content during this stage. It could be speculated that if there is a high atmospheric demand for moisture during the filling stage, the plant may be simply compensating by increasing moisture flow to the head to prevent drying of that tissue. If there is a lack of moisture supply, the moisture would be moved from other plant tissues rather than from the soil. Even if there was an adequate moisture supply (i.e. no water deficit), under high atmospheric water demand the plant would need to increase water flow to the head to compensate for the rapid drying that would otherwise occur in the head. This indicates that increased moisture flow to the head under high atmospheric demand may be the mechanism that is transporting N and C to the kernel and this might explain the relationship between ETp and the protein parameters and why water deficit was not a prominent factor.

Dough Properties

The dough properties were also fairly well predicted using only one variable. The most notable being FarDDT and FarSTAB (R^2 = 0.81 and 0.85, respectively), with the rest of the dough properties ranging from R^2= 0.45 to 0.64 (WIP and PBW, respectively) (Table 3.4).

The farinograph measured dough parameters, except FarSTAB, were driven by water related variables. FAB was best described by the water supply variable of SPI for August; this was the same variable that was found to best explain total flour pentosans. Previous research has shown that total flour pentosans are well correlated to FAB (Jarvis, 2006), which explains why the same weather variable was selected for each. Pentosans have a high affinity for water which in turn influences the ability of the flour to absorb water. If rain in August is higher than normal, then pentosans content is reduced thus reducing the FAB. Xu et al. (2006) found that excessive irrigation during the grain filling period reduced the amount of N translocated to the grain. It could be speculated that because N translocation to the grain is reduced, the components required for pentosans development would be reduced as well. With a lower percentage of protein in the kernel there could be a dilution effect of the pentosans by starch.

FarDDT, which is generally related to HMW glutenin and grain protein content, was also explained by a moisture related variable. FarDDT was best explained using a water demand variable accumulated from planting to milk stage (Table 3.4). With an increase in water demand during this stage, FarDDT was found to increase. Our data showed that during this stage, as water demand increased, the water deficit became greater as well. Zhang et al. (2005) found that an early season water deficit helped acclimatize the plant to later water deficits. It was found that root growth, water uptake and nutrient uptake were improved when a water deficit occurred early in the growing season. This would improve the amount of N taken into the plant and being stored in the stem and thus increase the potential for improved N translocation to the kernel during grain filling. As mentioned earlier, remobilization of nutrients may be driven by atmospheric demand drawing moisture to the head to prevent drying. So the relationship between water demand and FarDDT may be due to an indirect relationship to water deficit or by increased translocation due to increased moisture movement to the head.

Farinograph stability, which had a very strong R^2 value (R^2 = 0.85), was best predicted using a heat stress variable. Heat stress above 29^{o}C during the anthesis to soft dough stage was found to increase dough stability. Dough stability is often attributed to the HMW glutenin protein fraction. Most past research conducted on HMW glutenin and heat stress indicated that heat stress late in kernel development decreased the proportion of HMW glutenin (Ciaffi et al., 1996; Corbellini, 1997; Stone et al., 1997). The heat stress experienced in our field study may not have been as severe as the stress experienced in the other research. This could explain the positive relationship this study found between HMW glutenin and heat stress. A recent study by Spiertz et al. (2006) found that heat shock increased the proportion of HMW-glutenin, and Don et al. (2005) found an increased size of glutenin macro polymer with heat stress. These results are in agreement with our findings. Several studies have shown that heat stress during grain filling negatively affects starch biosynthesis, which leads to a lower level of dilution of grain protein (Fokar et al., 1998; Spiertz et al., 2006). HMW glutenins are laid down late in kernel development and therefore, heat stress earlier in kernel development reduces the amount of starch accumulated, and therefore increases the proportion of the HMW-glutenin fraction.

For the mixograph measured dough properties, useful heat variables and water stress variables showed up as the most important explanatory variables. An increase in GDD10, from anthesis to maturity, was found to decrease both the mixograph PDR and PBW. This indicates that useful heat during kernel development increases the strength of the dough most likely due to increased remobilization of N to the kernel. For MTP and WIP increased water deficit early in the growing season decreased these parameters.

Bread Properties

The bread characteristics were not as well predicted as the other quality properties (Table 3.4). The bread properties were found to be best predicted using useful heat and heat stress variables accumulated post anthesis. A weak explanatory model was expected for full formula mix time as the environment did not have a significant effect on this parameter (Chapter 2). For loaf volume, when GDD10 increased during the planting to maturity stage, loaf volume was found to decrease. This could be attributed to the relationship between GDD and calendar days. Generally, if GDD is higher, more calendar days were required to accumulate heat. This would increase the time starch synthesis would occur, thus diluting protein content, which is strongly related to loaf volume.

As shown in Chapter 2, the environment had a smaller impact on both loaf volume and full formula mix time, than the other quality properties. Genotype was found to impact the bread properties more than the other quality properties. This indicated that the variation in these properties would not be explained as well using environmental variables, compared to the other quality properties.

Several quality parameters were not very well predicted using one explanatory weather variable. These included flour ash, pentosans, starch damage, HMW-glutenin/soluble protein ratio, residue protein, WIP, and full formula mix time. The R^2 values for these quality parameters ranged from 0.13 to 0.51. In the previous chapter, it was found that these quality parameters did not have a significant relationship with the growing environment. The environment did not have a significant effect on two other quality parameters, flour colour and MTP. Despite that fact, these quality parameters exhibited moderately high R^2 values (R^2 = 0.60 and 0.58, respectively) when related to weather variables. For these cases, environment was still contributing a large portion to total variation. Grade is another quality parameter that was not well explained (R^2=0.44) with one weather variable. This is most likely due to the non-normal distribution of the grade data.

An extensive analysis of the effect of weather conditions during specific development stages will be completed in Chapter 4.

3.4.3.2 Three Variable Model

Three variable regression models were developed for each quality parameter in order to further improve the ability to predict end use quality (Table 3.5). However, for some quality parameters, two of the three variables were very closely correlated. For example, full formula mix time included degree hours above 30°C and 28°C for the heading to anthesis 50% and heading to beginning of anthesis stages, respectively for two of the three explanatory variables. In this case, the model was reduced to a two variable model. Also, some models were not significant with three variables (Falling Number, flour colour, and FAB). Two variable models are presented in these instances.

The increase in explanatory variables to three increased the average R^2 value by 17%. HMW-glutenin, FAB, farinograph MTI, mixograph PDR, and mixograph PBW all improved their R^2 values by over 22%, while test weight, kernel number/m^2, Falling Number, flour colour, FarDDT, and FarSTAB improved their R^2 values less than 10%. Test weight, kernel number/m^2, FarDDT and FarSTAB had very high R^2 values with only one explanatory variable, which explains the lack of improvement with the additional variables.

Using the three variable model, the grain and dough properties were once again the most predictable quality properties. Several quality parameters produced very strong R^2 values, above 0.9, with the three variable model (Table 3.5). These parameters included yield, test weight, kernel number, FarDDT, and FarSTAB (R^2 = 0.91, 0.92, 0.95, 0.92, and 0.92 respectively). For several more quality parameters, over 80% of the variation was explained with three weather variables. These parameters included GPC,

Table 3.5. Grain, flour, dough, and bread properties explained using a three complex weather variable explanatory model.

Quality Parameter	R^2	Equation
Grain Properties		
Yield	0.91***	Yield = 0.04833*TotalGlobRad_An50_Mlk - 19.68214*GDD5_An_Mlk - 142.78071*TmpDegDay29_Infl_Mlk + 5521.27366
Protein	0.87***	Protein = - 0.01928*GDD10_an50_Dgh - 0.01024*TempRange_Plt_An + 0.04211*FAOET_Plt_Dgh + 10.77189
Grade[z]	0.57***	Grade = -0.13388*BRET6_Infl_An + 0.0406*P5_17_31_Jnt_Infl - 0.02881*HarWU_Plt_Dgh + 7.26509
Test Weight[z]	0.92***	Test Weight = 0.09051*BRWUR6_An_Dgh + 0.20487*Precip_Infl_Mlk + 0.01745*GDD3_Infl_Mlk + 68.99301
TKW[z]	0.79***	TKW = -0.101*BRDef3_An50_Mat + 0.53802*Precip_Infl_Mlk - 0.10453*DegHr28_Plt_Jnt + 17.15029
Kernel No/m^2	0.95***	Kernel Number/m2 = 126.07797*HarET_An50_Mat - 24.02814*DegHr29_An_Dgh - 89.8754*GDD10_An_Mlk + 3675.86386
Flour Properties		
Flour Yield	0.66***	Flour Yield = -0.09254*ASCEET_Dgh_Mat + 0.25745*AE_Infl_An - 0.04821*AE_Plt_An + 78.42577
Flour Ash	0.43***	Flour Ash = 0.00093401*TmpDegDay20_Dgh_Mat - 0.00070174*BRWU3_Infl_Mlk - 0.00133*BRWU6_Plt_Jnt + 0.51057
Pentosans	0.50***	Pentosans = 0.0174*BRET3_Dgh_Mat + 0.00242*Precip_Plt_An - 0.23452*Aug_SPI + 1.15025
Starch Damage[z]	0.61***	Starch Damage = -0.03282*BRET6_An50_Mlk + 0.01257*GDD5b_An_Dgh + 0.07073*Precip_Infl_An + 2.10222
Falling Number[zx]	0.72***	Falling Number = 1.16745*HarET_Plt_Jnt - 0.8193*GDD5b_Plt_Mat + 1212.6352
Flour Colour[x]	0.64***	Flour Colour = 0.02644*GDD10_an50_Dgh + 0.04558*Precip_Infl_An + 78.91538
Soluble Protein[z]	0.73***	Soluble Protein = -0.01531*GDD10_An50_Mat - 0.01559*P5_19_28_Jnt_Infl + 0.0136*P5_17_31_Plt_Infl + 9.41813
HMW-Glutenin[z]	0.89***	HMW-Glutenin = 0.03478*PE_Infl_Mlk - 0.01494*PE_Infl_An + 0.01087*P5_17_31_Plt_Infl - 4.13446
HMW-G/Sol Ratio	0.29**	HMW-G/Sol Ratio = 0.00139*FAOET_An_Mat + 0.00281*FAOET_An_Mat - 0.00112*BRET3_Plt_Dgh + 0.61737
Flour Protein[z]	0.86***	Flour Protein= -0.01582*TmpDegDay15_An50_Mat - 0.01266*TempRange_Plt_An + 0.04996*FAOET_Plt_Dgh + 9.67609

Table 3.5 cont'd

Quality Parameter	R^2	Equation
Residue Protein	0.62***	Residue Protien = -0.14206*ASCEWUR_An_Mlk - 0.01751*TmpDegDay24_Infl_Mlk + 0.02505*TmpDegDay29_Plt_Jnt + 2.88121
Dough Properties		
FAB[x]	0.72***	FAB = -0.02257*TmpDegDay22_Plt_Dgh - 2.78045*Aug_SPI + 68.22861
FarDDT	0.92***	FarDDT = 0.16199*TmpDegDay27_An_Mlk + 0.06119*CumVaporPresDef_Infl_Mlk + 0.00978*TempRange_Plt_Mat - 12.7577
FarSTAB	0.92***	FarSTAB = 0.06656*DegHr28_An_Mat + 1.30585*BRWU6_Dgh_Mat + 0.31766*CumVaporPresDef_Infl_Mlk - 16.8158
MTI	0.86***	MTI = 0.33933*TmpDegDay16_an50_Dgh + 1.05869*P5_19_29_Plt_An - 1.08934*BRET3_Plt_Infl - 250.01727
MTP	0.79***	MTP = -0.00463*Precip_An50_Mat - 0.02529*FAOWU_Plt_Infl - 0.08687*BRDef3_Plt_Jnt + 5.31145
PDR	0.89***	TL_PDR = -0.15464*GDD10_An50_Mat + 0.66429*BRET6_An50_Mlk + 0.00137*TotalWRunKm_Dgh_Mat + 68.65961
PBW	0.87***	PBW = -0.13343*GDD10_An50_Mat + 0.50515*ASCEdem_An50_Mlk - 0.12181*HarET_Plt_Dgh + 92.18276
WIP[z]	0.65***	WIP = -23.74983*BRDef3_Dgh_Mat + 0.52867*AE_Jnt_Infl + 0.35232*GDD10_Plt_Mat - 156.81457
Bread Properties		
Full Formula Mix Time[x]	0.57***	Full Formula Mix Time = -0.01477*TempRange_An_Dgh - 0.01568*DegHr27_Infl_An + 10.20386
Loaf Volume	0.76***	Loaf Volume= -1.92195*GDD10_An50_Mat + 5.67515*FAOET_An_Mlk - 4.09883*Precip_Infl_An + 1205.92545

[z] Data not significantly different from normal at p<0.01
[x] Two variable model

HMW-glutenin, flour protein, MTI, PDR, and PBW (R^2 = 0.87, 0.89, 0.86, 0.86, 0.89, and 0.87, respectively). The ability to predict such parameters as flour protein, and protein quality is very important due to the strong relationship of these parameters to loaf volume. A few quality parameters were still not well explained using three explanatory variables. These included flour ash, pentosans, and HMW-Glutenin/soluble protein ratio (R^2 = 0.43, 0.50, and 0.29, respectively). Again, this is due to a lack of environment influence on these parameters as shown in Chapter 2.

Generally, the type of weather variable explaining the variation in quality was not consistent within a quality parameter or across the main quality groups. Overall, useful heat variables and water demand variables were the most prominent, occurring 25% and 22% of the time, respectively, in the three variable models. Useful heat variables appeared most frequently when explaining the grain properties, while useful heat and heat stress variables were the most frequent variables explaining dough properties. The flour properties appeared to be best explained by water demand variables. The bread properties had a mix of useful heat, heat stress, water supply and water demand variables. Surprisingly, within the 27 quality parameters, water stress variables are included only five times in total for all of the three variable predictor models. Considering previous research indicating the significance of water stress on wheat yield and protein content, it was expected that water stress would explain the variation in wheat quality more frequently (Campbell et al., 1997; Entz and Fowler, 1988; Guttieri et al., 2001; Simpson et al., 1983; Xu et al., 2006; Xu et al., 2005; Yang and Zhang, 2006; Yang et al., 2001a; Yang et al., 2001b). However, very few other studies have examined such a comprehensive list of weather variables. According to our results, the moisture stress measures employed in this analysis explained less of the quality variation than anticipated.

All quality parameter explanatory models included weather variables accumulated post anthesis or later during the kernel development stage. All models also included weather variables accumulated early in the growing season, either just prior to anthesis or from planting to early kernel development, except kernel number and PDR which used all post anthesis variables. This indicates that weather conditions throughout the growing season contribute to overall quality. The most important growth stage affecting each quality parameter will be addressed in Chapter 4.

The three variable explanatory models could predict wheat quality between two to five weeks prior to harvest. Models which included only weather parameters accumulated up to early kernel development would allow a very early estimation of end use quality parameters. Yield, HMW-glutenin, and residue protein could be estimated 4-5 weeks prior to harvest because the weather variables utilized in the model only need to be accumulated until the milk stage. Grain protein content, grade, test weight, starch damage, flour colour, flour protein, FAB, MTI, and full formula mix time could be estimated 3-4 weeks prior to harvest, as the latest stage for which weather data is required is the soft dough stage. The rest of the quality parameters could be estimated with weather variables accumulated up to 2-3 weeks before harvest. These parameters included a weather variable that must be accumulated until maturity, reducing the amount of time before harvest to predict the parameter. This would still allow forecasting 2-3 weeks prior to harvest based on the fact that physiological maturity occurs at 30% kernel moisture content and the crop would not be harvested until it dried to about 14% moisture content.

3.4.4 Prediction of Quality Using Simple Weather Data Variables

The capability to predict wheat quality early in the growing season is very important. Early knowledge of potential quality would improve the ability to market Canada's wheat supply. This study has found that strong relationships between growing season weather and wheat quality using detailed weather data were produced. However, the equipment required to obtain these data is very expensive and most of the weather variables require complex calculations. The ability to predict wheat quality using a simple weather station, which records only daily temperature and precipitation data, would significantly lower the cost of wheat quality forecasting. Therefore, a regression analysis was completed using only those variables that can be derived from daily temperature and precipitation data. These variables are indicated with z in Table 3.1.

3.4.4.1 One Variable Model

As expected, the reduction in the complexity of weather variables and number of explanatory variables used either maintained or reduced the R^2 value in the one variable regression equation (Table 3.6). Obviously, when a simple explanatory variable was selected as the strongest parameter in the complex weather variable models, the same variable would be selected again in the simple weather variable analysis. For example, in the original analysis, yield was explained by the accumulation of the number of degree days above 30°C during the inflorescence to milk stage. This variable was calculated using just daily temperature and thus showed up as the strongest explanatory variable in the simple weather variable analysis.

The grain properties remained the most predictable properties followed closely by the dough properties with an average R^2 of 0.68 and 0.62 respectively. With grade removed from the average, the grain properties had an average R^2 value of 0.75, considerably higher than that of the other quality properties. Again, this was expected due to the large environmental influence on the grain properties reported in Chapter 2.

The type of weather variable explaining each quality parameter changed in a few cases compared to the use of complex weather data. The protein content and composition parameters, along with FarDDT, were the main parameters where the type of weather variable switched. FarDDT probably responded in a similar fashion as the protein related variables due to the strong relationship between FarDDT and HMW-glutenin. For protein related variables, a useful heat variable was selected when the list was restricted to the simple weather variables. More of the variance in protein and its components were explained using more complex rather than simple weather variables.

The growth stage of the useful heat variables affecting the protein related parameters was also different. For the protein parameters the useful heat variable was accumulated post anthesis, whereas the more complex water use variables affected protein early in the growing season. It may be important for the moisture conditions to be favorable early in the growing season for N uptake into the plant for storage in the vegetative organs. Later in the growing season, during kernel development, the temperature conditions may be more important for N translocation to the kernel.

Table 3.6. Grain, flour, dough, and bread properties explained by a single simple weather variable explanatory model

Quality Parameter	Explanatory Variable	R^2	Equation
Grain Properties			
Yield	TmpDegDay30_Infl_Mlk	0.80***	Yield = -190.64043*TmpDegDay30_Infl_Mlk + 5009.19402
Protein	GDD8_An50_Mat	0.61***	Protein = -0.03355*GDD8_An50_Mat + 27.05171
Grade[z]	HarET_Plt_Dgh	0.33***	Grade = -0.02896*HarET_Plt_Dgh + 13.41093
Test Weight	Precip_Infl_Mlk	0.85***	Test Weight = 0.27451*Precip_Infl_Mlk + 73.8457
TKW	Precip_Infl_Mlk	0.63***	TKW = 0.46539*Precip_Infl_Mlk + 20.93278
Kernel No/m^2	BRDef3_Plt_Infl	0.86***	Kernel Number = 298.65054*BRDef3_Plt_Infl + 17690
Flour Properties			
Flour Yield	P6_21_30_Plt_Infl	0.49***	Flour Yield = -0.06783*P6_21_30_Plt_Infl + 97.54162
Flour Ash	TempRange_Plt_Mat	0.27**	Flour Ash = -0.00012848*TempRange_Plt_Mat + 0.54609
Pentosans	Aug_SPI	0.31***	Pentosans = -0.1211*Aug_SPI + 1.93636
Starch Damage	BRDef3_Jnt_Infl	0.42***	Starch Damage = 0.06747*BRDef3_Jnt_Infl + 6.29123
Falling Number	GDD5_Plt_Mat	0.65***	Falling Number = -0.87857*GDD5_Plt_Mat + 1502.5966
Flour Colour	GDD10_an50_Dgh	0.60***	Flour Colour = 0.02801*GDD10_an50_Dgh + 78.66341
Soluble Protein	GDD9_An50_Mat	0.53***	Soluble Protein = -0.02374*GDD9_An50_Mat + 17.22904
HMW-Glutenin	GDD9_An50_Mat	0.61***	HMW-Glutenin = -0.00975*GDD9_An50_Mat + 6.87709
HMW-G/Sol Ratio	TmpDegDay18_An50_Mlk	0.11*	HMW-G/Sol Ratio = 0.0008911*TmpDegDay18_An50_Mlk + 0.304
Flour Protein	GDD9_An50_Mat	0.66***	Flour Protein = -0.03939*GDD9_An50_Mat + 26.97943
Residue Protein[x]	GDD8_An_Mat	0.44***	Residue Protein = -0.006*GDD8_An_Mat + 3.21314
Dough Properties			
FAB	Aug_SPI	0.50***	FAB = -1.35449*Aug_SPI + 62.95015
FarDDT	TmpDegDay27_An_Mlk	0.68***	FarDDT = 0.19123*TmpDegDay27_An_Mlk + 2.89019
FarSTAB	TmpDegDay29_An_Dgh	0.85***	FarSTAB = 0.50513*TmpDegDay29_An_Dgh + 5.7533
MTI	BRET3_Plt_Infl	0.63***	MTI = -0.76947*BRET3_Plt_Infl + 215.18184
MTP	BRDef3_Plt_Jnt	0.58***	MTP = -0.09884*BRDef3_Plt_Jnt + 1.60149
PDR	GDD10_An50_Mat	0.60***	PDR = -0.1783*GDD10_An50_Mat + 112.64243
PBW	GDD10_An_Mat	0.64***	PBW = 0.11863*GDD10_An_Mat + 61.86821
WIP	BRDef3_Plt_Jnt	0.45***	WIP = -2.14395*BRDef3_Plt_Jnt + 81.96606

Table 3.6 cont'd

Quality Parameter	Explanatory Variable	R^2	Equation
Bread Properties			
Full Formula Mix Time	TempRange_An_Dgh	0.42***	Full Formula Mix Time= -0.01087*TempRange_An_Dgh + 8.40397
Loaf Volume	GDD10_An50_Mat	0.56***	Loaf Volume = -2.15663*GDD10_An50_Mat + 1614.23645

[z] Data does not transform to normal

[x] Data not significantly different from normal at p< 0.04

With an increase in useful heat accumulated during kernel development, there was a decrease in protein, indicating assimilate translocation and starch synthesis are favoured by an increase in useful heat, which dilutes the protein content. An important note is that the useful heat variable selected for the protein related parameters was always a GDD variable. GDD does not have an upper threshold and thus accumulates "useful" heat units at high temperatures which may be stressing the crop. As well, during the anthesis to maturity growth stage, there was a positive relationship between GDD and calendar days. As GDD increased, more calendar days were required to accumulate heat. This would allow more time for starch synthesis, resulting in a dilution of grain protein. The GDD variable selected always had a base temperature above 8^{o}C, indicating that late in the growing season the minimum temperature threshold is higher than the usual base temperature of 5^{o}C. As mentioned earlier, the timing and impact of weather conditions on each stage will be further analyzed in Chapter 4.

