DEVELOPMENT OF A SIMULATOR FOR SWEETCORN COLD CHAIN DISTRIBUTION

By

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To my family

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Fresh market sweetcorn, with sales exceeding $750 million in the United States in 2008, is now in higher demand than ever. In accordance with increasing demand, quality expectations have also grown. Sweetcorn should be precooled promptly following harvest and is optimally stored at 0°-1.1°C. A delay in precooling or improper temperature maintenance throughout subsequent steps of the cold chain will have significant effects on quality degradation and shelf-life. Therefore, a model for the prediction of sweetcorn quality index (QI) rating as a function of time and temperature was produced to quantify these affects.

Quality measurements were preformed on freshly harvested sweetcorn stored in temperature controlled chambers for ten days. The limiting quality factor was found to be external appearance when sweetcorn was stored at temperatures below 10°C and kernel appearance when stored at temperatures above 10°C. A series of quality-versus-time curves were produced. By linear regression analysis an equation for quality as a function of temperature was determined for each 24-hour time step from zero to ten days. These equations were integrated into a computer program whereby initial QI

in addition to time and temperature information for up to five cold chain steps could be inputted, with the output being final QI. A second model using theoretical data based on exponential decay and respiration rate was created for the purpose of comparison.

The complete cold chain of two sweetcorn shipments, from peak and late harvest times in Iron City, Georgia was tracked and monitored for temperature from the start of precooling to arrival at the store. Time-temperature profiles were then constructed from the monitoring data. In addition, samples of sweetcorn from each of these harvests were taken directly from the field as well as from retail. The quality of these samples was analyzed upon receiving them and then again after specified storage times at varying temperatures. The empirical and theoretical prediction models were tested and compared by inputting the time-temperature profiles into each and calculating the percent difference between the final QI outputs and the actual observed final QIs. On average, the values predicted by the empirical model fit the observed data more closely than did those from the theoretical model; with the overall average percent differences being 18.3% and 26.4%, respectively. It was concluded that the empirical model was successful in predicting quality; however, it is expected to be more accurate if based upon averages from multiple temperature-dependent quality tests and the expansion of data collection to 14 days or until reaching the lowest QI value (1.0).

CHAPTER 1
INTRODUCTION

Sweetcorn History and Production

Sweetcorn, as we are familiar with it today, is a mutant form of field corn and was first recorded to have been given to European settlers by the American Indians in the late 1700s. The result of this mutation is a corn kernel whose sugar content is approximately twice that of field corn. At present, several hundred varieties of sweetcorn are in existence. The quality of sweetcorn for consumption has increased in recent years with the introduction of new gene mutations such as sugary enhanced (*se*) and shrunken-2 (sh_2). The advantages over pre-existing varieties include increased sweetness and/or slower to negligible sugar-to-starch conversion (Schultheis, 1998).

An ear of sweetcorn is considered “market ready” when the kernels are yet immature. At this stage, the husks are tight and green, while the kernels are turgid and milky when compressed (Suslow & Cantwell, 2009). Quality is assessed based on general appearance, kernel content make-up, and level of damage and defect. Effective since February 1992, the United States has five standard grades for sweetcorn: U.S. Fancy, U.S. Fancy-Husked, U.S. No.1, U.S. No.1-Husked, and U.S. No.2 (United States Department of Agriculture, 1992). Each grading is well defined by specific requirements.

Following harvest and pre-cooling, all fresh market sweetcorn, whether of the standard or the supersweet variety, should optimally be stored at 0°-1.1°C at a relative humidity of 95-98%. In general, at optimal conditions, standard sweetcorn should not be stored for more than seven days and supersweet not more than 21 days (Suslow & Cantwell, 2009). At the post-harvest level, physiological disorders are most commonly a result of improper storage, such as extended storage time, rather than disease.

The Sweetcorn Industry

The trend toward healthier eating observed in America in the past few decades has resulted in higher produce spending and sales. Between 1987 and 1995, the per capita consumption of fresh fruit and vegetables increased by 6%, and another 8% between 1995 and 2000. With increased interest in the consumption of fresh produce comes the demand for greater variety, consistency, and quality (Dimitri et al., 2003). The United States has dominated the world market since the 1960s, and records from the United States Department of Agriculture (USDA) reported the production of fresh market sweetcorn at over $752.6 million in 2008. The advent of improved genetic lines has increased consumption, with the average American eating 24 pounds of sweetcorn in 2008, of which 9.2 pounds were fresh. Sweetcorn is harvested in all 50 states, with the coastal states leading fresh market production. Florida, California, Georgia, and New York – in that order – topped the list (Hensen, 2009).