Similar trends were found among the quality property groups using simple weather variables compared to complex weather variables. Grain and dough properties were the best explained properties and the flour and dough properties were the poorest explained. However, the simple one variable model R^2 values were not reduced drastically compared to the models using complex weather data, indicating that simple weather data can do as good a job as complex weather data in wheat quality forecasting. In fact, only 10 out of 27 quality parameter one variable prediction models improved with the use of complex weather variables. Of the models that did improve, the R^2 improvement ranged from only 0.025 to 0.134.

3.4.4.2 Three Variable Models

As expected, the three variable simple weather variable models produced lower R^2 values than the complex weather variable models (Table 3.7). However, the reduction in the R^2 value was minimal, only about 1% reduction on average across all of the quality parameters. The R^2 values remained very strong for all of the quality parameters. Several three parameter models were either not significant ($p>0.05$) with the addition of the third variable or had two variables highly correlated to each other. These quality properties included flour yield, flour ash, falling number, flour colour, and full formula mix time. In these cases, two variable models were reported.

On average, across all quality parameters, the R^2 values increased nearly 20% with the addition of the third variable compared to the simple one variable models. The dough property R^2 values increased the most, while the grain properties increased the least. The smaller increase in the grain properties was due to the higher initial R^2 value with the one variable model. Grain protein content, HMW-glutenin, FAB, mixograph PDR increased the most using the three variable model, while yield, test weight, kernel number m^{-2}, falling number, flour colour, and FarSTAB increased less than 10%.

Once again a similar trend was evident with the grain and dough properties being the most predictable properties, and the flour and bread properties being the poorest predicted properties. Yield, protein content, test weight, kernel number, HMW-glutenin, flour protein content, FarDDT, FarSTAB, MTI, mixograph PDR, and mixograph PBW all had explanatory models with R^2 values above 0.85 (R^2 = 0.90, 0.88, 0.92, 0.94, 0.87, 0.85, 0.90, 0.91, 0.86, 0.87, and 0.86, respectively) (Table 3.7). The poorest explained

Table 3.7. Grain, flour, dough, and bread properties explained using a three simple weather variable explanatory model

Quality Parameter	R^2	Explanatory Model
Grain Properties		
Yield	0.90***	Yield = 59.64334*BRDem3_Infl_Mlk - 118.80652*TmpDegDay28_Infl_Mlk + 20.55932*HarWU_Plt_Jnt - 884.64264
Protein[z]	0.88***	Protein = 0.01551*Precip_An_Mat + 0.10556*TmpDegDay27_Infl_Mlk + 0.00998*TempRange_Plt_Dgh - 0.35194
Grade[z]	0.55***	Grade = -0.05627*BRDef3_An50_Mlk + 0.02886*Precip_Jnt_Infl - 0.03916*HarET_Plt_Dgh + 15.97073
Test Weight	0.92***	Test Weight = -0.0267*GDD4_Dgh_Mat + 0.30327*Precip_Infl_Mlk - 0.17533* TmpDegDay30_Plt_Infl + 76.54834
TKW[z]	0.79***	TKW = -0.10199*BRDef3_An50_Mat + 0.53627*Precip_Infl_Mlk -0.55646*TmpDegDay29_Plt_Jnt + 17.03444
Kernel Number/m^2	0.95***	Kernel Number = 145.37442*HarET_An_Mat - 109.74163*TmpDegDay16_An_Mlk + 147.90584*HarWUR_Dgh_Mat + 1490.01955
Flour Properties		
Flour Yield[x]	0.62***	Flour Yield = -0.19499*BRET3_Dgh_Mat - 0.06338*P5_24_33_Plt_Infl + 101.41469
Flour Ash[x]	0.36**	Flour Ash = 0.00084839*TmpDegDay18_Dgh_Mat - 0.00065482*BRET3_Plt_Mat + 0.62706
Pentosans	0.50***	Pentosans = 0.0174*BRET3_Dgh_Mat + 0.00242*Precip_Plt_An - 0.23452*Aug_SPI + 1.15025
Starch Damage[z]	0.62***	Starch Damage = -0.03947*TmpDegDay27_Infl_Mlk + 0.05193*Precip_Infl_An - 0.02654*CDays_Plt_Mlk + 8.388
Falling Number[x]	0.72***	Falling Number = 1.16745*HarET_Plt_Jnt - 0.8193*GDD5b_Plt_Mat + 1212.6352
Flour Colour[x]	0.64***	Flour Colour = 0.02644*GDD10_an50_Dgh + 0.04558*Precip_Infl_An + 78.91538
Soluble Protein	0.73***	Soluble Protein = -0.01812*GDD9_An50_Mat - 0.0801*Precip_Infl_An + 0.02887*BRET3_Plt_Dgh + 4.09283
HMW-Glutenin	0.87***	HMW Glutenin = -0.0104*GDD9_An_Mat + 0.02103*TmpDegDay15_An_Mlk + 0.24334*Jun_Jul_SPI + 4.3963
HMW-G/Sol Ratio[x]	0.22**	HMW-G/Sol Prot Ratio = 0.00097001*TmpDegDay18_An50_Mlk - 0.00080959*BRWU3_Plt_Jnt + 0.37765
Flour Protein	0.85***	Flour Protein = 0.01493*Precip_An_Dgh - 0.53109*BRWUR3_An_Mlk + 0.01276*TempRange_Plt_Dgh + 2.16487

Table 3.7 cont'd

Quality Parameter	R^2	Explanatory Model
Residue Protein[z]	0.62***	Residue Protein = -0.01132*BRDef3_An_Dgh - 0.01125*GDD8_An_Dgh - 0.03934*TmpDegDay27_Infl_An + 4.18306
Dough Properties		
FAB[x]	0.72***	FAB = -0.02257*TmpDegDay22_Plt_Dgh - 2.78045*Aug_SPI + 68.22861
FarDDT[x]	0.89***	FarDDT = 0.19042*TmpDegDay27_An_Mlk + 0.06505*HarET_Plt_Mat - 25.17138
FarSTAB	0.92***	FarSTAB = 0.72331*TmpDegDay30_An_Mat + 0.24946*HarET_Infl_Mlk + 2.53751*May_Aug_SPI - 16.23944
MTI	0.86***	MTI = 0.33933*TmpDegDay16_an50_Dgh + 1.05869*P5_19_29_Plt_An - 1.08934*BRET3_Plt_Infl - 250.01727
MTP	0.79***	MTP = -0.01231*HarET_Plt_Infl - 0.13687*BRDef3_Plt_Jnt - 0.12531*TmpDegDay30_Plt_Jnt + 4.30734
PDR	0.87***	PDR = -0.38371*GDD8_An_Dgh + 0.99685*BRDem3_An_Mlk - 0.80305*TmpDegDay28_Infl_An + 129.91051
PBW	0.86***	PBW = -0.11655*GDD10_An50_Mat + 0.24776*TmpDegDay16_An50_Mlk + 2.20538*May_Jul_SPI + 31.14225
WIP[z]	0.65***	WIP = -22.09367*BRDef3_Dgh_Mat + 0.3339*P5_25_28_Jnt_Infl + 0.36611*GDD10_Plt_Mat - 170.42819
Bread Properties		
Full Formula Mix Time[x]	0.57***	Full Formula Mix Time = -0.01481*TempRange_An_Dgh - 0.14537*TmpDegDay29_Infl_An + 10.20486
Loaf Volume	0.75***	Loaf Volume = -2.27444*GDD9_An_Mat + 2.29417*TempRange_An_Mlk - 5.63242*Precip_Infl_An + 1372.08744

[z] Data not significantly different from normal at p<0.01
[x] Two variable model

quality properties included grade, flour ash, pentosans, and the HMW-Glutenin/soluble protein ratio which had R^2 values less than 0.55 (R^2 = 0.55, 0.39, 0.50, and 0.32, respectively).

A slightly different trend was evident between the complex weather variable models and simple weather variable models when comparing the type of weather variable selected. Overall, the most prominent variable selected was heat stress, followed closely by moisture supply, then useful heat which showed up in 26%, 24%, and 22% of the models, respectively. For the grain properties, heat stress and water supply were the main explanatory variables. Water supply variables were selected most often when explaining the flour properties, while heat stress variables were chosen most frequently for the dough properties. The bread properties were best explained using useful heat, heat stress and moisture supply variables. Water stress variables were only included in the models for 7 of the 27 quality variables (Grade, TKW, residue protein, mixograph MTP, and mixograph WIP). As stated earlier, it was expected that these variables would be more prominent in explaining quality variation, due to previous studies indicating the significance of water stress on quality.

The timing of the weather impacting quality appeared to be similar to the trend shown using complex weather variables. Each quality parameter explanatory model, excluding kernel number, HMW-glutenin/soluble protein ration, and MTP, included a weather variable accumulated post anthesis as well as a weather variable accumulated during the early part of the growing season.

These simple weather variable quality predictor models, like the complex weather variable models, present the opportunity to predict wheat quality several weeks prior to harvest. Models developed for yield and starch damage would potentially allow the estimation of these properties 4-5 weeks prior to harvest. Grade, flour colour, flour protein, residue protein, farinograph MTI, mixograph PDR, and full formula mix time could be predicted 3-4 weeks prior to harvest. The rest of the quality variable models require weather variables to be accumulated until maturity allowing forecasting 2-3 weeks prior to harvest.

The explanatory models derived using simple weather variables appear to be predicting quality just as well as models derived using the complex weather variables. With the multi variable models, only a small increase in predictability occurred in most cases. The ability of the simple weather variables to predict quality is very valuable information for grain buyers such as The Canadian Wheat Board. If quality can be predicted using simple instrumentation and calculations, significant operational and computational costs could be saved.

3.5 Conclusions

This study showed that with the use of a comprehensive set of weather variables, most wheat quality parameters can be predicted very well several weeks prior to harvest. The use of three explanatory weather variables increased the predictability of the quality parameters as compared to using a one variable model. The grain properties, excluding grade, were the best predicted quality variables, followed closely by the dough properties. Generally, the flour and bread properties were more poorly predicted than the grain and dough properties but still produced moderately strong R^2 values (average R^2 = 0.64 and 0.69, respectively). The use of detailed weather data for the prediction of quality would allow the forecasting of technological quality properties 2 to 5 weeks prior to harvest.

This study also showed that models including only weather variables derived from daily temperature and precipitation data, explained a significant portion of the variation in most technological quality properties. Similar to the complex variable models, the simple weather variable models could predict various wheat quality properties 2 to 5 weeks prior to harvest.

The ability to forecast wheat technological quality well in advance of harvest would provide very valuable information to the Canadian grain industry. Knowledge of potential bread making quality in advance of harvest would potentially improve grain sourcing, logistical planning and marketing. Grain buyers would be able determine what area and how much of the desired wheat quality was being grown and therefore adjust sales and grain car allocation accordingly. The use of simple weather variables to forecast wheat quality would reduce operational costs for weather monitoring equipment, maintenance as well as the complexity of the weather variable calculations.

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4. CRITICAL STRESS PERIODS AFFECTING GRAIN, FLOUR, DOUGH, AND BREAD PROPERTIES OF CANADIAN HARD SPRING WHEAT

4.1 Abstract

Growing season weather conditions are extremely variable in western Canada. Conditions can range from extremely hot and dry to cool and wet or some combination of the two throughout the growing season. The weather conditions both prior to and after anthesis have been shown to impact wheat yield and quality. Therefore, the extent to which yield and quality are impacted is dependent on the development stage at which particular weather conditions occur. This study was conducted in order to determine the most important crop development stage affecting wheat technological quality. The genotypes (CWRS) AC Barrie, Superb, Elsa, Neepawa, (CPS-white) Vista and (CWWS) Snowbird were grown in five locations across the Canadian prairies over two years to provide a total of seven site-years for analysis. Intensive weather data was collected during the growing season at each location and used to calculate accumulated heat stress, useful heat, moisture demand, moisture supply, moisture use and moisture stress variables for 18 different crop development stages, including five sequential stages from planting to maturity. Grain, flour, dough and bread properties were examined.

There was not one specific development period that impacted specific quality parameters or even overall wheat quality. Generally, it was found that the most sensitive stage differs among quality parameters. When the five sequential stages were considered, two main stages appeared to standout which were, the period prior to jointing and the anthesis to soft dough stage. An increased range of development stages improved the

amount of quality variation explained. Weather data spanning the entire growing season is required in order to accurately predict wheat technological quality variation.

4.2 Introduction

Wheat quality variation is driven mainly by growing season weather. The grain crop region of western Canada experiences a very wide range of weather conditions during the growing season. Conditions can range from very wet and cool all year to very dry and hot all year or from wet in the spring to hot and dry mid summer or the complete opposite. This directly affects the wheat yield and quality produced each year in Western Canada. Numerous studies, cited below, have shown that wheat yield and quality are affected by water and temperature stress as well as the general weather conditions (i.e. non stress conditions) during the growing season. Water and temperature stress occurring either before or after anthesis has been found to impact yield and quality. Also, it has been shown that general growing conditions before and after anthesis (ie. non stress conditions) affect overall quality as well. Therefore the extent to which yield and quality are impacted is depends on the development stage at which affecting conditions occur.

4.2.1 Pre Anthesis Weather Impacts on Yield and Quality

Numerous studies have shown that conditions prior to anthesis are important for N uptake, assimilate production, and N assimilate storage in the vegetative tissue (Simpson et al., 1983; Campbell et al., 1997; Blum, 1998; Guttieri et al., 2001; Yang et al., 2001b; Yang et al., 2001a; Xu et al., 2005; Asseng and Milroy, 2006; Xu et al., 2006; Yang and Zhang, 2006). Generally if severe stress conditions occurred prior to anthesis, storage capacity was reduced which in turn negatively affected final yield and protein content. Campbell et al. (1997) found that N taken up between heading and anthesis was most critical to obtaining protein response to fertilizer N and that if water was limiting during this period some N remains in the soil as its uptake is restricted. Studies by Zhang et al. (2005) and Xue et al. (2006) found that the highest yields were obtained when a high water deficit occurred at the jointing stage. These studies found that deficits early in the growing season acclimatize plants to handle later water deficits better by improving root systems and water extraction. Tahir and Nakata (2005) found that if a heat stress occurred at a time prior to anthesis, carbon reserves were negatively affected thus affecting grain yield. Several studies have also indicated that temperature prior to anthesis is critical for grain weight and yield as this is the period in which the structures of the ovaries are being developed (Wardlaw, 1994; Calderini et al., 1999; Calderini et al., 2001). Calderini et al. (2001) found that final grain weight increased with cooler average temperatures during this period. Several studies have also shown that yield, kernel number and kernel weight were most sensitive to temperature and water stress during the stem elongation to anthesis stage (Fischer and Maurer, 1976; Doorenbas and Kassam, 1979; Entz and Fowler, 1988). Entz and Fowler (1988) found that protein content was influenced by conditions both prior to and post anthesis.

4.2.2 Post Anthesis Weather Impacts on Yield and Quality

The studies mentioned above which found that weather conditions prior to anthesis were affecting yield and quality by affecting N and assimilate storage also noted that water stress conditions during the grain filling stage were critical for assimilate remobilization from the vegetative tissue to the developing kernel (Blum, 1998; Yang et al., 2001b; Yang et al., 2001a; Xu et al., 2005; Xu et al., 2006; Yang and Zhang, 2006).

These studies also demonstrated that a stress during grain filling had the effect of increasing the rate of grain filling but the grain filling period was decreased due to the increased rate of senescence resulting in decreased yield and increased protein content. Yang and Zhang (2006) specifically noted that a water stress during early grain development curtailed the kernel sink potential by reducing the number of endosperm cells and amyloplasts formed, thus reducing grain weight as a result of a reduction in the capacity of the endosperm to accumulate starch.

Generally, it has also been found that heat stress during grain filling has the effect of reducing yield and kernel weight due to the negative impact of heat on the starch synthase enzyme as well as the resulting reduction in the duration of the grain filling period (Randall and Moss, 1990; Rao et al., 1993; Graybosch et al., 1995; Fokar et al., 1998; Panozzo and Eagles, 2000; Panozzo et al., 2001; Chinnusamy and Khanna-Chopra, 2003; Tahir and Nakata, 2005; Tewolde et al., 2006). A heat stress post anthesis also has the effect of increasing protein content due to improved N translocation from the stem reserves to the kernel (Blum et al., 1994; Blum, 1998; Fokar et al., 1998; Yang et al., 2002; Tahir and Nakata, 2005; Asseng and Milroy, 2006; Dupont et al., 2006; Spiertz et al., 2006).

The previous chapter described various models for the prediction of wheat technological quality parameters. An extensive investigation into the specific development stages affecting wheat quality was not completed in that analysis. Numerous studies have looked at the critical development stages for yield and grain protein content however very little research has examined the critical development stage for the technological quality properties of wheat. Therefore the major objective of this study was to determine the most important crop development stage affecting wheat technological quality parameters.

4.3 Materials and Methods

This analysis considered five development stages that ran sequentially from planting to maturity as well as 18 different development stage combinations spanning varying portions of the growing season. These are listed in Table 3.2. Field setup, phenological observations, environmental parameters and wheat quality analysis methods were described in previous chapters.

4.3.1 Statistical Analysis

The SAS Proc Reg procedure, with the MAXR option, as explained in Chapter 3, was used to determine the best one variable model for each specific development stage (SAS Institute, 2001). For each quality parameter, the weather variable with the highest R^2 value to the quality parameter was determined for each development stage. The development stages were then ranked from highest R^2 value to lowest. The stage with the highest R^2 value was considered the most important development stage explaining variation within that quality parameter. Each development stage was assigned a rank according to order of R^2 values with 1 being the highest rank. The rankings were averaged across quality properties for each development stage. The weather variable selected for each stage was characterized by type (useful heat, heat stress, water stress, water demand, water use, water supply, and other). The frequency of the selection of each type of weather variable explaining the greatest amount of quality variation was used to determine what type of weather was influencing overall quality most frequently during each development stage. The analysis was done first using just the five sequential development stages and then using all 18 different stages.

4.4 Results and Discussion

4.4.1 Five Sequential Development Stage Analysis

A summary of the R^2 values and weather variables explaining quality variation for each of the sequential development stages can be seen in Table 4.1. The development stage with the highest R^2 is in bold. The stage with the highest average ranking for explaining variance of the grain properties was the 50% anthesis to soft dough stage (average ranking of 1.7, Table 4.2). For the yield related grain properties (yield, test weight, TKW, and kernel number), the anthesis to soft dough stage was the highest ranked development stage. This stage produced the highest R^2 values for these parameters (R^2 = 0.755, 0.595, 0.553, and 0.819, respectively). The highest ranked stage for grain protein content (GPC) was planting to jointing and the second highest ranked stage was anthesis to soft dough (R^2 = 0.593 and 0.531, respectively).

Table 4.1. R^2 values and explanatory variable for 5 development stages for grain, flour, dough, and bread properties. Development stage with the highest R^2 is in bold.

Quality Property	Development Stage	R^2	Explanatory Variable
Grain Properties			
Yield	Plt_Jnt	0.6694	PMdef_Plt_Jnt
	Jnt_Infl	0.5196	BRDef6_Jnt_Infl
	Infl_An50	0.7441	TmpDegDay30_Infl_An50
	An50_Dgh	***0.7553***	***DegHr30_an50_Dgh***
	Dgh_Mat	0.5885	DegHr30_Dgh_Mat
Protein	***Plt_Jnt***	***0.5930***	***PMET_Plt_Jnt***
	Jnt_Infl	0.5093	BRDef3_Jnt_Infl
	Infl_An50	0.4843	PE_Infl_An50
	An50_Dgh	0.5308	PMdef_an50_Dgh
	Dgh_Mat	0.3805	GDD9_Dgh_Mat
Grade	Plt_Jnt	0.1786	P5_24_28_Plt_Jnt
	Jnt_Infl	0.2899	BRET6_Jnt_Infl

Table 4.1 cont'd

Quality Property	Development Stage	R^2	Explanatory Variable
	Infl_An50	***0.3220***	***BRWU6_Infl_An50***
	An50_Dgh	0.1615	TotalGlobRad_an50_Dgh
	Dgh_Mat	0.1385	AE_Dgh_Mat
Test Weight	Plt_Jnt	0.5696	BRDef6_Plt_Jnt
	Jnt_Infl	0.5516	BRDef6_Jnt_Infl
	Infl_An50	0.4144	FAOWUR_Infl_An50
	An50_Dgh	***0.5949***	***AE_an50_Dgh***
	Dgh_Mat	0.2735	DegHr30_Dgh_Mat
TKW	Plt_Jnt	0.5057	FAOdef_Plt_Jnt
	Jnt_Infl	0.4994	BRDef6_Jnt_Infl
	Infl_An50	0.4987	DegHr30_Infl_An50
	An50_Dgh	***0.553***	***AE_an50_Dgh***
	Dgh_Mat	0.3134	DegHr30_Dgh_Mat
Kernel Number	Plt_Jnt	0.7120	PMdef_Plt_Jnt
	Jnt_Infl	0.5006	PMdef_Jnt_Infl
	Infl_An50	0.7707	TmpDegDay30_Infl_An50
	An50_Dgh	***0.8192***	***DegHr30_an50_Dgh***
	Dgh_Mat	0.6716	DegHr30_Dgh_Mat
Flour Properties			
Flour Yield	***Plt_Jnt***	***0.5184***	***AE_Plt_Jnt***
	Jnt_Infl	0.2825	CDays_Jnt_Infl
	Infl_An50	0.4872	AE_Infl_An50
	An50_Dgh	0.3911	Precip_an50_Dgh
	Dgh_Mat	0.4525	AE_Dgh_Mat
Flour Ash	***Plt_Jnt***	***0.2510***	***BRWUR6_Plt_Jnt***
	Jnt_Infl [z]		
	Infl_An50 [z]		
	An50_Dgh	0.1752	PMdef_an50_Dgh
	Dgh_Mat	0.2067	BRWUR3_Dgh_Mat
Pentosans	Plt_Jnt	0.1440	TmpDegDay19_Plt_Jnt
	Jnt_Infl	0.1211	Precip_Jnt_Infl
	Infl_An50	***0.2573***	***Precip_Infl_An50***
	An50_Dgh	0.2084	TmpDegDay15_an50_Dgh
	Dgh_Mat	0.2278	TmpDegDay17_Dgh_Mat
Starch Damage	Plt_Jnt	0.3866	FAOET_Plt_Jnt
	Jnt_Infl	***0.4537***	***BRDef6_Jnt_Infl***
	Infl_An50	0.3128	DegHr30_Infl_An50
	An50_Dgh	0.3612	GDD7_an50_Dgh
	Dgh_Mat	0.2122	BRDef3_Dgh_Mat
Falling Number	***Plt_Jnt***	***0.6190***	***TotalGlobRad_Plt_Jnt***
	Jnt_Infl	0.5636	TotalWRunKm_Jnt_Infl
	Infl_An50	0.5168	TotalWRunKm_Infl_An50
	An50_Dgh	0.3313	FAOdef_an50_Dgh
	Dgh_Mat	0.5383	BRDef3_Dgh_Mat
Flour Colour	Plt_Jnt	0.1933	TotalWRunKm_Plt_Jnt
	Jnt_Infl	0.3502	BRDef3_Jnt_Infl
	Infl_An50	0.3139	Hardef_Infl_An50

Table 4.1 cont'd

Quality Property	Development Stage	R^2	Explanatory Variable
	An50_Dgh	***0.6008***	***GDD10_an50_Dgh***
	Dgh_Mat	0.3428	TmpDegDay16_Dgh_Mat
Soluble Protein	***Plt_Jnt***	***0.5003***	***FAOET_Plt_Jnt***
	Jnt_Infl	0.4249	BRDef3_Jnt_Infl
	Infl_An50	0.3725	FAOET_Infl_An50
	An50_Dgh	0.4248	GDD9_an50_Dgh
	Dgh_Mat	0.3154	GDD10_Dgh_Mat
HMW-Glutenin	Plt_Jnt	0.5185	TotalWRunKm_Plt_Jnt
	Jnt_Infl	0.4458	BRDef3_Jnt_Infl
	Infl_An50	0.4517	PE_Infl_An50
	An50_Dgh	***0.5237***	***PMdef_an50_Dgh***
	Dgh_Mat	0.4393	BRDef3_Dgh_Mat
HMW/Sol Ratio	Plt_Jnt [z]		
	Jnt_Infl [z]		
	Infl_An50 [z]		
	An50_Dgh [z]		
	Dgh_Mat	0.0820	Hardef_Dgh_Mat
Flour Protein	***Plt_Jnt***	***0.5675***	***FAOET_Plt_Jnt***
	Jnt_Infl	0.5331	BRDef3_Jnt_Infl
	Infl_An50	0.4438	PE_Infl_An50
	An50_Dgh	0.5240	PMdef_an50_Dgh
	Dgh_Mat	0.4109	GDD10_Dgh_Mat
Residue Protein	Plt_Jnt	0.3203	BRDem6_Plt_Jnt
	Jnt_Infl	***0.4321***	***BRDef6_Jnt_Infl***
	Infl_An50	0.3409	BRDef6_Infl_An50
	An50_Dgh	0.3883	FAOdef_an50_Dgh
	Dgh_Mat	0.3365	BRDef3_Dgh_Mat
Dough Properties			
FAB	Plt_Jnt	0.3153	Precip_Plt_Jnt
	Jnt_Infl	0.2426	Precip_Jnt_Infl
	Infl_An50	***0.3217***	***Precip_Infl_An50***
	An50_Dgh	0.3059	TmpDegDay16_an50_Dgh
	Dgh_Mat	0.2351	AE_Dgh_Mat
FarDDT	Plt_Jnt	0.4902	PMET_Plt_Jnt
	Jnt_Infl	0.4450	FAOET_Jnt_Infl
	Infl_An50	0.5127	TempRange_Infl_An50
	An50_Dgh	***0.6288***	***TmpDegDay28_an50_Dgh***
	Dgh_Mat	0.4979	AE_Dgh_Mat
FarSTAB	Plt_Jnt	0.5259	TmpDegDay28_Plt_Jnt
	Jnt_Infl	0.4327	CumVaporPresDef_Jnt_Infl
	Infl_An50	0.5797	TmpDegDay30_Infl_An50
	An50_Dgh	***0.8423***	***TmpDegDay29_an50_Dgh***
	Dgh_Mat	0.7139	TmpDegDay30_Dgh_Mat
MTI	Plt_Jnt	0.3809	PMdef_Plt_Jnt
	Jnt_Infl	0.4305	PMdem_Jnt_Infl
	Infl_An50	0.3718	TmpDegDay29_Infl_An50
	An50_Dgh	***0.6280***	***TmpDegDay27_an50_Dgh***

Table 4.1 cont'd

Quality Property	Development Stage	R^2	Explanatory Variable
	Dgh_Mat	0.4748	TmpDegDay30_Dgh_Mat
MTP	***Plt_Jnt***	***0.5806***	***BRDef3_Plt_Jnt***
	Jnt_Infl [z]		
	Infl_An50 [z]		
	An50_Dgh	0.5257	TempRange_an50_Dgh
	Dgh_Mat	0.4407	TmpDegDay21_Dgh_Mat
PDR	Plt_Jnt	0.4935	TotalWRunKm_Plt_Jnt
	Jnt_Infl	0.2878	TotalWRunKm_Jnt_Infl
	Infl_An50	0.3147	FAOdem_Infl_An50
	An50_Dgh	0.4788	PMdef_an50_Dgh
	Dgh_Mat	***0.5252***	***PMET_Dgh_Mat***
PBW	Plt_Jnt	0.4870	TotalWRunKm_Plt_Jnt
	Jnt_Infl	0.2039	BRDef3_Jnt_Infl
	Infl_An50	0.3392	Precip_Infl_An50
	An50_Dgh	0.4747	GDD10_an50_Dgh
	Dgh_Mat	***0.5748***	***TmpDegDay16_Dgh_Mat***
WIP	***Plt_Jnt***	***0.4495***	***BRDef3_Plt_Jnt***
	Jnt_Infl [z]		
	Infl_An50	0.2204	TmpDegDay30_Infl_An50
	An50_Dgh	***0.4482***	***TempRange_an50_Dgh***
	Dgh_Mat	0.2500	DegHr28_Dgh_Mat
Bread Properties			
Full Formula Mix Time	***Plt_Jnt***	***0.4162***	***BRDef3_Plt_Jnt***
	Jnt_Infl [z]		
	Infl_An50 [z]		
	An50_Dgh	0.4027	TempRange_an50_Dgh
	Dgh_Mat	0.2402	CumVaporPresDef_Dgh_Mat
Loaf Volume	Plt_Jnt	0.3965	TotalWRunKm_Plt_Jnt
	Jnt_Infl	0.3318	BRDef3_Jnt_Infl
	Infl_An50	0.3149	PE_Infl_An50
	An50_Dgh	***0.6486***	***GDD10_an50_Dgh***
	Dgh_Mat	0.3738	TmpDegDay15_Dgh_Mat

Bold and italicized font indicate stage with highest R^2 value for each quality property
[z] No significant explanatory variable relationships with that quality property for that stage

The most critical stage for several protein related properties (grain protein content, flour protein content, and soluble protein content) occurred during the early part of the growing season, from planting to jointing. This development stage was ranked as the most important for these properties and ranked second most important for HMW glutenin (Table 4.1). The highest ranked stage for residue protein was jointing to inflorescence. The jointing to inflorescence stage along with the anthesis to soft dough stage had very similar R^2 values for all of the protein properties. This demonstrates that the period prior to heading was the most critical in determining final protein content of the grain, however the early kernel development stage was also very important. These results indicate that both early and late season weather have a significant influence on final protein content.

GPC, flour protein and soluble protein were positively related to water demand during the planting to jointing stage (Table 4.1). The ASCE Penman-Monteith ETp variable explained the greatest amount of variance for GPC and the FAO56 Penman-Monteith ETp variable for flour and soluble protein content. The HMW glutenin protein fraction was most strongly correlated to water stress during the anthesis to soft dough stage. HMW glutenin develops later during kernel development, thus the soft dough to maturity stage should be the most influential for HMW-glutenin. However, it has also been found that when moisture stress occurred during grain filling, the rapid rate of protein polymerization occurred earlier than normal in the kernel (Daniel and Triboi, 2002). Therefore, water stress earlier in grain development would have the effect of increasing the HMW glutenin content.

The other flour properties, except flour colour, were also best explained by weather variables prior to anthesis (Table 4.1). Flour yield was best explained by atmospheric water demand during the planting to jointing stage. Flour ash was best explained by a water stress variable from planting to jointing.

Overall, the planting to jointing stage was found to be the most important stage determining the flour properties with an average rank of 2.2 (Table 4.2). Pentosan content, residue protein and flour colour were the only flour properties with the planting to jointing stage ranking below 2.

Table 4.2. Ranking of 5 sequential development stages for grain, flour, dough and bread properties

Quality Parameter	Plt_Jnt	Jnt_Infl	Infl_An50	An50_Dgh	Dgh_Mat
Grain Properties					
Yield	3	5	2	1	4
Protein	1	3	4	2	5
Grade	3	2	1	4	5
Test Weight	2	3	4	1	5
TKW	2	3	4	1	5
Kernel Number	3	5	2	1	4
Average Rank	**2.3**	**3.5**	**2.8**	**1.7**	**4.7**
Flour Properties					
Flour Yield	1	5	2	4	3
Flour Ash	1	5	4	3	2
Pentosans	4	5	1	3	2
Starch Damage	2	1	4	3	5
Falling Number	1	2	4	5	3
Flour Colour	5	2	4	1	3
Soluble Protein	1	2	4	3	5
HMW-glutenin	2	4	3	1	5
HMW/Sol Ratio	1	5	3	4	2
Flour Protein	1	2	4	3	5
Residue Protein	5	1	3	2	4
Average Rank	**2.2**	**3.1**	**3.3**	**2.9**	**3.5**
Dough Properties					
FAB	2	4	1	3	5
FarDDT	4	5	2	1	3
FarSTAB	4	5	3	1	2
MTI	4	3	5	1	2
MTP	1	5	4	2	3
PDR	2	5	4	3	1
PBW	2	5	4	3	1
WIP	1	5	4	2	3
Average Rank	**2.5**	**4.6**	**3.4**	**2.0**	**2.5**
Bread Properties					
Full Formula Mix Time	1	5	4	2	3
Loaf Volume	2	4	5	1	3
Average Rank	**1.5**	**4.5**	**4.5**	**1.5**	**3.0**
Overall Stage Rank	**2.3**	**3.7**	**3.3**	**2.3**	**3.4**

The dough properties were most affected by conditions during the anthesis to soft dough stage (average rank of 2, Table 4.2) with the farinograph strength properties having the highest R^2 ranking during this stage. Generally, it is known that dough strength is related to protein content and protein composition, so it is not surprising that GPC and HMW-Glutenin also have the anthesis to soft dough stage ranked 1 or 2.

On average, the bread properties were explained equally well by variables in the planting to jointing and anthesis to soft dough stages, with an average rank of 1.5 for both (Table 4.2).

Over all of the quality parameters, weather variables for planting to jointing and anthesis to soft dough explained the largest amount of wheat quality variation. These two stages are also the longest in duration out of the 5 sequential stages used in the analysis. This would mean that there would be more time for weather conditions to affect plant growth and kernel development during these stages as compared to the other shorter stages.

This study found that a stress, either heat or water, occurring post anthesis had a negative impact on yield, kernel number, HMW glutenin, HMW-G/Soluble protein ratio, MTI, and PBW. Conversely, stress occurring post anthesis had a positive impact on FarDDT and FarSTAB. The negative impact of post anthesis stress on yield, kernel number, HMW-glutenin and MTI has been reported in previous studies (Blum, 1998; Fokar et al., 1998; Yang et al., 2001b; Yang et al., 2001a; Chinnusamy and Khanna-Chopra, 2003; Don et al., 2005; Tahir and Nakata, 2005; Xu et al., 2005; Asseng and Milroy, 2006; Spiertz et al., 2006; Tewolde et al., 2006; Xu et al., 2006; Yang and Zhang, 2006). Stress would cause starch synthesis to be reduced and the filling period to be shortened resulting in decreased yield which would result in higher protein content and stronger dough. Stress during this stage would also negatively affect HMW-glutenin by reducing the duration of the filling period, resulting in a reduction in time available for HMW-glutenin synthesis. The positive relationship found between the dough strength properties of FarDDT and FarSTAB could be attributed to the increase in protein content resulting from the increased yield. Studies have also shown that remobilization of nitrogen to the kernel is improved when a stress occurs during grain filling, therefore increasing the protein content (Blum, 1998; Yang et al., 2001b; Yang et al., 2001a; Xu et al., 2005; Xu et al., 2006; Yang and Zhang, 2006). Due to the role of HMW-glutenin in dough strength, it was unexpected that a negative impact on HMW-glutenin did not negatively impact dough strength properties. However, Don et al. (2005) found that HMW-glutenin content was reduced by heat stress during grain filling, but the glutenin particles increased in size and did not affect the dough strength.

When a stress occurred prior to anthesis, starch damage, flour ash, MTP, WIP, and full formula mix time were negatively impacted. A pre-anthesis stress was found to have a positive impact on residue protein. An increased amount of the starch fraction amylopectin generally leads to increased starch damage. Therefore, when a stress occurred during the jointing to inflorescence stage, starch damage may have been negatively affected due to the decrease in assimilate production and storage, reducing the potential for amylopectin synthesis later on. An increase in stress prior to anthesis also decreased MTP, WIP, and full formula mix time, which indicates that a weaker dough was produced. It is possible that the early season stress prevented nutrient uptake and storage in the vegetative tissue, therefore negatively affecting protein content and dough strength.

When the non-stress variables (useful heat, water use, water supply, and water demand) were accumulated post anthesis, a positive impact was found for test weight, TKW, flour colour and PDR. Loaf volume was negatively impacted by non-stress weather factors occurring post anthesis. Test weight and TKW would be expected to increase because less stress post anthesis will lengthen the filling period and provide more time for starch synthesis and accumulation. The increase in starch synthesis due to a longer filling period would be expected to dilute protein content and reduce loaf volume.

Non-stress conditions during the pre anthesis stage had a positive impact on GPC, flour protein content, soluble protein content, pentosans content and FAB. Flour yield was negatively impacted by the non-stress weather parameters pre-anthesis. Ideal growing conditions prior to anthesis would allow assimilate production and nutrient uptake to be maximized therefore increasing the potential for higher N concentrations in the kernel during grain filling.

The types of weather variables that were selected for each of the five stages over all of the quality properties were examined. Heat stress variables impacted wheat technological quality mainly post anthesis, and were the variables explaining the largest proportion of quality variance after anthesis, occurring 22 out of 32 times. Conversely, water stress variables were most highly correlated to wheat quality prior to anthesis, appearing 25 out of 38 times in the pre-anthesis stages. Water demand, water supply and the “other” weather variables were also most highly correlated to some quality variables prior to anthesis, while water use and useful heat were more common post anthesis. Heat and water stress however were the variable types that most commonly explained quality variation using the 5 sequential stages.

Some of the R^2 values included in the previous data were quite low. An arbitrary minimum R^2 value of 0.50 was set to eliminate some of the more poorly explained parameters. Using this analysis, there were again two distinct stages that explained the majority of quality variation, namely planting to jointing and anthesis to dough. The type of weather variable that most frequently explained the majority of quality variation was, again, heat stress followed by moisture stress.

4.4.2 Analysis of 18 Development Stage Combinations

The development stages used in the previous analysis were sequential and non-overlapping which gave an indication of the distinct stage was influencing wheat quality the most. However, the most critical stage that affects wheat quality may not correspond exactly to one of the above mentioned stages. The extensive phenological data collected in this study enabled the creation of numerous development stage combinations and provided an opportunity to test the ability of numerous stages to explain quality variation. These stages are quite variable in duration and overlap other development stages.

By including more combinations of development stages, the overall average R^2 value for the regression equations explaining the most variation in the quality parameters was increased 6.6% (Figure 4.1). This indicates that the 5 discrete stages selected earlier did not necessarily capture the most critical development period for each quality parameter and some variance explanation was lost by restricting the analysis to just the five sequential stages.

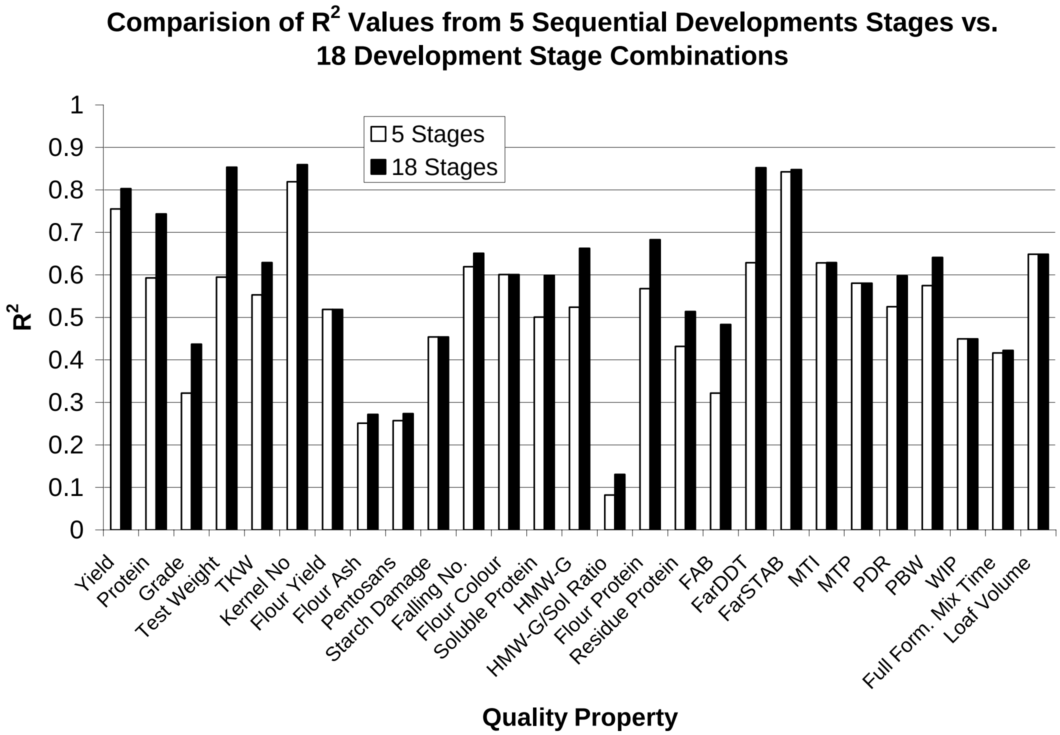

Figure 4.1. Comparison of the R^2 values for the regression equations explaining the greatest amount of variation in each quality parameter using just 5 sequential development stages compared to using 18 different development stages.

The grain properties were better explained using the increased number of development stage combinations, with an average R^2 value increase of 11%. Both the flour and dough properties were also better explained using this method, with the average R^2 values increasing by 5% and 7%, respectively.