Defining Cold Chain and Post Harvest

A series of carefully controlled procedures, performed mostly unbeknownst to the average consumer, is essential to fulfill the demands of the evolving American shopper. They combine to provide an array of consistent, high quality and reasonably-priced items in the retail produce section. The term “cold chain” encompasses the practices, equipment, and flow of information utilized to construct an unbroken, temperature-controlled supply chain. Most notably, it is applied to the industries of pharmaceuticals and food – both fresh and processed. Ideally, a properly applied cold chain will ensure and potentially extend product shelf-life.

The term postharvest, as its name implies, refers to any and all dealings happening after harvest. Including all events from grower to retailer; namely cooling,

storage, transportation, and distribution, postharvest is tied closely to cold chain. The investigation of postharvest handling of fresh market sweetcorn and the development of a model to predict quality outcomes thereof will be the focus of this thesis.

CHAPTER 2
REVIEW OF LITERATURE

Cold Chain Processing of Fresh Produce

Packaging

Currently, there are three common forms of crating for fresh horticultural products: corrugated cardboard, wooden, and reusable plastic. The form of packaging chosen for a given product is based on several variables such as market chain characteristics, postharvest handling procedures, environmental conditions, and availability and cost of equipment (Vigneault et al., 2007).

Corrugated cardboard

Corrugated cardboard or fiberboard boxes, specifically double-faced, are favored for their low cost, light weight, and versatility for the use of horticultural product packaging. There are several further advantages to their use. The ability to print directly onto the box adds marketing value to product packaging. Because they can be stored flat and assembled as necessary, storage space is of little concern. In addition, when dry, corrugated boxes can hold a significant amount of weight (Vigneault et al., 2009).

Time and moisture are the main contributing factors to the shortcomings of corrugated container usage. The strength of corrugated cardboard diminishes over time, even in a matter of days. Venting, which is necessary for precooling and proper air circulation, also has the effect of decreasing strength. Increased relative humidity (RH) incurred by respiring produce within the box or from the surrounding ambient air will be absorbed by the corrugate. When the cardboard moisture content reaches equilibrium with air at a RH of 90%, the strength of a stacked corrugated box will be reduced by 60%. Accordingly, containers of this nature are not suited for produce that is

hydrocooled or iced. A wax coating may be added to the box for increased waterproofing; however it adds weight and renders the box non-recyclable and non-reusable (Vigneault et al., 2009). The primary method for cooling sweetcorn at this time is hydrocooling (see page 23). As a result, cardboard boxes are not utilized for packaging this commodity.

Wooden crates

Wooden crates, pictures in Figure 2-1 were the initial principal replacement for corrugated cardboard boxes (Brosnan & Sun, 2001). They come in various designs, all constructed to maintain their strength when wet. Wire-bound crates (Figure 2-3), especially, can withstand water and retain stacking strength. This makes them ideal for products that are hydrocooled such as sweetcorn. Like corrugated crates, wire-bound crates can be disassembled and flattened for reduced shipping and waste costs (Boyette et al., 1996).

There are many problems connected with wire-bound wooden crate use, the least of these being the trouble associated with affixing labels. Post-use cleaning is also an issue. International standards have limited the reuse of wooden crates due to lack of appropriate sanitation. This, in combination with cost and palletization efficiency, has constrained usage to smaller, less regulated operations (Vigneault et al., 2009).

Reusable plastic containers

The use of reusable plastic containers (RPCs), since their introduction in the late 1990s, has rapidly become commonplace (Vigneault et al., 2009). The original intent was to create a container for the purpose of storing and transporting horticultural products, namely fruits and vegetables, which was strong and long-lasting. Particular attention has been paid to the design of RPCs to promote efficient air and water

circulation for the purpose of product preservation. The main goal is product quality rather than ease of container production (Emond & Vigneault, 1998).

Versatility, in addition to increased quality, is one of the RPCs defining characteristics. They are indented for use with multiple commodities and postharvest procedures. RPCs must be designed in a way that can accommodate various precooling methods, as they may be used in combination. For example, the slotting must be large enough so as not to restrict air flow during forced-air cooling but not too large to allow the escape of ice particles during icing. Also considering forced-air cooling needs, folding RPCs, as opposed to nesting, are desirable for fresh produce. Folding RPCs, to be cost effective, must be easy to clean and simple fold and unfold (Vigneault et al., 2009).

Precooling

Precooling is the first and arguably most important step in the postharvest cold chain of any perishable product, with sweetcorn being no exception. By definition, precooling is the rapid removal of field heat from freshly harvested produce with the intention of slowing metabolism and deterioration, and reducing postharvest losses (Brosnan & Sun, 2001). In addition, hasty cooling can slow water loss and the production of ethylene, a gas that has the effect of shortening shelf-life by inducing ripening .The time between harvest and cooling is critical. While this gap should be no more than a few hours, according to some researchers, even a difference of minutes may have an effect on the preservation of final quality (Sullivan et al., 1996).