Overall, the stages that most commonly explained the greatest variation in wheat grain parameters were the planting to inflorescence and inflorescence to milk stages. These stages had an average rank of 3.8 and 4.0 respectively out of the 18 development stages (Table 4.3). Yield, TKW, and test weight were best explained using weather accumulated during the inflorescence to milk stage. Kernel number was found to be positively related to water stress occurring from planting to heading (Table 4.4).

Table 4.3. Ranking of 18 development stage combinations for grain, flour, dough, and bread properties

Quality Parameter	Plt_ Jnt	Plt_ Infl	Plt_ An	Plt_ An50	Plt_ Mlk	Plt_ Dgh	Plt_ Mat	Jnt_ Infl	Infl_ An	Infl_ An50	Infl_ Mlk	An_ Mlk	An50_ Mlk	An_ Dgh	An50_ Dgh	An_ Mat	An50_ Mat	Dgh_ Mat
Grain Properties																		
Yield	13	2	15	16	7	11	12	18	17	6	1	5	10	8	3	9	4	14
Protein	10	5	6	4	3	2	1	15	17	16	7	12	11	13	14	9	8	18
Grade	13	9	5	4	1	2	3	8	6	7	10	12	11	15	14	17	16	18
Test Weight	9	4	6	8	11	14	15	10	13	17	1	2	3	5	7	12	15	18
TKW	8	2	7	13	15	17	16	9	11	10	1	5	6	3	4	12	14	18
Kernel Number	13	1	15	16	5	7	8	18	17	11	4	10	12	2	3	9	6	14
Average Rank	**11.0**	**3.8**	**9.0**	**10.2**	**7.0**	**8.8**	**9.2**	**13.0**	**13.5**	**11.2**	**4.0**	**7.7**	**8.8**	**7.7**	**7.5**	**11.3**	**10.5**	**16.7**
Flour Properties																		
Flour Yield	1	2	12	17	13	10	9	15	6	3	4	16	18	7	8	11	14	5
Flour Ash	2	4	13	12	14	3	1	18	16	17	8	15	11	9	10	7	6	5
Pentosans	16	8	1	5	3	11	7	18	15	4	13	14	17	12	10	6	2	9
Starch Damage	11	2	4	3	5	9	7	1	17	16	8	10	6	14	15	12	13	18
Falling Number	6	2	3	4	7	5	1	8	12	10	11	16	17	13	18	15	14	9
Flour Colour	18	11	6	5	15	17	16	8	7	10	12	14	13	3	1	4	2	9
Soluble Protein	9	6	4	5	2	3	1	11	16	17	10	14	13	15	12	8	7	18
HMW-Glutenin	14	9	8	7	5	3	2	16	18	15	1	11	10	13	12	6	4	17
HMW/Sol Ratio	3	12	10	14	4	7	16	18	15	9	17	1	2	6	13	8	11	5
Flour Protein	12	6	7	5	4	3	1	13	17	16	9	11	10	14	15	8	2	18
Residue Protein	18	14	11	10	6	4	3	8	17	15	5	1	2	12	13	7	9	16
Average Rank	**10.0**	**6.9**	**7.2**	**7.9**	**7.1**	**6.8**	**5.8**	**12.2**	**14.2**	**12.0**	**8.9**	**11.2**	**10.8**	**10.7**	**11.5**	**8.4**	**7.6**	**11.7**
Dough Properties																		
FAB	11	12	6	8	5	4	1	17	13	10	2	3	7	9	14	15	16	18
FarDDT	16	4	6	3	1	2	5	17	18	14	7	8	9	10	11	13	12	15
FarSTAB	16	12	14	13	7	4	6	17	18	15	10	8	11	1	2	3	5	9
MTI	14	1	8	6	7	10	9	12	18	15	16	13	17	3	2	5	4	11
MTP	1	9	13	15	14	8	7	18	16	17	11	12	10	3	5	2	4	6
PDR	7	8	10	11	12	6	3	18	15	16	4	14	17	13	9	2	1	5
PBW	6	9	10	11	12	5	3	17	18	15	16	14	13	7	8	1	2	4
WIP	1	9	15	16	10	11	12	17	18	14	6	8	7	3	2	5	4	13

Table 4.3 cont'd

Quality Parameter	Plt_ Jnt	Plt_ Infl	Plt_ An	Plt_ An50	Plt_ Mlk	Plt_ Dgh	Plt_ Mat	Jnt_ Infl	Infl_ An	Infl_ An50	Infl_ Mlk	An_ Mlk	An50_ Mlk	An_ Dgh	An50_ Dgh	An_ Mat	An50_ Mat	Dgh_ Mat
Average Rank	**9**	**8**	**10.3**	**10.4**	**8.5**	**6.25**	**5.8**	**16.6**	**16.8**	**14.5**	**9**	**10**	**11.4**	**6.1**	**6.6**	**5.8**	**6**	**10.1**
Bread Properties																		
Full Formula Mix Time	2	13	14	15	11	12	7	18	16	17	8	9	6	1	3	4	5	10
Loaf Volume	9	14	10	11	6	8	4	17	15	18	7	12	13	5	1	3	2	16
Average Rank	**5.5**	**13.5**	**12.0**	**13.0**	**8.5**	**10.0**	**5.5**	**17.5**	**15.5**	**17.5**	**7.5**	**10.5**	**9.5**	**3.0**	**2.0**	**3.5**	**3.5**	**13.0**

Table 4.4. Key development stages, using 18 development stages, for grain, flour, dough and bread properties with the explanatory weather variable and their Pearson correlation coefficient (r)

Quality Parameter	Stage	Explanatory Variable	r
Grain Properties			
Yield	Infl_Mlk	TmpDegDay30	-0.8960
Protein	Plt_Mat	FAOET	0.8623
Grade	Plt_mlk	BRWU6	-0.6612
Test Weight	Infl_Mlk	Precip	0.9236
TKW	Infl_Mlk	Precip	0.7932
Kernel Number	Plt_Infl	BRDef3	0.9272
Flour Properties			
Flour Yield	Plt_Jnt	AE	-0.7200
Flour Ash	Plt_Mat	TempRange	-0.5216
Pentosans	Plt_An	Aug_SPI	-0.5564
Starch Damage	Jnt_Infl	BRDef6	0.6736
Falling Number	Plt_Mat	GDD5	-0.8067
Flour Colour	An50_Dgh	GDD10	0.7751
Soluble Prot	Plt_Mat	FAOET	0.7740
HMW-Glutenin	Infl_Mlk	PE	0.8139
HMW-G/Sol Ratio	An_Mlk	PE	0.3615
Flour Protein	Plt_Mat	FAOET	0.8264
Residue Protein	An_Mlk	FAOWUR	-0.7166
Dough Properties			
FAB	Plt_Mat	Aug_SPI	-0.7065
FarDDT	Plt_mlk	BRDem6	0.9033
FarSTAB	An_dgh	TmpDegDay29	0.9207
MTI	Plt_Infl	BRET3	-0.7930
MTP	Plt_Jnt	BRDef3	-0.7620
PDR	An50_Mat	GDD10	-0.7731
PBW	An_Mat	GDD10	-0.8007
WIP	Plt_Jnt	BRDef3	-0.6704
Bread Properties			
Full Formula Mix Time	An_dgh	TempRange	-0.6499
Loaf Volume	An50_Dgh	GDD10	-0.7487

Overall, the critical stage for explaining flour property variation was the entire growing season, with an average rank of 5.8 out of 18 (Table 4.3). The protein content related properties (GPC, flour protein, soluble protein, HMW-glutenin, and residue protein content) required weather data acquired over the entire growing season. These protein properties all had the planting to maturity stage ranked within the top 3 out of 18 stage combinations. HMW-Glutenin was found to be most sensitive to weather during the heading to milk stage and the anthesis to milk stage was most critical in determining residue protein.

Flour yield, starch damage, and pentosans were most sensitive to weather accumulated prior to anthesis. Flour yield was influenced most during the planting to jointing stage. Starch damage was affected from jointing to inflorescence, while pentosan content was most affected by weather accumulated from planting to anthesis. Flour colour was best explained by weather conditions from 50% anthesis to soft dough stage.

The flour properties, in general, were best explained by the growing conditions from planting to maturity and from planting to milk stages. These stages had an average rank of 5.8 and 7.1 out of the 18 development stages. By using the 18 development stage combinations we did not find a single specific stage that was critical for explaining the flour properties.

The anthesis to maturity stage and the planting to maturity stage were found to explain the dough properties the best with an average rank of 5.8 each (Table 4.3). However, several post anthesis stages and the planting to soft dough stage had rankings just above 6. Since the dough properties were generally related to protein quality, it was expected that the anthesis to maturity stage would be an important stage. Gliadin and especially HMW-glutenin accumulation occur later in the kernel development stage and should be most affected by conditions post anthesis. However, conditions prior to anthesis were most likely influencing these parameters as well due to nutrient uptake and assimilate production and remobilization. Another important factor is conditions prior to anthesis, which set the potential for protein and starch accumulation during kernel development.

The bread properties were found to be most affected by weather during the 50% anthesis to soft dough stage. An average rank of 2 was found for this stage out of the 18 development stages. Again, bread properties have been found to be related to protein content and composition which are synthesized post anthesis.

Some properties were found to be much better explained using the 18 development stage combinations, test weight and FarDDT R^2 values increased over 20%, while protein, grade, flour protein, soluble protein, and HMW-glutenin and FAB increased by over 10% (Table 4.4). For test weight and insoluble protein the improvement was made by using the inflorescence to milk stage development stage, while the other properties were improved by using a development stage that spanned the planting to milk or maturity stages.

The most commonly selected weather variable type followed a similar trend to that for the 5 sequential stage analysis. Heat stress most commonly explained the highest level of variance in CWRS quality during the post anthesis period, while water stress was most highly correlated to CWRS quality during the early development stages (Table 4.5). More specifically, quality was most strongly related to water stress during the jointing to inflorescence and planting to inflorescence stages. Water demand was also found to be the main weather variable explaining wheat quality variance when it was accumulated over the majority of the growing season. The planting to maturity, planting to dough and planting to milk stages were the most commonly selected stages when water demand was considered (Table 4.5). This is an important point because water demand was not

Table 4.5. Frequency of the appearance of each weather variable type during each development stage for all quality parameters

Development Stage	Heat Stress	Water Stress	Water Demand	Water Use	Water Supply	Useful Heat	Other
Plt_Jnt	2	9	6	1	1	1	2
Plt_Infl	0	10	7	2	0	2	4
Plt_An	0	9	8	3	0	3	2
Plt_An50	3	8	7	3	0	1	1
Plt_mlk	4	4	8	2	0	4	3
Plt_Dgh	6	4	8	1	0	6	1
Plt_Mat	7	4	9	1	0	5	0
Jnt_Infl	0	13	3	0	2	0	2
Infl_An	7	2	8	2	1	0	2
Infl_An50	8	3	6	2	3	0	0
Infl_Mlk	7	1	9	0	4	2	0
An_Mlk	7	10	3	3	1	0	2
An50_Mlk	9	8	2	3	0	2	1
An_dgh	9	7	3	2	0	5	0
An50_Dgh	10	7	0	2	1	5	0
An_Mat	10	0	2	3	0	11	0
An50_Mat	10	1	2	2	0	10	0
Dgh_Mat	12	6	1	4	0	3	1

selected as a critical variable in the previous 5 sequential stage analysis because that analysis did not consider weather accumulated for the duration of the growing season. Water use was, again, most important post anthesis while water supply was mainly selected from the heading to milk stage as well as the heading to anthesis stage. Similar to the 5 stage analysis, useful heat was most strongly correlated to quality during the post anthesis period and the "other" variables during the pre anthesis period (Table 4.5).

The importance of the early development stages for wheat quality most likely relates to the ability of the plant to take up nutrients, produce assimilates and store those nutrients and assimilates in the plant tissue for later translocation to the kernel (Simpson et al., 1983; Blum, 1998; Guttieri et al., 2001; Yang et al., 2001b; Yang et al., 2001a; Xu et al., 2005; Asseng and Milroy, 2006; Xu et al., 2006; Yang and Zhang, 2006). The pre-anthesis stage is also the period when carpels are growing and developing, setting the potential for kernel size and number (Calderini et al., 1999). Assimilate storage capacity of the stem has also been found to be set during this stage, which in turn affects the starch and protein synthesis during kernel development (Blum, 1998).

Growing conditions post anthesis affect wheat quality by altering the rate of nutrient and assimilate translocation to the kernel and by altering the duration of the filling period. The early kernel development period is also important for wheat quality due to the sensitivity of the starch synthase enzyme to stress, resulting in changes in the amount of starch accumulated and therefore the amount protein is diluted. A stress during early kernel development also alters kernel sink potential by reducing the number of endosperm cells and amyloplasts formed, which would affect yield and quality.

4.5 Conclusions

Even though the quality properties were more sensitive to the environment at some stages than others, it can concluded that there was not one specific development period that impacted specific quality parameters or even overall wheat quality. The most sensitive periods generally differed between quality parameters. However, when the sequential development stages were analyzed, there were two main development stages that explained the highest level of variance in wheat quality, which were the period prior to jointing and the anthesis to soft dough stage. These periods correspond with previous research which indicated that the pre anthesis period is important for nutrient uptake and assimilate storage and that the early kernel development period is important for nutrient and assimilate remobilization as well as starch and protein biosynthesis.

An increased range of development stages improved the amount of quality variation explained. For some properties, such as the protein related properties, it was found that weather conditions from planting to the kernel development stage or to maturity noticeably increased the R^2 values for the quality parameter regressions.

This information combined with the results from the 5 sequential stages demonstrated that weather data accumulated over the entire growing season is required to accurately predict wheat quality. This means that one should not just focus on a single development stage in an effort to reduce resource requirements; the entire growing season should be monitored. These results are consistent with those reported in Chapter 3 which showed that regressions using multiple weather variables to predict quality contained weather parameters from a stage prior to anthesis as well as from a stage post anthesis or that span the entire growing season.

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5. GRAIN PROPERTY PREDICTION MODEL VALIDATION USING 2005 GROWING SEASON WEATHER DATA AT THREE SITES IN WESTERN CANADA

5.1 Abstract

The ability to predict grain quality would be valuable for the Canadian grain industry. If knowledge of yield and quality were known in advance of harvest, grain marketing and sourcing could be improved. The objective of this study was to validate grain quality prediction models developed in Chapter 3 and modify those models to improve prediction accuracy and reliability. Weather and crop data from field trials in three locations in 2005 were utilized to predict the grain properties at those sites. The difference between the predicted value and the actual value along with the standard error of prediction were utilized to determine the effectiveness of each model. New regression equations, which grouped genotypes according to similar wheat class as well as similar environmental response were also tested. Forecast accuracy was found to improve substantially with the equation modifications. Yield was predicted to within 120 to 530 kg/ha, on average, between the three sites using the modified model. The standard error of prediction (SEP) for yield improved from 927 using the original model to 288 using a modified model. Test weight was forecast to within 2.2 to 3.0 kg/hL using a modified model and the original SEP of 6.15 improved to 1.46 using a modified equation. TKW was predicted between 0.4 and 3 g at each location using a modified regression equation. The original TKW model had an SEP value of 13.19, which improved to 0.91 using the best modified model. Protein content results were more varied, with protein content in Regina predicted to within 0.6 %, while at the other two test sites, predicted grain protein

content was more than 1.5% from the actual. SEP results for protein content likely reflected the large variability in grain protein for individual replicates of each genotype at Winnipeg and Swift Current. The SEP values for grain protein did not improve using modified models.

5.2 Introduction

The ability to predict grain quality would be valuable for the Canadian grain industry. If knowledge of yield and quality were known in advance of harvest, grain marketing and sourcing could be improved. Consistent quality in customer deliveries would be facilitated with better knowledge of the spatial variation in location of high quality grain. This knowledge would assist Canada in maintaining its high standards for delivery of consistent quality wheat. Forecast models would not only be useful to gain knowledge of the yield and quality of Canadian wheat produced in a given year but could also be useful to estimate yield and quality of wheat being produced in other countries.

End-use quality forecast models were developed and reported in Chapter 3 using weather and crop development data for bread making wheat grown in western Canada. These prediction models demonstrated a good potential for wheat quality prediction using only three weather variables accumulated during certain key crop development stages. Very strong relationships were found between most quality parameters and the weather. The prediction models were developed using six genotypes grown in seven environments during the 2003 and 2004 growing season. The genotypes spanned three commercial classes of wheat, and the seven environments provided very diverse growing conditions for wheat growth.

The data collected during the 2005 growing season provided an opportunity to validate the relationships developed during the previous two growing seasons and to determine how robust they were for wheat quality prediction. The first objective of this study was to determine the validity of the regression models developed in Chapter 3 using weather and grain quality data from the 2005 growing season. The second objective was to determine if quality prediction could be improved with forecast models that were genotype or commercial class specific or by targeting key weather parameters and growing stages as independent variables.

5.3 Materials and Methods

Field trials were carried out during the 2005 growing season at Regina, Swift Current and Melfort, Saskatchewan as well as Winnipeg and Carman, Manitoba. The data from Carman and Melfort in 2005 were not included because of the impacts of severe Fusarium damage and severe sprout damage, respectively. These post-season effects mask the impact of growing season weather on wheat quality and therefore, the relationships developed in this study would not be applicable. Field setup and data collection was the same as that for 2003 and 2004 and have been described in detail in Chapter 2. For 2005, only the grain properties were available for testing because the 2005 grain samples were not yet milled at the time of analysis. Grain quality property means were produced by averaging the three replicates at each site.

Using the three complex weather variable regression models developed in Chapter 3, grain quality forecasts were generated using weather variables collected during the 2005 growing season. New regression equations were developed using the 2003 and

2004 data and tested using the 2005 grain properties in an attempt to improve predictability.

AC Vista is a Canadian Prairie Spring wheat genotype, which was developed for considerably higher yields than the other hard spring wheat genotypes and so it was decided that an improvement could be made by removing this genotype from the regression analysis. Regression equations were also developed using several other genotype groupings based on significant differences between genotypes for various grain properties as reported in Chapter 2. Individual genotype regression equations were developed using the 2003 and 2004 variables to determine the most influential weather parameters affecting grain properties for individual genotypes. The individual regression equations were then tested on the 2005 grain properties. In an attempt to reduce the number of explanatory variables required, the regression equations were limited to the three main weather variables selected for each genotype. Genotype groupings were then re-analyzed using the reduced explanatory variable data set.

A summary of the various regression equation groupings are listed in Table 5.1.

Table 5.1. Summary of the various regression equation groupings.

Step #	Regression equation grouping
1	AC Vista Removed
2	CWRS genotypes
3	Genotypes grouped with no significant difference in weather response by grain property
4	Individual genotype
5	Reduced variable set, all genotypes
6	Reduced variable set, AC Vista removed
7	Reduced variable set, with genotypes grouped with no significant difference in weather response by grain property

All statistical analysis was completed using the same procedures outlined in Chapter 3. Prediction models for grade were not tested due to the relatively poor predictability of this property. Kernel number was also not included because of its close correlation to yield.

5.4 Results and Discussion

5.4.1 Yield

The prediction models produced varied outcomes for the grain properties in 2005. Within the three sites, predicted yield, using the original model, ranged from 2625 kg/ha below to 2271 kg/ha above the observed yield and came as close as 70 kg/ha below the observed yield (Table 5.2). The yield at the Winnipeg site was predicted the best with the average predicted yield being 263 kg/ha different than the observed. The Swift Current site was the poorest with predicted yield averaging 1456 kg/ha off the observed yield. Yields at Regina were generally not well predicted either, with the exception of AC Barrie, AC Snowbird and Superb, which were predicted within 600 kg/ha of the actual yield. Predicted AC Vista yield was very inaccurate as AC Vista experienced a very large yield in 2005 compared to the other genotypes (Figure 5.1).

Table 5.2. Predicted yield (kg/ha) and difference from actual yield using original prediction model (same model for all genotypes).

			Original Prediction Model		
			SEP[z] = 927.51		
Siteyear	**Genotype**	**Actual Yield**	**Predicted Yield**	**Difference**	**Absolute Difference**
Reg05	AC Barrie	3349.20	2973.84	-375.36	375.36
Reg05	AC Elsa	4183.09	3051.23	-1131.86	1131.86
Reg05	Neepawa	2329.37	3265.43	936.06	936.06
Reg05	AC Snowbird	3654.97	3071.26	-583.71	583.71
Reg05	Superb	3577.79	3071.26	-506.53	506.53
Reg05	AC Vista	5476.82	2851.55	-2625.27	2625.27
	Average	**3761.87**	**3047.43**		**1026.47**
SC05	AC Barrie	3537.19	5134.97	1597.77	1597.77
SC05	AC Elsa	3613.24	4914.15	1300.90	1300.90
SC05	Neepawa	2953.37	5224.87	2271.50	2271.50
SC05	AC Snowbird	3349.31	5121.22	1771.91	1771.91
SC05	Superb	4171.43	5038.48	867.05	867.05
SC05	AC Vista	4094.60	5024.56	929.96	929.96
	Average	**3619.86**	**5076.37**		**1456.51**
Wpg05	AC Barrie	3666.48	3415.26	-251.22	251.22
Wpg05	AC Elsa	3513.95	3248.77	-265.18	265.18
Wpg05	Neepawa	3245.79	3528.30	282.52	282.52
Wpg05	AC Snowbird	3573.07	3475.62	-97.46	97.46
Wpg05	Superb	3794.03	3723.29	-70.74	70.74
Wpg05	AC Vista	3970.10	3357.35	-612.75	612.75
	Average	**3627.24**	**3458.10**		**263.31**
Yield =	-19.68214***GDD5_An_Mlk** -142.7807***TmpDegDay29_Infl_Mlk** +0.04833***TotalGlobRad_An50_Mlk** + 5521.2737				

[z] Standard Error of Prediction

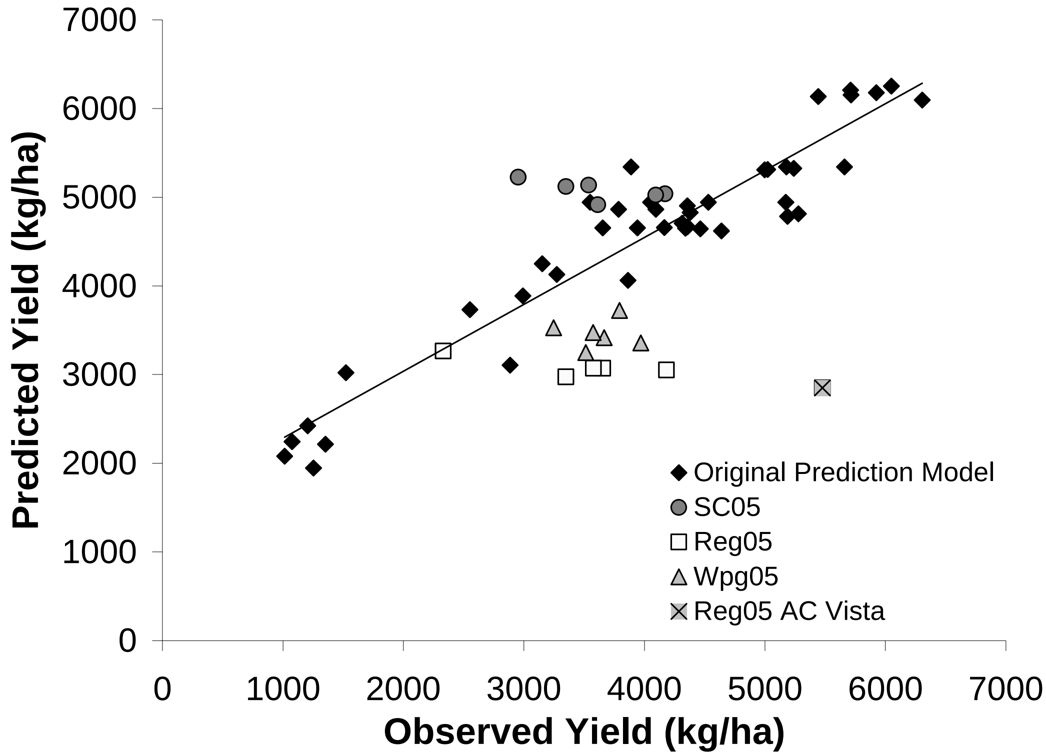

Figure 5.1. Observed average wheat yield (for all genotypes) vs. yield predicted using the original 3 parameter regression model (Chapter 3) for three 2005 growing locations.

In Chapter 2, a significant difference was reported between the yield of AC Vista and the other genotypes as well as for the other grain properties, which suggested that AC Vista grain properties were responding differently to the growing season weather conditions at each site. This is evident in Figure 5.2, where AC Vista yield has a slope to the regression line that is visibly different from the other genotypes and was generally under predicted. This indicated that a separate regression should be utilized for this genotype or class of wheat.

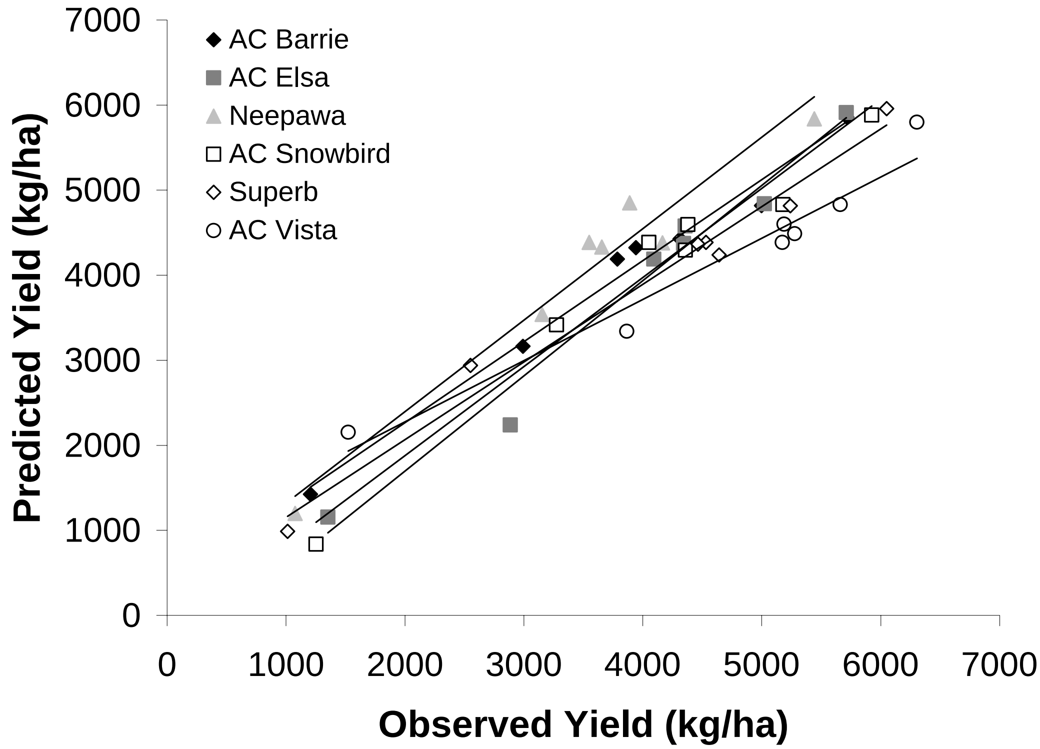

Figure 5.2. Observed vs. predicted wheat yield separated by genotype, using the original 3 parameter regression model.

The 2005 predicted yields were improved substantially for the Regina and Swift Current site with AC Vista removed from the regression equation (Table 5.3). The standard error of prediction dropped from 928 with Vista included to 711 with Vista removed from the equation. Regina predicted yields averaged 516 kg/ha off the actual and Swift Current improved to 776 kg/ha from the actual yield. The Winnipeg yield prediction became worse using the new equation, averaging 840 kg/ha below the observed yield.

The data set was further modified by removing Neepawa from the regression. It is an older, lower yielding genotype, and its yield was being consistently over predicted. The removal of both Neepawa and Vista from the regressions did not improve prediction accuracy compared to just removing AC Vista, with the standard error of prediction (SEP) increasing to 769.

Table 5.3. Predicted yield (kg/ha) and difference from actual yield using a model developed with AC Vista removed.

			AC Vista Removed		
			SEP[z] = 711.41		
Siteyear	Genotype	Actual Yield	Predicted Yield	Difference	Absolute Difference
Reg05	AC Barrie	3349.20	3214.80	-134.40	134.40
Reg05	AC Elsa	4183.09	3298.33	-884.76	884.76
Reg05	Neepawa	2329.37	3298.33	968.96	968.96
Reg05	AC Snowbird	3654.97	3317.98	-336.98	336.98
Reg05	Superb	3577.79	3317.98	-259.81	259.81
Reg05	AC Vista	5476.82			
	Average	**3761.87**	**3265.16**		**516.98**
SC05	AC Barrie	3537.19	4343.59	806.40	806.40
SC05	AC Elsa	3613.24	4139.83	526.58	526.58
SC05	Neepawa	2953.37	4374.37	1421.00	1421.00
SC05	AC Snowbird	3349.31	4374.37	1025.06	1025.06
SC05	Superb	4171.43	4273.40	101.97	101.97
SC05	AC Vista	4094.60			
	Average	**3619.86**	**4291.21**		**776.20**
Wpg05	AC Barrie	3666.48	2704.22	-962.26	962.26
Wpg05	AC Elsa	3513.95	2452.40	-1061.55	1061.55
Wpg05	Neepawa	3245.79	2910.10	-335.69	335.69
Wpg05	AC Snowbird	3573.07	2704.22	-868.85	868.85
Wpg05	Superb	3794.03	2823.50	-970.53	970.53
Wpg05	AC Vista	3970.10			
	Average	**3627.24**	**2702.17**		**839.77**
Yield =	+ 0.05512***TotalGlobRad_An50_Mlk** - 30.01648***HarET_An50_Mlk** - 12.99471***DegHr27_Infl_Mlk** + 2766.15966				

[z] Standard Error of Prediction

The data set was modified again to include only Canadian Western Red Spring (CWRS) wheat genotypes, so AC Vista and AC Snowbird were removed. Once again this did not improve the prediction accuracy compared to just removing AC Vista. The SEP increased from 711 with just AC Vista removed to 722 with AC Vista and AC Snowbird removed from the equation.

Genotypes were then grouped according to statistically similar yield responses across environments, as reported in Chapter 2. This led to the analysis of AC Elsa, AC Snowbird, and Superb as a group. This combination of genotypes produced a SEP of only 288 (Table 5.4). Variability within a site between genotypes was still evident, especially at Swift Current where Superb was under predicted by 1000 kg/ha while AC Snowbird was predicted within 10 kg/ha.

Individual regression equations were tested and on average, did not work satisfactorily, producing the highest standard error of prediction for all the methods attempted (SEP = 1284). Generally, a genotype would be predicted well at one location but then be very poorly predicted at another location.

The weather variable data set was then reduced by using only the weather parameters selected in each of the individual regression equations in an attempt to use only the most important weather variables in the regression analysis. All genotypes were initially included, which led to satisfactory forecast results for the Winnipeg location only. The standard error of prediction was 947, very similar to that for the original regression model.

Due to the obvious difference between AC Vista and the rest of the genotypes, AC Vista was removed from the reduced data set analysis. However, the improvement in prediction accuracy when AC Vista was removed was minimal. Average predicted yield was worse at each site and the standard error of prediction was 805.

Table 5.4. Predicted yield (kg/ha) and difference from actual yield using a model developed with AC Elsa, AC Snowbird, and Superb.

			AC Elsa_AC Snowbird_ Superb		
			SEP[z] = 288.34		
Siteyear	**Genotype**	**Actual Yield**	**Predicted Yield**	**Difference**	**Absolute Difference**
Reg05	AC Barrie	3349.20			
Reg05	AC Elsa	4183.09	3412.17	-770.92	770.92
Reg05	Neepawa	2329.37			
Reg05	AC Snowbird	3654.97	3233.63	-421.34	421.34
Reg05	Superb	3577.79	3233.63	-344.16	344.16
Reg05	AC Vista	5476.82			
	Average	**3761.87**	**3293.14**		**512.14**
SC05	AC Barrie	3537.19			
SC05	AC Elsa	3613.24	3041.17	-572.07	572.07
SC05	Neepawa	2953.37			
SC05	AC Snowbird	3349.31	3338.69	-10.62	10.62
SC05	Superb	4171.43	3162.95	-1008.49	1008.49
SC05	AC Vista	4094.60			
	Average	**3619.86**	**3180.94**		**530.39**
Wpg05	AC Barrie	3666.48			
Wpg05	AC Elsa	3513.95	3563.56	49.61	49.61
Wpg05	Neepawa	3245.79			
Wpg05	AC Snowbird	3573.07	3841.55	268.48	268.48
Wpg05	Superb	3794.03	3754.05	-39.98	39.98
Wpg05	AC Vista	3970.10			
	Average	**3627.24**	**3719.72**		**119.36**
Yield =	+ 0.03801***TotalGlobRad_An50_Mlk** - 20.78557***DegHr30_An_Dgh** + 28.73699***BRDef6_Plt_Infl** + 2170.56681				

[z] Standard Error of Prediction

The genotype grouping of AC Elsa, AC Snowbird, and Superb, was also assessed using the reduced data set. This grouping produced better results than the other attempts using the reduced data set, however, the predictive ability was not as strong as that using the same grouping of genotypes and all independent variables (Table 5.4) (SEP = 315 and 288, respectively).

For yield data, the use of all the weather variables along with a grouping of genotypes that responded similarly to weather created the best predictive model. This combination had the lowest SEP value of 288.34 (Table 5.4). The next best forecast model had an SEP value of 315.67, which was the model using the same genotype group as above but with a reduced explanatory data set. The SEP values of the other models ranged from 711.41 to 1284.70, which were clearly poorer performing models. The model prediction accuracy and variability between could be partially attributed to the GxE interaction effect. Chapter one showed that the GxE interaction was significant but relatively smaller than the environment effect. However, even though the GxE effect is small, it may be important to take into consideration when developing quality prediction models.

5.4.2 Test Weight

Test weight was reasonably well predicted at Regina and Swift Current using the original prediction models (Table 5.5). At Regina, predicted test weight ranged between 1.5 and 4.2 kg/hL below the observed test weight. At Swift Current, predicted test weight ranged between 0.55 and 4.9 kg/hL above the actual test weight. Winnipeg however, was very poorly predicted, with an average predicted test weight of 12 kg/hL higher than the actual. The SEP for the original model was 6.15.

The three parameter model was then broken apart into the three weather components and test weight was plotted against each of the individual weather variables in order to determine why Winnipeg test weight was over predicted in 2005. As shown in Figure 5.3, precipitation data was causing the over prediction in test weight in Winnipeg.

Table 5.5. Predicted test weight (kg/hL) and difference from actual test weight using original prediction model.

			Original Prediction Model		
			SEP[z] = 6.15		
Siteyear	**Genotype**	**Actual Test Weight**	**Predicted Test Weight**	**Difference**	**Absolute Difference**
Reg05	AC Barrie	84.07	79.87	-4.19	4.19
Reg05	AC Elsa	83.20	80.13	-3.07	3.07
Reg05	Neepawa	83.00	79.53	-3.47	3.47
Reg05	AC Snowbird	82.67	80.57	-2.10	2.10
Reg05	Superb	83.00	80.07	-2.93	2.93
Reg05	AC Vista	81.67	80.15	-1.52	1.52
	Average	**82.93**	**80.05**		**2.88**
SC05	AC Barrie	79.40	79.92	0.52	0.52
SC05	AC Elsa	77.70	80.05	2.35	2.35
SC05	Neepawa	75.10	80.01	4.91	4.91
SC05	AC Snowbird	78.33	80.47	2.14	2.14
SC05	Superb	79.47	80.02	0.55	0.55
SC05	AC Vista	75.77	79.94	4.17	4.17
	Average	**77.63**	**80.07**		**2.44**
Wpg05	AC Barrie	82.20	92.64	10.44	10.44
Wpg05	AC Elsa	80.40	92.45	12.05	12.05
Wpg05	Neepawa	80.53	91.20	10.67	10.67
Wpg05	AC Snowbird	80.43	92.63	12.20	12.20
Wpg05	Superb	80.83	93.79	12.95	12.95
Wpg05	AC Vista	77.57	91.11	13.54	13.54
	Average	**80.33**	**92.30**		**11.98**

Test weight = + 0.09051***BRWUR6_An_Dgh**
+ 0.20487***Precip_Infl_Mlk**
+ 0.01745***GDD3_Infl_Mlk** + 68.99301

[z] Standard Error of Prediction

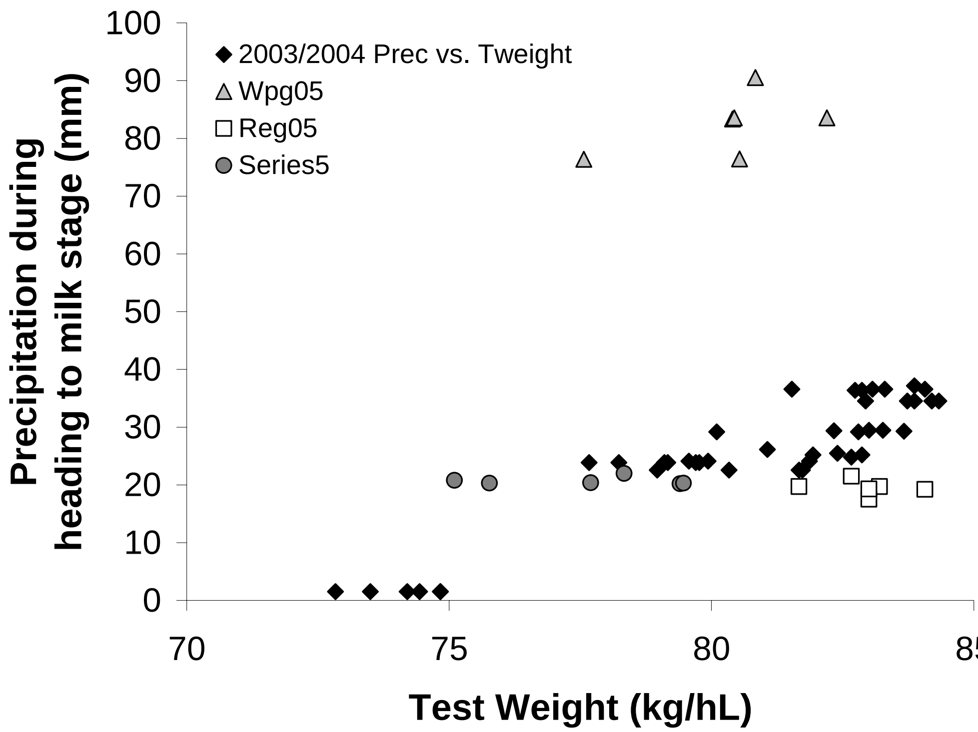

Figure 5.3. Relationship between test weight and precipitation accumulated during the inflorescence to milk stage.

In Winnipeg during 2005, a very severe storm occurred during the early kernel development stage in which over 25 mm of rain fell in just 1 hour and over 40 mm fell in under 4 hours. This created a situation where the precipitation data for Winnipeg 2005 fell far outside the range that was experienced during this stage in 2003 and 2004. This situation resulted in very inaccurate predicted test weights for Winnipeg 2005 (Table 5.5) (Figure 5.4). Precipitation data may not be an effective variable to use in predicting quality because of extreme events such as this. Most of the precipitation that fell during the severe storm would not be effective precipitation. The majority of rain would run off and not be utilized by the crop. Due to this fact, precipitation data was removed from the 2003/2004 data set and was not included in any future regression analysis.

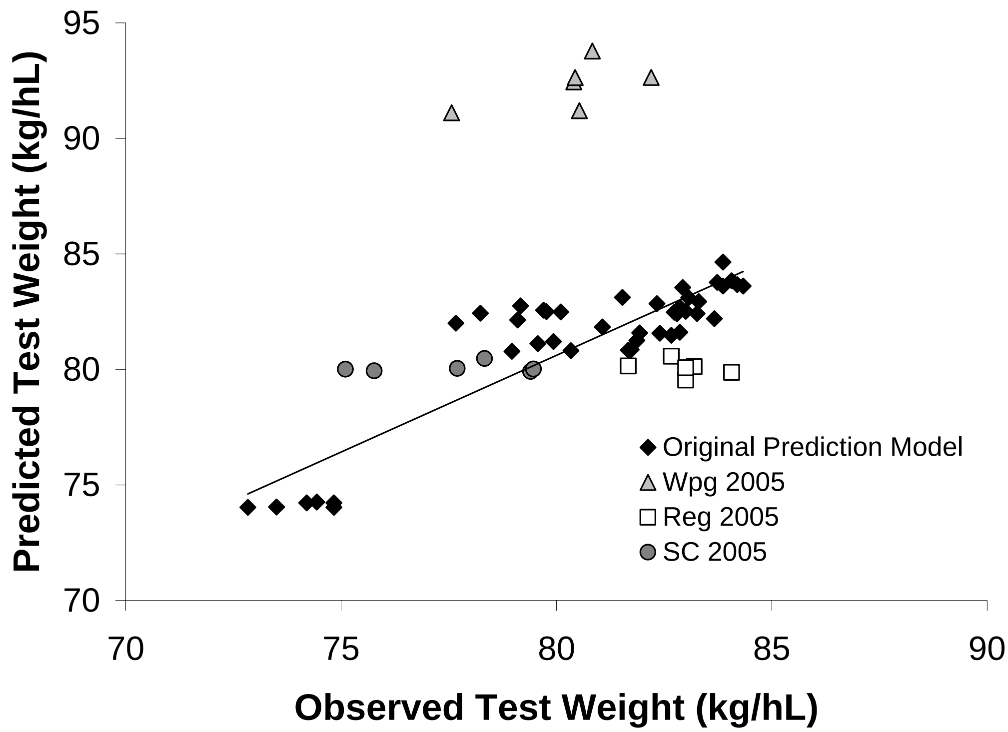

Figure 5.4. Observed vs. predicted test weight using original 3 parameter regression model compared to predicted test weight produced from three 2005 growing locations.