Specific research into the effect of temperature on respiration provides further insight into the importance of immediate precooling. All horticultural products are still living following harvest, and therefore continue to respire (Talbot et al., 1991). For

example, as soon as an ear of corn is detached from the rooted plant it will begin to consume itself to fuel respiration. Respiration is the process by which sugars and starches are converted into energy and respiration rate is the speed at which this reaction occurs. Respiration rate is specific to a given commodity and affected by such factors as cultivar, maturity, and atmospheric makeup. During the process of respiration, a product will consume its natural energy and water stores and produce carbon dioxide. The result is a loss of intrinsic nutrient value and diminished appearance (Cortbaoui, 2005). Respiration rate is directly dependent on temperature. Table 2-1 details the respiration rate of sweetcorn at varying temperatures.

The temperature quotient of respiration, known familiarly at Q_{10}, is the temperature coefficient for a 10°C interval. It characterizes the changes in reaction rates as a result of temperature and is calculated in the following way:

$$Q_{10} = \frac{\text{Respiration rate at T+10}}{\text{Respiration rate at T}} \tag{2-1}$$

This relationship can be useful in predicting temperature effects and subsequent quality loss. For a temperature range from 5 to 25°C an expected Q_{10} for many products is between 2 and 2.5. This translates to a 2 to 2.5 factor rise in respiration rate for every 10°C increase in temperature. Generally, Q_{10} decreases with increasing temperature, corresponding to lower metabolism. Certain constraints apply, however, that limits use. For example, at temperatures higher than 25°C, Q_{10} decreases as a result of enzyme denaturation. In addition, Q_{10} values do not apply to chilling sensitive products held at low temperatures. More notably, Q_{10} values may only be applied to initial rates (i.e. early stage vegetables) due to differing chemical composition that accompanies increased age (Bartz & Brecht, 2003).

In the case of sweetcorn, decreased sugar content is the quantitative gauge of the effect of delayed, ineffective, or absent precooling. According to Thompson et al., the estimated maximum allowable cooling delay is four hours in the case of sweetcorn, to minimize sugar loss (Thompson et al., 2001). Studies have shown that, left at 30°C (not an uncommon internal temperature for sweetcorn harvested in the heat of summer) for 24 hours, an ear of sweetcorn could experience a 60% sugar content loss. At 5°C, just above the optimum storage temperature of 0°C for sweetcorn, sugar content loss was found to occur at rates four times as much as at optimum (Herber, 1991). Sugar loss equates to product loss, decreased customer satisfaction and subsequent lower sales.

Due to time and equipment restraints, it is often not feasible to lower the temperature of a fresh product completely down to the optimum storage within the boundaries of the precooling process. Accordingly, there are two important terms that help determine more feasible cooling procedures. The half cooling time (HCT) is the duration of time required achieve a pulp temperature that is half the difference between the initial pulp temperature and the cooling medium (air, water, etc.) temperature. The value is utilized in experimentation. For the purposes of commercial precooling, the 7/8 cooling time is the accepted recommendation and equates to approximately three times the HCT. The 7/8 cooling time refers the time at which the removal of 7/8 of the difference between the initial pulp temperature and the cooling medium temperature has been achieved. This is to be complete prior to storage and/or transport (Sargent et al., 1988).

With the importance of precooling, especially in the case of sweetcorn, established, the next consideration is the method. There are many methods for precooling sweetcorn, with appropriate usage being determined by factors such as product type, product flow, available equipment, subsequent storage and shipping conditions, and economic constraints (Talbot et al., 1991). Included among the options for precooling techniques are room, forced air, vacuum, ice, and hydrocooling.

Room cooling

Room cooling, while not considered an actual precooling method, is worth mentioning because it is the most simple and prevalent means of refrigeration among horticultural products. It is accomplished by placing pallets of warm, freshly harvested products in an insulated, refrigerated room for hours or days. The cooling air is circulated by the fans of the room's evaporator coils.

The advantages of room cooling include low labor and equipment cost in comparison to other methods (Cortbaoui, 2005). However, since cooling occurs slowly with the use of this method, it is appropriate only for products with a low respiration rate and those that are not affected by slower cooling such as onions or potatoes (Sargent, et al., 1988). Increased moisture loss is an additional concern for sweetcorn. Based on this knowledge, Talbot et al. (1991) determined that room cooling is too slow to be considered an acceptable method for precooling sweetcorn. In his study, Cortbaoui (2005) found the half cooling time (HCT) to be 436 minutes – many times that of any other precooling method.