The regression equation developed without precipitation data substantially improved the accuracy of test weight prediction in Winnipeg, improving the average predicted test weight to 2.5 kg/hL above the actual from 12 kg/hL using the original model (Table 5.5 and Table 5.6, respectively). Test weight prediction at Regina was also improved, with an average predicted test weight for all genotypes being 0.88 kg/hL below the actual. At Swift Current, test weight prediction became very poor with the average predicted value dropping to 11 kg/hL from 2.4 kg/hL. Swift Current 2005 experienced higher water use than what was experienced in 2003 or 2004, leading to over prediction of test weight. Overall, the standard error of prediction decreased substantially from 6.15 for the original model to 2.05 with precipitation data excluded.

In an attempt to further improve test weight prediction, AC Vista was again removed from the data set. Precipitation data was also excluded in this analysis. The regression analysis produced a three variable model with two highly correlated independent variables, so a two variable model was used. Test weight was again predicted very well at Regina (average difference from actual = -0.98) and improved slightly for both Winnipeg and Swift Current (Table 5.7). The standard error of prediction decreased from 2.05 for the model including Vista to 1.51 for the model where Vista was excluded. Water use was selected again as a variable in the modified regression equation, creating the same over estimation of test weight at Swift Current. Test weight was still predicted within 10% of the actual for the Swift Current site using this model.

Regression equations were developed using genotypes grouped by statistically similar responses to environment. The group of AC Elsa, Neepawa, AC Snowbird, and Superb did not substantially improve test weight prediction as compared to the model developed with just AC Vista removed. The SEP was found to be 1.51 for the model developed with AC Vista removed and 1.52 for the grouped genotype model. When the same genotype group was analyzed using the reduced weather variable set the strongest predictive model was developed. This analysis produced a regression curve that led to test weight being forecast within 5% of the actual test weight at all three sites in 2005 (Table 5.8) and an SEP of 1.46.

Table 5.6. Predicted test weight (kg/hL) and difference from actual test weight using a model developed with precipitation data removed.

			No Precipitation Data		
			SEP[z] = 2.05		
Siteyear	**Genotype**	**Actual Test Weight**	**Predicted Test Weight**	**Difference**	**Absolute Difference**
Reg05	AC Barrie	84.07	82.27	-1.80	1.80
Reg05	AC Elsa	83.20	82.62	-0.58	0.58
Reg05	Neepawa	83.00	81.74	-1.26	1.26
Reg05	AC Snowbird	82.67	82.41	-0.25	0.25
Reg05	Superb	83.00	82.23	-0.77	0.77
Reg05	AC Vista	81.67	82.28	0.62	0.62
	Average	**82.93**	**82.26**		**0.88**
SC05	AC Barrie	79.40	88.80	9.40	9.40
SC05	AC Elsa	77.70	88.82	11.12	11.12
SC05	Neepawa	75.10	88.89	13.79	13.79
SC05	AC Snowbird	78.33	89.39	11.05	11.05
SC05	Superb	79.47	88.72	9.26	9.26
SC05	AC Vista	75.77	88.89	13.12	13.12
	Average	**77.63**	**88.92**		**11.29**
Wpg05	AC Barrie	82.20	83.05	0.85	0.85
Wpg05	AC Elsa	80.40	82.84	2.44	2.44
Wpg05	Neepawa	80.53	83.17	2.64	2.64
Wpg05	AC Snowbird	80.43	82.74	2.31	2.31
Wpg05	Superb	80.83	82.13	1.30	1.30
Wpg05	AC Vista	77.57	82.91	5.34	5.34
	Average	**80.33**	**82.81**		**2.48**

Test weight = - 0.00043802***TotalWRunKm_An50_Mat**
+ 0.32797***HarWU_An_Mlk**
+ 0.03129***P5_17_31_Plt_An50**+59.90596

[z] Standard Error of Prediction

Table 5.7. Predicted test weight (kg/hL) and difference from actual test weight using a model developed with AC Vista removed.

			AC Vista Removed		
			SEP[z] = 1.51		
Siteyear	**Genotype**	**Actual Test Weight**	**Predicted Test Weight**	**Difference**	**Absolute Difference**
Reg05	AC Barrie	84.07	82.05	-2.02	2.02
Reg05	AC Elsa	83.20	82.59	-0.61	0.61
Reg05	Neepawa	83.00	81.82	-1.18	1.18
Reg05	AC Snowbird	82.67	82.35	-0.32	0.32
Reg05	Superb	83.00	82.21	-0.79	0.79
Reg05	AC Vista	81.67			
	Average	**82.93**	**82.20**		**0.98**
SC05	AC Barrie	79.40	87.65	8.25	8.25
SC05	AC Elsa	77.70	87.33	9.63	9.63
SC05	Neepawa	75.10	87.88	12.78	12.78
SC05	AC Snowbird	78.33	88.34	10.00	10.00
SC05	Superb	79.47	87.43	7.96	7.96
SC05	AC Vista	75.77			
	Average	**77.63**	**87.73**		**9.73**
Wpg05	AC Barrie	82.20	82.83	0.63	0.63
Wpg05	AC Elsa	80.40	82.46	2.06	2.06
Wpg05	Neepawa	80.53	83.14	2.61	2.61
Wpg05	AC Snowbird	80.43	82.56	2.13	2.13
Wpg05	Superb	80.83	82.19	1.36	1.36
Wpg05	AC Vista	77.57			
	Average	**80.33**	**82.64**		**1.76**

Test weight = + 0.08171***BRWUR6_An_Dgh**
+ 0.22964***Precip_Infl_Mlk**
- 0.08767***TmpDegDay29_Plt_Jnt** + 74.22926

[z] Standard Error of Prediction

Table 5.8. Predicted test weight (kg/hL) and difference from actual test weight using a model developed with a reduced weather variable data set and only AC Elsa, Neepawa, AC Snowbird, Superb.

			Reduced Variable Set Elsa_Neepawa_Snowbird_Superb		
			SEP^{z} = 1.46		
Siteyear	**Genotype**	**Actual Test Weight**	**Predicted Test Weight**	**Difference**	**Absolute Difference**
Reg05	AC Barrie	84.07			
Reg05	AC Elsa	83.20	79.88	-3.32	3.32
Reg05	Neepawa	83.00	78.79	-4.21	4.21
Reg05	AC Snowbird	82.67	80.81	-1.85	1.85
Reg05	Superb	83.00	80.15	-2.85	2.85
Reg05	AC Vista	81.67			
	Average	**82.93**	**79.91**		**3.06**
SC05	AC Barrie	79.40			
SC05	AC Elsa	77.70	80.44	2.74	2.74
SC05	Neepawa	75.10	79.96	4.86	4.86
SC05	AC Snowbird	78.33	80.77	2.44	2.44
SC05	Superb	79.47	80.95	1.49	1.49
SC05	AC Vista	75.77			
	Average	**77.63**	**80.53**		**2.88**
Wpg05	AC Barrie	82.20			
Wpg05	AC Elsa	80.40	82.67	2.27	2.27
Wpg05	Neepawa	80.53	83.02	2.49	2.49
Wpg05	AC Snowbird	80.43	82.83	2.40	2.40
Wpg05	Superb	80.83	82.71	1.88	1.88
Wpg05	AC Vista	77.57			
	Average	**80.33**	**82.81**		**2.26**

Test weight = + 0.05807***GDD9_An_Dgh**
+ 0.03601***BRWU6_Plt_Dgh**
+ 0.27857 ***BRDef6_Plt_Jnt** + 59.99005

^{z} Standard Error of Prediction

Test weight appeared to be very predictable using growing season weather variables. In this case, it was demonstrated that the most accurate prediction model was developed using a group of genotypes that respond similarly to the environment and using a limited set of weather variables that are significant to each genotype. This particular model had an SEP value of 1.46 (Table 5.8), which compared closely to the model using the same genotype group but with all weather variables and to the model with AC Vista removed (SEP = 1.52 and 1.51, respectively). The first model mentioned above was considered the most accurate model due to more consistent results across all three locations. The other two models mentioned above predicted test weight very well at two locations and less accurately at the third.

5.4.3 Grain Protein Content (GPC)

GPC was very well predicted in Regina 2005. Besides AC Elsa and AC Vista, which were under and over predicted by -1.3 and 1.5%, respectively, protein content in Regina came as close as 0.19 and -0.42% (Table 5.9). The average difference across all genotypes in predicted protein was 0.73. However, the protein forecast at the other two sites was not especially accurate. Protein content in Winnipeg was over predicted by an average of almost 2%. In Swift Current, protein content was over predicted by about 2.5 points. Figure 5.5 clearly demonstrates the over prediction at Swift Current and Winnipeg. The SEP of the original forecast model was 1.02.

The data set was once again modified in an attempt to better predict protein content. Initially, AC Vista was removed from the 2003/2004 data set and a new regression equation was developed which included precipitation data from anthesis to maturity. As indicated earlier, precipitation data was not considered to be a very reliable variable due to extreme rainfall events and, therefore, this variable was removed. The regression analysis with AC Vista and precipitation data excluded slightly decreased the protein content prediction accuracy at Swift Current and Winnipeg and marginally improved the prediction at Regina. Overall, the SEP increased from 1.02 using the original model to 1.09 with AC Vista removed.

Table 5.9. Predicted protein content (%) and difference from actual protein content using original prediction model.

			Original Prediction Model		
			SEP[z] = 1.02		
Siteyear	**Genotype**	**Actual Protein**	**Predicted Protein**	**Difference**	**Absolute Difference**
Reg05	AC Barrie	14.33	14.07	-0.26	0.26
Reg05	AC Elsa	15.27	13.92	-1.35	1.35
Reg05	Neepawa	14.27	13.84	-0.42	0.42
Reg05	AC Snowbird	14.60	13.96	-0.64	0.64
Reg05	Superb	13.77	13.96	0.19	0.19
Reg05	AC Vista	12.57	14.11	1.54	1.54
	Average	**14.13**	**13.98**		**0.73**
SC05	AC Barrie	14.23	16.29	2.06	2.06
SC05	AC Elsa	14.10	16.48	2.38	2.38
SC05	Neepawa	15.23	16.08	0.84	0.84
SC05	AC Snowbird	13.33	16.20	2.87	2.87
SC05	Superb	12.70	16.52	3.82	3.82
SC05	AC Vista	13.37	16.29	2.92	2.92
	Average	**13.83**	**16.31**		**2.48**
Wpg05	AC Barrie	13.53	14.90	1.37	1.37
Wpg05	AC Elsa	13.37	14.98	1.62	1.62
Wpg05	Neepawa	13.47	14.86	1.39	1.39
Wpg05	AC Snowbird	13.00	14.89	1.89	1.89
Wpg05	Superb	12.83	14.82	1.98	1.98
Wpg05	AC Vista	11.60	14.97	3.37	3.37
	Average	**12.97**	**14.90**		**1.94**

Protein = - 0.01928***GDD10_an50_Dgh**
- 0.01024***TempRange_Plt_An**
+ 0.04211***FAOET_Plt_Dgh** + 10.77189

[z] Standard Error of Prediction

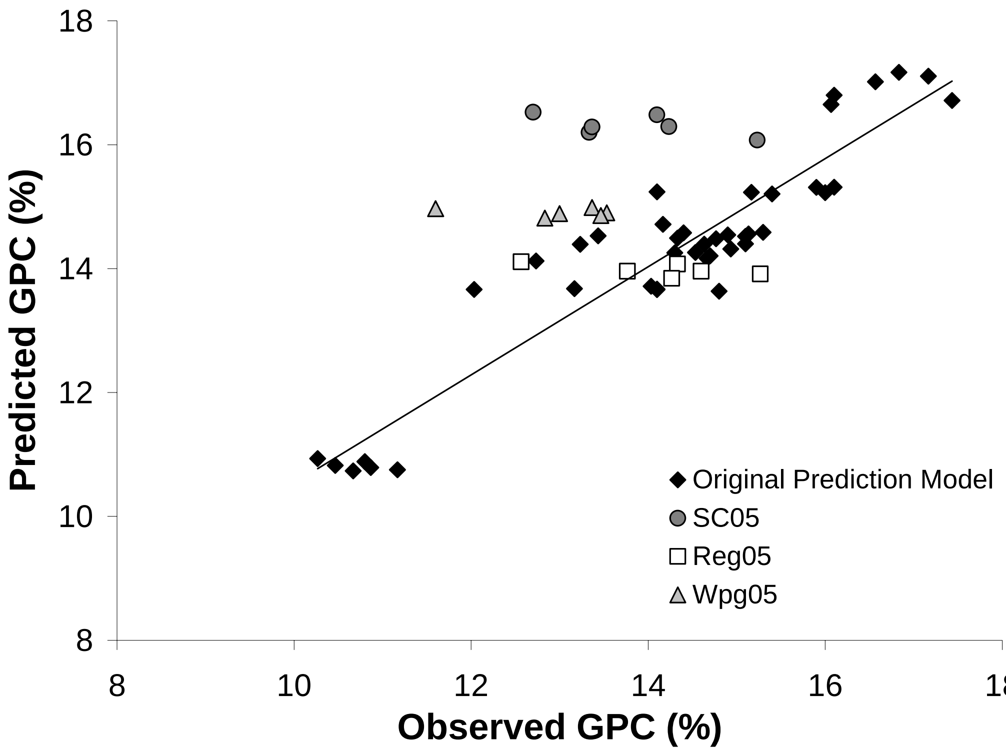

Figure 5.5. Observed vs. predicted GPC using original 3 parameter regression model compared to predicted GPC produced from three 2005 growing locations.

Another attempt was made to improve forecast accuracy by removing AC Vista and AC Snowbird, leaving only CWRS wheat genotypes. Figure 5.6 demonstrates that both AC Vista and AC Snowbird have different response curves in comparison to the other genotypes. AC Snowbird's response produced a steeper curve while AC Vista's response was outside the range of the other genotypes and would generally be over predicted. The removal of these two genotypes slightly improved protein content prediction at Regina but again decreased the prediction accuracy at Swift Current and Winnipeg compared to the original model and SEP increased to 1.10.

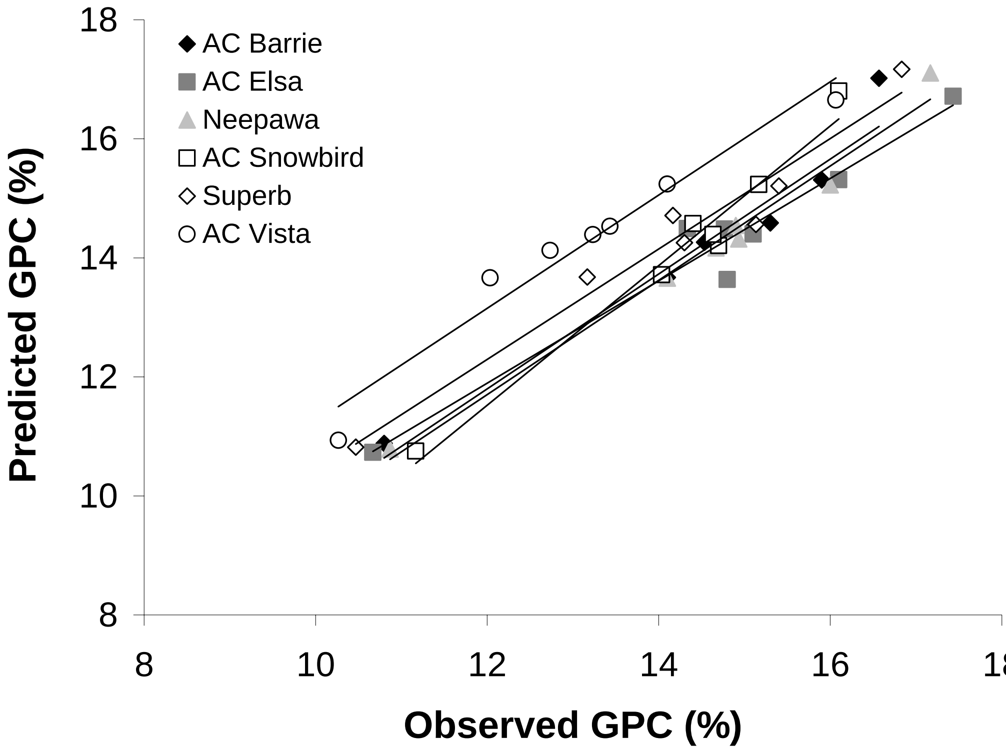

Figure 5.6. Observed vs. predicted GPC separated by genotype, using original 3 parameter regression model.

Due to the variation in prediction accuracy of each individual genotype at each location, separate regression models were developed for each genotype. The biggest improvement was found in the prediction of AC Vista (Table 5.10). At all three sites, protein content was very poorly predicted for AC Vista using the original model. When a genotype specific model was developed for AC Vista, protein content was predicted within 0.02, 0.03, and 0.11 at Regina, Swift Current and Winnipeg, respectively. For the other genotypes, the results were more varied. For example, Neepawa protein content in Regina was over predicted by only 0.36%, but in Winnipeg, protein content was over estimated by 3.7%. Stronger regression equations for individual genotypes could be developed with the inclusion of more data points, considering that currently, the single genotype models only have 7 points in the regression.

Table 5.10. Predicted protein content (%) and difference from actual protein content using models developed for individual genotypes.

			Individual Genotype Regression Models		
			SEP[z] = 1.55		
Siteyear	**Genotype**	**Actual Protein**	**Predicted Protein**	**Difference**	**Absolute Difference**
Reg05	AC Barrie	14.33	15.17	0.84	0.84
Reg05	AC Elsa	15.27	16.39	1.13	1.13
Reg05	Neepawa	14.27	14.63	0.36	0.36
Reg05	AC Snowbird	14.60	15.23	0.63	0.63
Reg05	Superb	13.77	12.70	-1.07	1.07
Reg05	AC Vista	12.57	12.58	0.02	0.02
	Average	**14.13**	**14.45**		**0.68**
SC05	AC Barrie	14.23	17.28	3.04	3.04
SC05	AC Elsa	14.10	14.36	0.26	0.26
SC05	Neepawa	15.23	16.88	1.65	1.65
SC05	AC Snowbird	13.33	16.90	3.56	3.56
SC05	Superb	12.70	15.11	2.41	2.41
SC05	AC Vista	13.37	13.34	-0.03	0.03
	Average	**13.83**	**15.64**		**1.82**
Wpg05	AC Barrie	13.53	15.54	2.00	2.00
Wpg05	AC Elsa	13.37	13.66	0.29	0.29
Wpg05	Neepawa	13.47	17.21	3.74	3.74
Wpg05	AC Snowbird	13.00	10.98	-2.02	2.02
Wpg05	Superb	12.83	13.54	0.71	0.71
Wpg05	AC Vista	11.60	11.71	0.11	0.11
	Average	**12.97**	**13.77**		**1.48**

Barrie protein = + 0.02035***GDD7_Dgh_Mat**
- 0.01466***TempRange_Plt_An**
+ 0.06064***FAOET_Plt_Mat** - 0.28143

Elsa protein = + 0.17605***BRET6_An50_Mlk**
- 0.05075***GDD9_An_Dgh**
- 0.02681* **BRDef6_Plt_An** + 19.47471

Neepawa protein = + 0.01479***GDD3_Dgh_Mat**
+ 0.06602***PMET_Plt_Mat**
- 0.01841***TempRange_Plt_Mlk** + 3.26452

Snowbird protein = - 0.0434***GDD10_An_Mlk**
+ 0.09626 ***TmpDegDay17_Infl_An50**
+ 0.04326***P5_23_32_Jnt_Infl** + 11.07435

Superb protein = - 0.03394***GDD9_An_Mat**
+ 0.07937***PMET_Infl_Mlk**
- 0.00548***CumVaporPresDef_Plt_An50** + 20.67803

Vista protein = + 0.16025***FAOET_An_Mlk**
+ 0.0719 ***BRDem3_Dgh_Mat** + 3.0042

[z] Standard Error of Prediction

Genotypes were again grouped according to similar environment responses. Two groups were made, the first, AC Barrie, AC Elsa, and Neepawa (SEP = 1.10) (Table 5.11), and the second of Superb and AC Snowbird (SEP = 1.31). These genotype groups did not improve the forecasting ability of protein content. Protein content at Regina was still found to be very well predicted for both groups while Swift Current and Winnipeg were still relatively poorly predicted.

Table 5.11. Predicted protein content (%) and difference from actual protein content using a model developed with AC Barrie, AC Elsa, and Neepawa.

			AC Barrie_AC Elsa_Neepawa		
			SEP^z = 1.10		
Siteyear	**Genotype**	**Actual Protein**	**Predicted Protein**	**Difference**	**Absolute Difference**
Reg05	AC Barrie	14.33	15.02	0.69	0.69
Reg05	AC Elsa	15.27	14.81	-0.45	0.45
Reg05	Neepawa	14.27	14.96	0.70	0.70
Reg05	AC Snowbird	14.60			
Reg05	Superb	13.77			
Reg05	AC Vista	12.57			
	Average	**14.13**	**14.93**		**0.61**
SC05	AC Barrie	14.23	17.25	3.01	3.01
SC05	AC Elsa	14.10	17.44	3.34	3.34
SC05	Neepawa	15.23	17.01	1.78	1.78
SC05	AC Snowbird	13.33			
SC05	Superb	12.70			
SC05	AC Vista	13.37			
	Average	**13.83**	**17.23**		**2.71**
Wpg05	AC Barrie	13.53	15.57	2.03	2.03
Wpg05	AC Elsa	13.37	15.66	2.29	2.29
Wpg05	Neepawa	13.47	15.60	2.13	2.13
Wpg05	AC Snowbird	13.00			
Wpg05	Superb	12.83			
Wpg05	AC Vista	11.60			
	Average	**12.97**	**15.61**		**2.15**

Protein = - 0.01871***GDD10_An_Dgh**
- 0.01107 ***TempRange_Plt_An**
+ 0.04338***PMET_Plt_Mat** + 10.23006

[z] Standard Error of Prediction

The weather variable data set was reduced in the same manner as utilized for the other properties. A regression equation was developed using all genotypes and using the genotype groups. Again, no improvements were made for prediction of protein content in Swift Current and Winnipeg in either of these attempts. The SEP values again were very similar to previous attempts (SEP = 0.98 and 1.08, respectively).

Protein content was well predicted at Regina using several different regression models but poorly predicted at the other two locations. The most accurate prediction at Regina was found using the genotype group of AC Barrie, AC Elsa, and Neepawa (Table 5.11). All of the models had relatively similar SEP values, which ranged from 0.98 to 1.55. The best protein content forecast model utilized the reduced set of explanatory variables and all genotypes (SEP = 0.98).

Protein content was investigated further due to the clear difference between the accuracy of prediction at Regina compared to the other two sites. An accurate predictive model was not found that worked at all three test sites. As mentioned earlier, the actual protein content was produced by taking the mean of the three replicates at each site. At Regina, grain protein content was more stable across the replicates compared to Swift Current and Winnipeg (average genotype standard deviation = 0.20, 0.65 and 0.47, Regina, Swift Current, and Winnipeg, respectively) (Table 5.12). In 2005, at Swift Current and Winnipeg, protein content was found to vary by up to 1.6 points within a genotype. At Winnipeg, replicate one had a considerably lower protein and lower yield than the other reps. This may have been due to replicate one being located in a slightly lower and wetter area. The protein content variation at Swift Current was much more erratic and cannot be explained. The extreme variation between replicates within a site may be the reason why the forecast models were not accurately predicting protein content at these two locations.

Table 5.12. Standard deviation for the grain properties of each genotype at each site and the average standard deviation for each site.

Siteyear	Genotype	Yield SD[z]	Protein SD	Test Weight SD	TKW SD
Reg05	AC Barrie	209.58	0.15	0.12	1.05
Reg05	AC Elsa	487.30	0.15	0.20	0.24
Reg05	Neepawa	597.86	0.21	0.35	0.82
Reg05	AC Snowbird	273.15	0.10	0.12	0.47
Reg05	Superb	650.58	0.21	0.40	0.65
Reg05	AC Vista	188.97	0.35	0.23	2.05
	Average SD	**401.24**	**0.20**	**0.23**	**0.88**
SC05	AC Barrie	542.16	1.02	1.49	1.81
SC05	AC Elsa	304.80	0.87	1.47	0.83
SC05	Neepawa	55.59	0.49	0.40	0.56
SC05	AC Snowbird	259.88	0.40	0.35	0.72
SC05	Superb	450.45	0.46	0.47	0.51
SC05	AC Vista	537.93	0.67	1.30	2.98
	Average SD	**358.47**	**0.65**	**0.92**	**1.23**
Wpg05	AC Barrie	486.08	0.50	0.20	1.63
Wpg05	AC Elsa	112.95	0.67	0.66	0.72
Wpg05	Neepawa	226.38	0.45	0.45	0.91
Wpg05	AC Snowbird	262.41	0.20	0.51	0.26
Wpg05	Superb	13.19	0.38	0.67	0.75
Wpg05	AC Vista	187.71	0.60	0.81	0.96
	Average SD	**214.79**	**0.47**	**0.55**	**0.87**

[z] Standard Deviation

5.4.4 Thousand Kernel Weight (TKW)

Using the original regression equation, TKW was reasonably well predicted at Regina and Swift Current (average difference from actual = 4.9 and 3.6 grams, respectively) (Table 5.13). Superb and AC Vista TKW were under-estimated more than the others at both of these locations. Predicted TKW was over estimated by about 24 g at the Winnipeg site. The original TKW model included a precipitation variable and, as mentioned before, this caused the extreme overestimation of TKW at Winnipeg and led to the high SEP value of 13.2.

The regression analysis was completed with precipitation and AC Vista data removed. Figure 5.7 showed the noticeable difference between the response of AC Vista compared to the other genotypes. The removal of AC Vista marginally improved the TKW forecast for both Regina and Swift Current, while the TKW estimation at Winnipeg was noticeably improved to an average underestimation of 8.0 g. Again, Superb was one genotype most poorly estimated using this model (Table 5.14). This model improved the SEP value from the original 13.19 to 4.33 with AC Vista and precipitation data removed.

The CWRS genotypes were grouped and a regression equation was developed. This produced results slightly worse than those with only AC Vista removed and the SEP increased from 4.33 to 7.40. AC Elsa, Neepawa, and AC Snowbird were grouped as a result of similar TKW response to environment. This grouping produced the most accurate predicted TKW results, forecasting TKW within 10% at each site (Table 5.15). The SEP value (SEP = 0.91) for this model clearly indicated the improvements made with this particular genotype grouping since it was substantially lower than the SEP for other models tested.

Individual genotype regression curves and reduced weather variable models were developed and tested but did not provide more accurate predictions for TKW in 2005.

Table 5.13. Predicted TKW (g) and difference from actual TKW using original prediction model.

			Original Prediction Model		
			SEP[z] = 13.19		
Siteyear	**Genotype**	**Actual TKW**	**Predicted TKW**	**Difference**	**Absolute Difference**
Reg05	AC Barrie	34.56	30.83	-3.73	3.73
Reg05	AC Elsa	34.41	31.10	-3.31	3.31
Reg05	Neepawa	32.05	29.92	-2.13	2.13
Reg05	AC Snowbird	32.76	32.06	-0.70	0.70
Reg05	Superb	37.89	30.87	-7.01	7.01
Reg05	AC Vista	43.32	31.10	-12.22	12.22
	Average	**35.83**	**30.98**		**4.85**
SC05	AC Barrie	34.38	30.78	-3.60	3.60
SC05	AC Elsa	30.75	30.97	0.22	0.22
SC05	Neepawa	28.48	30.94	2.47	2.47
SC05	AC Snowbird	31.10	31.76	0.66	0.66
SC05	Superb	38.56	30.90	-7.65	7.65
SC05	AC Vista	37.55	30.72	-6.83	6.83
	Average	**33.47**	**31.01**		**3.57**
Wpg05	AC Barrie	33.89	58.86	24.96	24.96
Wpg05	AC Elsa	30.37	59.32	28.95	28.95
Wpg05	Neepawa	31.32	52.67	21.35	21.35
Wpg05	AC Snowbird	31.33	58.27	26.94	26.94
Wpg05	Superb	35.46	60.85	25.39	25.39
Wpg05	AC Vista	38.17	55.00	16.83	16.83
	Average	**33.42**	**57.49**		**24.07**

TKW = - 0.101***BRDef3_An50_Mat**
+ 0.53802***Precip_Infl_Mlk**
- 0.10453***DegHr28_Plt_Jnt** + 17.15029

[z] Standard Error of Prediction

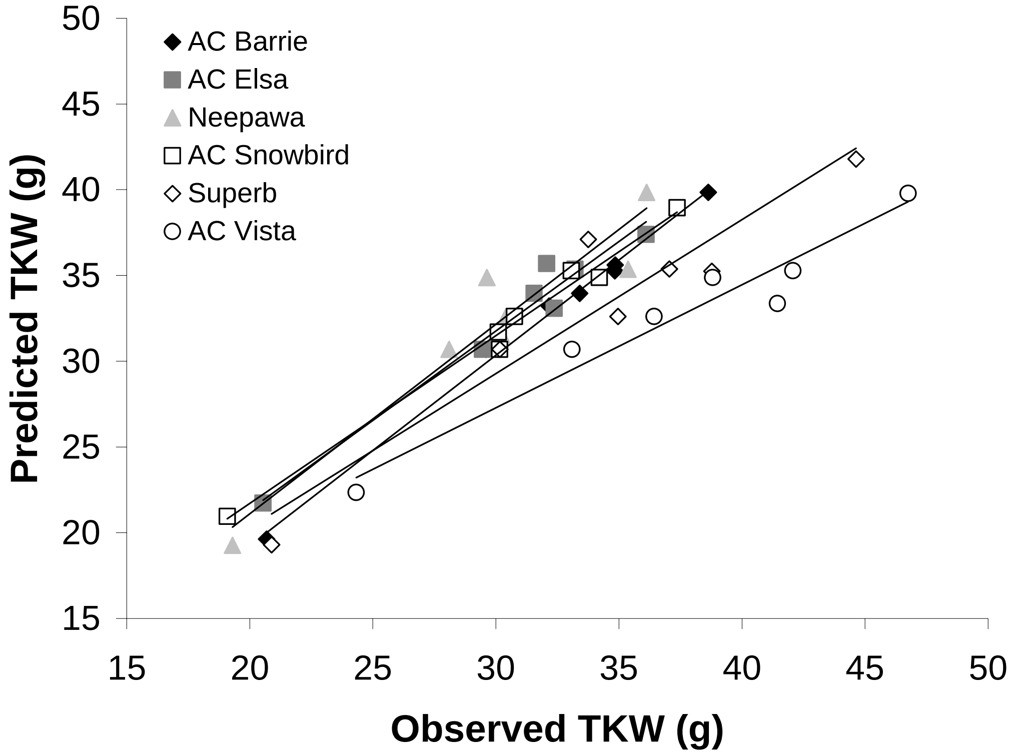

Figure 5.7. Observed vs. predicted TKW, separated by genotype, using original 3 parameter regression model.

Table 5.14. Predicted TKW (g) and difference from actual TKW using a model developed with AC Vista removed.

			AC Vista Removed		
			SEP^z = 4.33		
Siteyear	**Genotype**	**Actual TKW**	**Predicted TKW**	**Difference**	**Absolute Difference**
Reg05	AC Barrie	34.56	30.41	-4.15	4.15
Reg05	AC Elsa	34.41	31.57	-2.85	2.85
Reg05	Neepawa	32.05	30.41	-1.64	1.64
Reg05	AC Snowbird	32.76	31.30	-1.45	1.45
Reg05	Superb	37.89	31.09	-6.79	6.79
Reg05	AC Vista	43.32			
	Average	**35.83**	**30.96**		**3.38**
SC05	AC Barrie	34.38	33.79	-0.59	0.59
SC05	AC Elsa	30.75	33.25	2.49	2.49
SC05	Neepawa	28.48	34.28	5.80	5.80
SC05	AC Snowbird	31.10	35.16	4.06	4.06
SC05	Superb	38.56	33.52	-5.04	5.04
SC05	AC Vista	37.55			
	Average	**33.47**	**34.00**		**3.60**
Wpg05	AC Barrie	33.89	24.49	-9.40	9.40
Wpg05	AC Elsa	30.37	23.86	-6.51	6.51
Wpg05	Neepawa	31.32	24.70	-6.62	6.62
Wpg05	AC Snowbird	31.33	24.07	-7.26	7.26
Wpg05	Superb	35.46	24.84	-10.62	10.62
Wpg05	AC Vista	38.17			
	Average	**33.42**	**24.39**		**8.08**

TKW = - 0.08618***DegHr29_An_Mlk**
+ 0.63406***CDays_Infl_Mlk**
- 0.15247***P5_20_33_Plt_An** + 87.49242

[z] Standard Error of Prediction

Table 5.15. Predicted TKW (g) and difference from actual TKW using a model developed with only AC Elsa, Neepawa, and AC Snowbird.

			AC Elsa_Neepawa_AC Snowbird		
			SEP[z] = 0.91		
Siteyear	**Genotype**	**Actual TKW**	**Predicted TKW**	**Difference**	**Absolute Difference**
Reg05	AC Barrie	34.56			
Reg05	AC Elsa	34.41	30.60	-3.81	3.81
Reg05	Neepawa	32.05	30.23	-1.83	1.83
Reg05	AC Snowbird	32.76	30.82	-1.94	1.94
Reg05	Superb	37.89			
Reg05	AC Vista	43.32			
	Average	**35.83**	**30.55**		**2.53**
SC05	AC Barrie	34.38			
SC05	AC Elsa	30.75	33.10	2.34	2.34
SC05	Neepawa	28.48	32.71	4.23	4.23
SC05	AC Snowbird	31.10	33.28	2.18	2.18
SC05	Superb	38.56			
SC05	AC Vista	37.55			
	Average	**33.47**	**33.03**		**2.92**
Wpg05	AC Barrie	33.89			
Wpg05	AC Elsa	30.37	31.32	0.95	0.95
Wpg05	Neepawa	31.32	31.43	0.11	0.11
Wpg05	AC Snowbird	31.33	31.58	0.25	0.25
Wpg05	Superb	35.46			
Wpg05	AC Vista	38.17			
	Average	**33.42**	**31.44**		**0.44**

TKW = + 0.18366***BRWUR6_An_Dgh**
+ 0.67918***CDays_Infl_Mlk**
+ 0.24526***BRDef6_Plt_Infl** +18.99344

[z] Standard Error of Prediction

5.5 Conclusions

The original forecast models developed using 2003 and 2004 weather data, did not necessarily accurately predict the grain properties in 2005. It became apparent that other factors beyond goodness-of-fit for a regression equation must be considered in developing forecast models. The first important issue was the occurrence of weather conditions that fell outside the range that occurred in 2003 and 2004. This could indicate that prediction accuracy could be significantly improved with the inclusion of more site years in the regression analysis. The inclusion of weather and quality data from the 2005 and 2006 growing seasons should help extend the range of weather conditions within the dataset, thus improving the predictability of the quality parameters over a wider range of conditions. It also appeared that precipitation data should not be utilized in model development due to the potential of extreme storm events leading to inaccurate quality prediction.

The forecast models developed using six genotypes grouped together to predict quality generally did not provide satisfactory prediction accuracy. Each quality parameter prediction model was improved by removing AC Vista from the data set. The best predictive models were developed by using data from a group of genotypes which responded similarly to the environment. In some cases, such as AC Vista protein content, individual regression equations worked significantly better than genotype grouped models. It is expectd that with an increase in site years used in model development, individual genotype prediction models may be substantially improved, as the current individual genotype models used only seven data points to produce the regression equation.

Protein content was the most difficult grain property to forecast. Two of the 2005 test sites had exceptionally variable protein content within the site for a single genotype. Therefore, one cannot expect to accurately predict protein content at a location when a single genotype exhibits such large variability in protein content response in the same environment.

Model prediction accuracy may also be affected by the small but significant GxE interaction that was found for most quality properties. The magnitue of the GxE interaction may lead to some quality parameters to be predicted better than others.

The sheer number of independent weather variables available for this study was extremely useful for developing good prediction models. There were a number of weather variables strongly correlated to each quality property. However, it was challenging to determine which weather variables were the most robust in predicting the quality property. It was also important to determine which genotypes responded in a similar manner to weather variables and develop prediction models accordingly.

A similar approach to the quality prediction analysis for the grain properties must be taken for the flour, dough, and bread properties in order to develop accurate end-use quality forecast models.

It can also be concluded that more research will be required for all bread wheat genotypes as well as newly developed genotypes in order to have accurate quality prediction for all wheat in Canada. The models developed using the group of all six genotypes did not provide the most accurate quality prediction for all grain properties and all genotypes. Thus, it cannot be assumed that the models can be applied to all bread wheat genotypes. Due to the variation in quality prediction accuracy between genotypes, it may be more useful to have genotype specific prediction models. However, if certain genotypes demonstrate a statistically similar response to growing season weather then creating models from groups of similar genotypes may be more effective. Creating groups would reduce the amount of work required for developing prediction models and increase the number of data points in each prediction model, which would likely improve prediction accuracy.

6. OVERALL SYNTHESIS

This study investigated wheat technological response to growing season weather conditions in the prairie region. It was found that genotype, environment, and their interactions all contributed to quality variation; however, the environment contributed substantially more to the variation in quality for most properties. Due to the strict quality regulations applied in Canada for the adoption of new wheat genotypes, quality variation between genotypes is evidently low. This fact combined with the knowledge of the significant role that environment plays on wheat quality, emphasized the importance of growing season weather impacts on end-use quality.

Due to the significant role of environment on wheat quality, strong prediction models which utilized growing season weather data were developed. The environment was found to influence grain and dough property quality variation more than flour or bread property quality variation. This relationship was seen again when the prediction models were developed. The grain and dough properties produced the strongest forecast models, while the bread property models were weaker in comparison.

High frequency and detailed weather data along with the knowledge of crop development appears to be a very effective means to predict wheat yield and end-use quality well in advance of harvest. Currently, the network of basic weather stations is increasing substantially across western Canada. These stations are relatively inexpensive in comparison to full scale weather stations and record basic weather data such as air temperature and precipitation. Knowledge that reliable forecast models can be developed using only variables derived from data collected using a basic weather station would save interested model users a substantial amount of operational and computational time and expenses. This study demonstrated that reliable models can be produced using limited weather data and thus makes the application of this study much more practical. Without a strong network of weather stations, accurate end-use quality prediction would be more unlikely.

Improved information regarding wheat quality prediction will be valuable for the Canadian grain industry, especially for companies such as the Canadian Wheat Board with key market development and retainment goals. Once the quality forecast models are further validated, these companies could benefit from improved marketing and sales. Knowledge of the locations where wheat with specific quality attributes is going to be produced would improve the ability of wheat buyers to match wheat quality requirements to specific customers and improve the consistency of the wheat being sold.

This research study will also benefit wheat breeders. Currently, there is a lack of understanding of GxE interaction on end-use quality. Experimental wheat lines are tested across a number of environments and averaged in order to eliminate the environmental component. At present, experimental lines may be selected based on a superior quality score in one environment, however, that line may not perform well in another set of environmental conditions. Based on the results of this study environment has a significant effect on wheat quality and thus indicates that an experimental line should not be pooled across environments during variety development. Knowledge of environment, genotype and GxE interaction effects on end-use quality can facilitate improved experimental line selection ability. The relative effect of genotype, environment, and genotype by environment interactions should be characterized for all quality characteristics in order to properly assess new wheat lines.

Enhanced knowledge of the most significant development stage influencing end-use quality and the weather variable affecting quality at that stage is also beneficial information to wheat breeders. Breeding efforts could focus on selecting genotypes which respond less negatively to a stress at the critical stage or that respond more positively to favorable weather conditions during the critical stage.

The opportunity to validate the forecast models developed for the grain properties using 2005 data identified some potential problems and issues with the original models. Forecast model validation also highlighted the need for more research and analysis in order to accurately and consistently forecast all of the technological quality properties. Although the 2003 and 2004 growing seasons were very diverse, they did not represent all possible growing conditions that could occur in western Canada. This leads to the first recommendation for further study in this field.

Wheat samples and weather data were collected as part of this study for the 2005 and 2006 growing seasons. The quality analysis of these samples was not completed at the time of this writing. The addition of two more growing seasons to the data set is expected to produce more robust forecast equations. Two additional years of weather and quality data would encompass a wider range of growing conditions thus leading to a more consistent and reliable prediction model.

It was also clear that forecast models developed using a group of genotypes which encompassed three commercial classes were not effective in predicting quality. Further research opportunities also exist in the development of models for specific groups or classes of genotypes or for individual genotypes. The data set utilized in this study was not large enough to produce accurate models for individual genotypes. The development of individual genotype forecast models would also require additional weather and wheat sampling to determine the response of all genotypes utilized for milling and food production.

Another obvious research opportunity is to test the forecast models in a field scale trial across western Canada. A study will have to be conducted to determine how close a weather station needs to be to the wheat crop in order to accurately predict quality in that area. Numerous future research opportunities are evident from this study. This includes the investigation of issues such as the impact of estimating phenological stage or spring soil moisture on the accuracy of quality prediction as opposed to using observed values. There may also be issues associated with in-field variability of wheat quality, such as that noted for grain protein content at the Winnipeg and Swift Current sites in 2005 (Chapter 5).

Wheat customers in the global market continue to increase the demand for high quality wheat or wheat of a specific quality. These buyers will not hesitate to source this wheat from any exporting nation that can meet the quality specifications at the best price, unless there is uncertainty of the quality specifications being met. Therefore, the ability to provide wheat with predictable and consistent quality characteristics does have an economic value from the fact that quality-conscious customers will pay a premium for the assurance of its delivery. An improvement to grain sourcing and logistical planning as well as an enhancement in the guarantee to supply wheat of consistent quality, therefore, will improve the welfare of the Canadian grain industry and thus improve the welfare of Canadians supported by this industry.

7. Appendices

7.1 Appendix A – Crop Coefficient Determination

A.1. Crop Coefficient Determination

In order to determine a crop water demand from potential evapotranspiration (ETp), a crop coefficient value was required. The change in measured soil moisture during a given period was calculated from neutron probe measurements. Actual ET (ETa) during a specific time period was then calculated using Equation A.1.

*ETa = (Change in Soil Moisture – Precipitation during same period) * -1* (A.1)

The Ref-ET program was utilized to calculate ETp using the FAO56 Penman Montieth method. The crop coefficient (Kc) was calculated as ETa / ETp. This provided a Kc value for each day a phenological observation was taken (Table A.1). Growing degree days (GDD) were then accumulated during the corresponding time periods. A relationship was then developed between Kc and GDD using data from all seven site years (Figure A.1). Daily GDD data was then utilized to calculate a daily Kc value. Certain Kc values did not make sense as they were either too high or too low for the given development period, these values were consequently removed from the GDD and Kc relationship.

The accuracy of the above Kc determination method was tested against a Kc value determined using the biometeorlogical time scale to model physiological daily development. The Kc value started at 0.3 at seeding and increased to 1.0 at anthesis and then decreased to 0 at physiological maturity. As shown in Figure A.1, the method which used actual crop water use to determine daily Kc values proved to be comparable to the biometeorlogical derived daily Kc value.

Table A.1. Soil water, precipitation, ET, and crop coefficient values during the growing season at seven sites.

Melfort 2003	Date	Avg. Water in 120 cm (mm)	Available Water (mm)	Change in Soil Water (mm)	Precipitation	ETa	ETref	Kc	GDD	Biomet Derived Kc
	5-May-03	531.67	174.43		10.92		48.75		6.64	
	29-May-03	510.87	153.63	-20.80	34.79	55.59	109.98	0.51	167.58	0.61
	11-Jun-03	522.46	165.22	11.59	17.27	5.68	51.61	***0.11***	282.96	0.83
	25-Jun-03	496.85	139.61	-25.61	31.50	57.11	66.30	0.86	457.17	0.95
	9-Jul-03	469.22	111.98	-27.64	33.52	61.16	60.85	1.01	614.09	0.94
	24-Jul-03	444.60	87.36	-24.62	10.16	34.78	69.42	0.50	825.06	0.81
	8-Aug-03	409.77	52.53	-34.83	8.38	43.21	61.38	0.70	1045.13	0.00
	20-Aug-03	376.00	18.76	-33.77	2.79	36.57	61.09	***0.60***	1273.11	0.00
Regina 2003										
	22-May-03	612.30	212.10							
	27-May-03	578.53	178.33	-33.77	8.89	42.66	27.53	***1.55***	60.50	0.30
	9-Jun-03	598.09	197.89	19.56	9.65	-9.91	57.54	***-0.17***	200.08	0.63
	24-Jun-03	553.41	153.21	-44.68	13.72	58.39	78.38	0.74	392.74	0.87
	8-Jul-03	476.30	76.10	-77.11	3.81	80.92	72.83	1.11	570.54	0.99
	23-Jul-03	444.04	43.84	-32.26	36.58	68.84	79.20	0.87	793.95	0.86
	7-Aug-03	411.48	11.28	-32.56	7.88	40.44	78.62	0.51	1039.13	0.52
	18-Aug-03	318.04	-82.16	-93.44	8.64	102.08	66.60	***1.53***	1263.90	0.00
Swift Current 2003										
	17-May-03	288.02	117.74				55.49		42.47	0.30
	28-May-03	288.56	118.28	0.54	0.00	-0.54	60.89	***-0.01***	119.07	0.42
	10-Jun-03	345.47	175.19	56.91	21.34	-35.57	57.78	***-0.62***	223.29	0.72
	25-Jun-03	334.44	164.16	-11.03	44.96	55.99	81.47	0.69	380.45	0.89
	9-Jul-03	292.16	121.88	-42.28	5.59	47.87	83.13	0.58	542.54	1.00
	24-Jul-03	240.04	69.76	-52.12	2.03	54.16	104.36	0.52	785.77	0.84
	8-Aug-03	229.97	59.69	-10.07	2.29	12.35	103.58	0.12	1037.10	0.00
	28-Aug-03	152.48	-17.80	-77.49	23.88	101.37	136.04	***0.75***	1372.57	0.00

Table A.1 cont'd

Winnipeg 2003	Date	Avg. Water in 120 cm (mm)	Available Water (mm)	Change in Soil Water (mm)	Precipitation	ETa	ETref	Kc	GDD	Biomet Derived Kc
	24-May-03	536.35	206.11		50.55		46.39		51.54	0.34
	6-Jun-03	495.74	165.50	-40.61	19.81	60.43	38.82	***1.56***	199.56	0.66
	17-Jun-03	490.29	160.05	-5.45	43.18	48.63	42.26	***1.15***	328.83	0.85
	2-Jul-03	466.73	136.49	-23.56	31.24	54.80	50.01	1.10	529.98	0.99
	16-Jul-03	440.19	109.95	-26.54	19.30	45.84	51.98	0.88	730.70	0.89
	29-Jul-03	426.19	95.95	-14.00	10.67	24.66	44.56	0.55	941.27	0.72
	14-Aug-03	420.32	90.08	-5.87	28.96	34.83	61.66	***0.56***	1212.27	0.00
Carman 2004										
	18-May-04	476.09	145.29							
	24-May-04	469.72	138.92	-6.37	9.14	15.52	20.12	***0.74***	24.60	0.30
	8-Jun-04	531.69	200.89	61.97	65.79	3.82	49.89	0.30	140.26	0.62
	15-Jun-04	491.97	161.17	-39.72	2.79	42.51	25.04	***1.63***	200.97	0.80
	21-Jun-04	502.13	171.33	10.16	13.80	3.64	28.81	***0.11***	259.42	0.83
	5-Jul-04	462.35	131.55	-39.79	6.00	45.79	55.90	0.82	390.63	0.93
	19-Jul-04	389.82	59.02	-72.52	2.29	74.81	63.38	***1.52***	586.62	0.93
	29-Jul-04	357.96	27.16	-31.86	21.85	53.71	40.45	1.32	726.59	0.86
	6-Aug-04	330.95	0.15	-27.01	4.32	31.33	29.32	1.04	815.79	0.81
	16-Aug-04	342.33	11.53	11.38	21.33	9.96	23.10	0.28	911.55	0.66
	30-Aug-04	375.05	44.25	32.72	66.30	33.58	38.37	0.56	1021.75	0.00
	17-Sep-04	420.16	89.36	45.11	80.01	34.90	37.46	0.50		

Table A.1 Cont'd

Swift Current 2004	Date	Avg. Water in 120 cm (mm)	Available Water (mm)	Change in Soil Water (mm)	Precipitation	ETa	ETref	Kc	GDD	Biomet Derived Kc
	26-Apr-04	268.73	98.45							
	20-May-04	266.91	96.63	-1.82	22.20	24.02	80.49	0.30	53.69	0.46
	3-Jun-04	294.70	124.42	27.78	55.60	27.82	44.99	0.62	122.45	0.74
	17-Jun-04	310.55	140.27	15.86	62.10	46.24	45.94	1.01	212.78	0.84
	29-Jun-04	255.71	85.43	-54.85	2.10	56.95	55.10	1.03	297.20	0.91
	14-Jul-04	209.88	39.60	-45.82	32.00	77.82	64.56	1.21	468.31	0.98
	27-Jul-04	185.89	15.61	-23.99	23.30	47.29	70.68	***0.67***	666.11	0.86
	10-Aug-04	178.75	8.47	-7.14	41.80	48.94	49.78	0.98	813.94	0.71
	24-Aug-04	173.39	3.11	-5.36	22.90	28.26	54.41	0.52	954.28	0.00
Winnipeg 2004										
	9-Jun-04	428.01	97.77		84.00		35.95		115.95	0.47
	21-Jun-04	432.04	101.80	4.03	23.10	19.07	39.03	0.49	227.55	0.77
	5-Jul-04	410.02	79.78	-22.02	13.80	35.82	48.17	0.74	358.94	0.89
	19-Jul-04	393.81	63.57	-16.20	34.60	50.80	50.29	1.01	567.80	0.97
	24-Jul-04	380.67	50.43	-13.14	0.60	13.74	18.34	0.75	640.98	0.93
	3-Aug-04	373.53	43.29	-7.14	21.60	28.74	34.65	0.83	775.75	0.85
	16-Aug-04	376.62	46.38	3.08	38.10	35.02	30.16	1.16	913.37	0.73
	30-Aug-04	419.25	89.01	42.64	109.40	66.76	30.04	***2.22***	1031.74	0.00
	14-Sep-04	428.70	98.46	9.44	54.00	44.56	23.39	***1.90***	1188.50	

Bold and italicized Kc values indicate outliers which were not included in the GDD/Kc relationship determination.

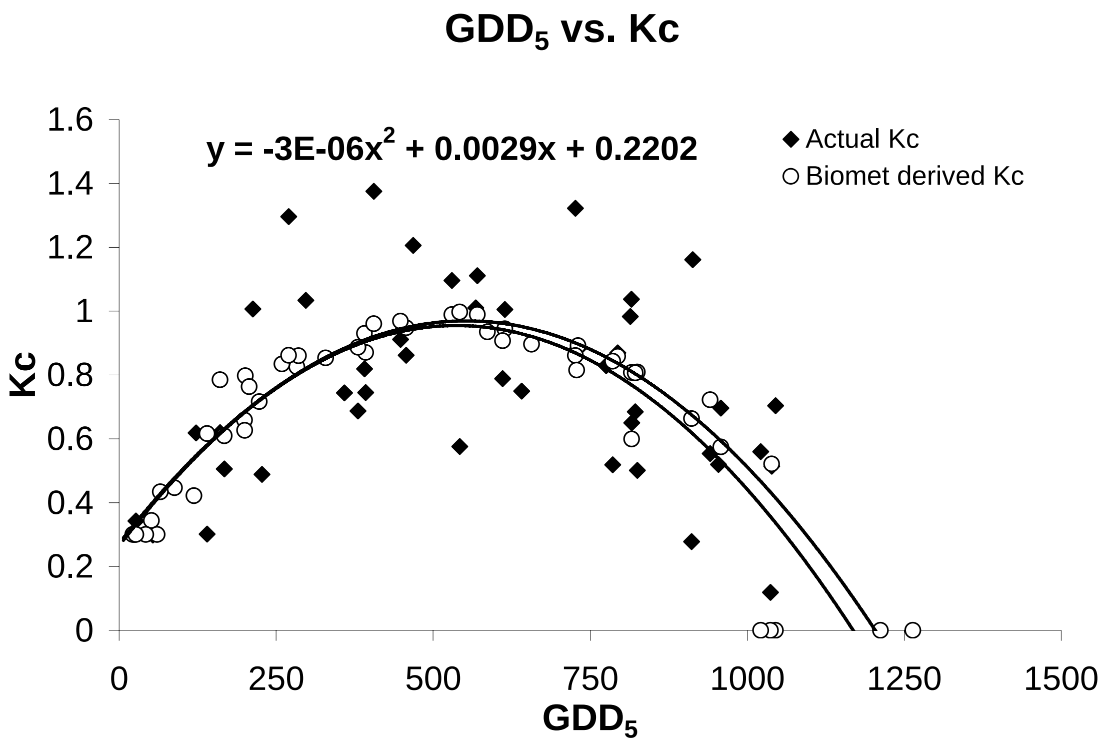

Figure A.1. Relationship between crop coefficient and GDD_5 and the equation used to calculate daily Kc values from daily GDD values.

7.2 Appendix B – Soil Characteristics

A.2 Soil Characteristics

Numerous soil characteristics were determined to further characterize each site. These included texture, permanent wilting point, field capacity, bulk density and available water holding capacity (Table A.2.).

Table A.2. Soil characteristics at the research sites.

Location	Depth (cm)	% Clay	% Sand	% Silt	Soil Texture	PWP (% by Vol.)	PWP (mm)	FC (% by Vol.)	FC (mm)	BD (g/cc)	AWC (mm)
Winnipeg	0-15	56	4	40	SiC	22.80	34.20	39.72	59.58	0.94	25.38
	15-30	54	6	40	SiC	28.55	42.83	36.73	55.10	1.23	12.26
	30-45	54	8	38	C	28.89	43.34	36.75	55.13	1.25	11.79
	45-60	50	4	46	SiC	27.88	41.82	36.75	55.13	1.30	13.30
	60-90	50	6	44	SiC	28.12	84.37	34.00	102.00	1.41	17.63
	90-120	50	6	44	SiC	28.88	86.64	36.00	108.00	1.40	21.36
Wpg 0-120cm	**0-120**						**333.21**		**434.93**	**1.26**	**101.72**
Melfort	0-15	26	14	60	SiL	20.07	30.11	35.80	53.70	0.94	23.59
	15-30	36	12	52	SiCL	27.17	40.75	48.16	72.24	1.36	31.49
	30-45	58	10	32	C	29.46	44.19	59.12	88.68	1.56	44.49
	45-60	58	6	36	C	31.77	47.66	55.50	83.26	1.60	35.60
	60-90	68	4	28	C	33.47	100.42	48.90	146.70	1.65	46.28
	90-120	78	4	18	C	36.65	109.94	40.38	121.15	1.70	11.21
Mel 0-120cm	**0-120**						**373.06**		**565.73**	**1.47**	**192.66**
Regina	0-15	40	16	44	SiC	23.82	35.74	38.33	57.50	0.99	21.77
	15-30	52	10	38	C	33.29	49.94	48.96	73.43	1.35	23.50
	30-45	56	8	36	C	34.24	51.35	58.87	88.31	1.41	36.95
	45-60	66	6	28	C	35.91	53.86	58.21	87.32	1.51	33.45
	60-90	70	4	26	C	34.88	104.65	54.57	163.70	1.52	59.05
	90-120	70	6	24	C	37.97	113.92	49.93	149.78	1.67	35.86
Reg 0-120cm	**0-120**						**409.45**		**620.04**	**1.41**	**210.58**
Swift Current	0-15	10	32	58	SiL	10.42	15.63	32.52	48.77	1.23	33.14
	15-30	18	30	52	SiL	12.99	19.49	31.20	46.81	1.35	27.32
	30-45	24	26	50	SiL	13.82	20.73	30.41	45.61	1.41	24.88
	45-60	18	20	62	SiL	13.74	20.61	35.41	53.12	1.41	32.51
	60-90	22	28	50	SiL	16.65	49.94	30.12	90.36	1.62	40.42
	90-120	22	34	44	L	17.52	52.57	31.76	95.27	1.81	42.71
SC 0-120cm	**0-120**						**178.97**		**379.94**	**1.47**	**200.97**
Carman	0-15	18	52	30	SL	14.03	21.05	35.09	52.63	1.15	31.58
	15-30	28	42	30	SCL	19.63	29.45	36.97	55.46	1.49	26.02
	30-45	50	26	24	C	27.73	41.59	46.09	69.13	1.46	27.54
	45-60	56	20	24	C	28.11	42.16	41.39	62.09	1.54	19.93
	60-90	58	12	30	C	30.97	92.91	43.76	131.28	1.66	38.37
	90-120	64	4	32	C	32.34	97.01	43.79	131.37	1.60	34.36
Car 0-120cm	**0-120**						**324.16**		**501.96**	**1.48**	**177.80**

7.3 Appendix C – Prediction model size determination

A.3 Determination of the Maximum number of parameters to include in Multi Variable Models

The initial regression analysis was completed in order to determine how many independent variables to include in the explanatory models. The Stop=10 command was selected, which created models that had 10 explanatory variables included. The increase in R^2 with the addition of each new variable was examined as well as the significance of the variables included in the model. These factors were utilized as an indication of how many variables to include in the final prediction model. We considered that if the R^2 increased less than 2%, it was not worthwhile to include another explanatory variable. In general it was found that with the addition of more than three variables the R^2 increase became less than 2% and the variables added became non significant. This lead to the selection of three parameters being selected as the maximum number of variables used to explain wheat quality. Figure A.2 demonstrates the typical response of R^2 with the addition of more variables. Models generally become insignificant once 4 or 5 variables were added.

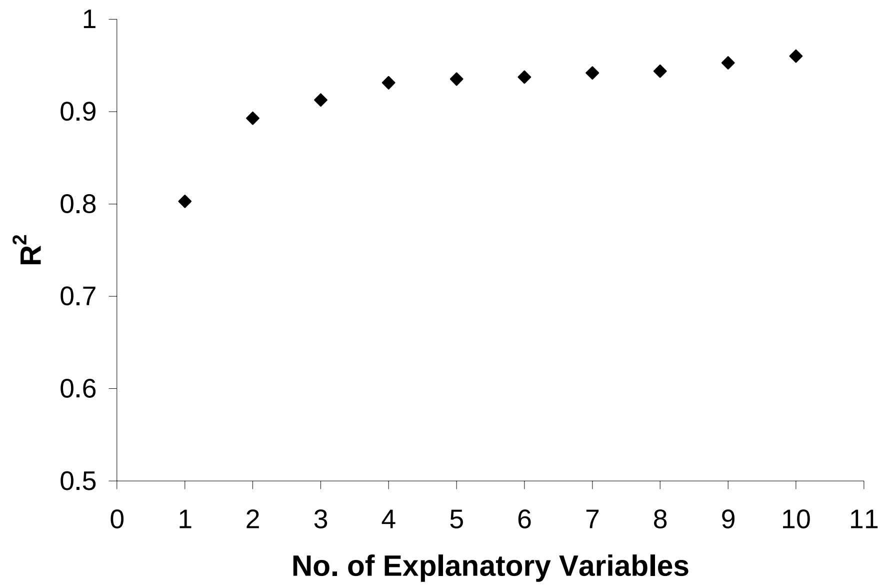

Figure A.2. Increase in R^2 with the addition of more explanatory variables. Typical response demonstrated using yield.

7.4 Appendix D – SAS program code samples

A.4 Chapter 2 SAS program code

Step 1. Analysis of each site individually (output of residuals, test of normality, and test of homogeneity of variance)

Produce plot of residuals for each location

```
Title Analysis of each siteyear with RCB model;
proc glm data=stage.qualityreduced; by siteyear;
      class rep variety;
      model protein = Rep Variety;
        Output out=Qout Residual=YRes Predicted=YPred;
run;quit;
```

Produce plot of residuals for each location

```
Proc Plot Data=Qout; by siteyear;
  Plot YRes*YPred;
```

Test for Homogeneity of Variance within each site

```
Title Analysis of residuals from separate RCB models, levenes test;
Proc GLM Data=Qout;
  Classes SiteYear;
  Model YRes=SiteYear;
  Means SiteYear/hovtest=levene;
run;quit;
```

Test for Normality within each site

```
Proc Univariate Plot Normal Data=Qout; by siteyear;
  Var YRes;
Run; Quit;
```

Step 2. Analysis of site years pooled together (output of residuals, test of normality, and test of homogeneity of variance)

ANOVA with all site years pooled (not correct ANOVA) and produce residuals

```
Title Model across site-years - GLM;
Proc GLM Data=stage.qualityreduced;
  Classes siteyear rep variety;
  Model protein = siteyear rep(siteyear) variety siteyear*variety;
  Random siteyear rep(siteyear) siteyear*variety/test;
  Output out=Qout2 Residual=YRes Predicted=YPred;
run;quit;
```

Produce plot of all site year residuals together

```
Proc Plot Data=Qout2;
  Plot YRes*YPred;
```

Test of Normality of residuals across all site years.

This output produced a list of 'extreme' observations, which are later removed as outliers

```
Proc Univariate Plot Normal Data=Qout2;
  Var YRes;
Run; Quit;
```

Test for homogeneity of variance across all site years

```
Title Analysis of residuals from combined dataset, levenes test;
Proc GLM Data=Qout2;
  Classes SiteYear;
  Model YRes=SiteYear;
  Means SiteYear/hovtest=levene;
run;quit;
```

Step 3. Removal of outliers (if necessary)

YRes numbers adjusted to remove outliers as found in the Proc Univariate output from above (step 2)

```
Data stage.qualityreduced2;
  Set Qout2;
  If  YRes >1.6 or YRes <-2 then delete;
```

Step 4. Repeat steps 1 & 2 if outliers were removed

Step 5a. ANOVA test using proc mixed if homogeneous variance

ANOVA test when homogeneous variance

```
Title Model across site-years - using Mixed, homogeneity assumed;
Proc Mixed Data=stage.qualityreduced covtest;
  Classes siteyear rep variety;
  Model protein = variety;
  Random siteyear rep(siteyear) siteyear*variety;
  Lsmeans variety / PDIFF ;
  Lsmeans variety / adjust=tukey ;
    ods output diffs=ppp lsmeans=mmm;
      ods listing exclude diffs lsmeans;
run;
```

Macro program to produce LSD for genotype

```
%include 'C:\Program Files\SAS Institute\SAS\V8\pdmix800.sas';
%pdmix800(ppp,mmm,alpha=.05,sort=yes);
run;
quit;
```

Step 5b. Anova test using proc mixed if __heterogeneous__ variance

ANOVA test when heterogeneous variance

```
Title1 Model across site-years using Proc Mixed and allowing;
Title2 for heterogeneous variance across site years;
Proc Mixed Data=stage.qualityreduced covtest;
  Classes siteyear rep variety;
  Model protein = variety/ddfm = satterth;
  Random siteyear rep(siteyear) siteyear*variety;
  Repeated /group=siteyear;
  Lsmeans variety / PDIFF ;
  Lsmeans variety / adjust=tukey ;
    ods output diffs=ppp lsmeans=mmm;
      ods listing exclude diffs lsmeans;
run;
```

Macro program to produce genotype LSD

```
%include 'C:\Program Files\SAS Institute\SAS\V8\pdmix800.sas';
%pdmix800(ppp,mmm,alpha=.05,sort=yes);
run;
quit;
```

A.5 Chapter 3 SAS program code

Regression Analysis

```
Proc Reg data=chapter2.wthrqualmn;
      Model Yieldkg Protein...... =
CDays_an50_Dgh P5_17_31_an50_Dgh P5_21_35_an50_Dgh.......
...Jun_Aug_SPI May_Aug_SPI / selection=maxr stop=10;
run;quit;
```