Forced air cooling

Forced air cooling is a modification upon room cooling in which air is actively pulled through, as opposed to around, palletized containers, resulting in a 75 to 90%

faster process (Cortbaoui, 2005). The premise of this method is the presence of a pressure gradient that causes air to flow through the vents of product packed containers (Talbot & Chau, 1998). Distinct stacking and baffling patterns are required in which the container venting is placed in the direction of the moving air. This allows for air circulation throughout the whole container (Brosnan & Sun, 2001). In addition, increased product contact with the cooling air results in rapid heat transfer.

The factors affecting how quickly this process occurs are numerous and include the size, shape, configuration, and thermal properties of the commodity; venting area of the container; initial and desired final temperature of the commodity; and finally the temperature, humidity and flow rate of the moving air. Several researchers agree, however, that the cooling air velocity is the primary controlling factor in the overall cooling rate because the product characteristics are generally unchangeable and the air temperature is limited by the potential for chilling injury (Brosnan & Sun, 2001). Cortbaoui (2005) compared cooling times for sweetcorn at 1 and 3 $L \cdot s^{-1} \cdot kg^{-1}$ and found that the increase in flow rate equated to a 49.3% decrease in HCT. Similar to room cooling, mass (i.e. water) loss is a concern. Cortbaouri (2005) found that increasing the flow rate resulted in an increased loss in mass.

Currently, there are three common kinds of forced air cooling configurations. The forced air tunnel set-up consists of two rows of palletized containers with a gap between that acts as a plenum. A fan placed at one end of the plenum causes a slight negative air pressure, effectively pulling air toward the zones of lower pressure and cooling the product in the process. Similarly, the cold wall system (Figure 2-2) also utilizes a plenum. This air plenum is permanently constructed and a built-in exhaust fan and

opening are designed so pallets can be cooled individually against the cooling room wall (Talbot & Chau, 1998).

Serpentine forced air cooling is an adaptation of the wall set-up that utilizes the forklift openings as venting for air supply and return. By blocking some vents and not others, air is directed through the produce containers in a serpentine manner. While slower than the other two options, this method is advantageous in that space requirements are less and cooling capacity greater (Cortbaoui, 2005).

Vacuum cooling

The method of vacuum cooling is accomplished by the evaporation of free water from a product. Evaporation occurs when the vapor pressure at the surface of a material exceeds the pressure in the air. It is driven by vapor pressure gradients and is achieved by reducing total pressure and subsequently the temperature at which water boils. Vacuum cooling is based on certain basic principles. First, boiling occurs when the vapor pressure of a liquid exceeds the total pressure of the atmosphere. For example, at 0.609kPa the boiling temperature of water is at 0°C. Second, the latent heat of vaporization required for the phase change from liquid to vapor must be supplied by the ambient surroundings. Finally, the water vapor released from the product must be removed. The process occurs in two phases. Total pressure drops occur until the desired temperature is reached; however, pressure is rarely reduced below 0.609kPa because of additional work required and potential for undesired produce freezing (Brosnan & Sun, 2001). Figure 2-3 details a vacuum cooler.

The efficiency of vacuum cooling is proportional to the amount of moisture that evaporates from the surface (Barger, 1961). Because this evaporative capacity is based

on the surface area available for evaporation to occur, it has been found that vegetables with a large surface area-to-mass ratio cool more rapidly (Showalter & Thompson, 1956). In other words, vacuum cooling would be more suitably applied to a product such as lettuce than sweetcorn. It was previously reported that after 25-30 minutes of cooling, lettuce would reach a final temperature of 1°C, while after that same period of time sweetcorn would only cool to 4.5°C (ASHRAE, 1994).

A disadvantage to vacuum cooling is the increased potential for weight loss. Moisture content and retention is vital for the succulence of sweetcorn and therefore a very important consideration. Showalter and Thompson (1956) measured weight loss of sweetcorn under dry and pre-wetted conditions, and found the weight loss to be reduced by wetting the corn prior to cooling. In one test the dry and pre-wetted weight losses were 6.1% and 0%, respectively. According to Talbot et al. (1991), vacuum cooling is the most rapid method of cooling sweetcorn; however it is not the most common method used due to such constraints as cost.

Ice cooling

Prior to the introduction of modern precooling methods involving refrigeration technology, ice cooling was used extensively for both precooling produce and maintaining temperature during transit. The efficiency of ice is two-fold in that it removes heat from the products to which it is applied while it is still in a solid state, and then absorbs heat as it makes the phase change to a liquid state (Brosnan & Sun, 2001). There are several variations upon which this method can be applied including top-icing and package icing.

Commonly used now only as a complement to other cooling methods, top-icing consists of the addition of finely crushed ice atop packed produce prior to closing the container (Brosnan & Sun, 2001). Although relatively cheap, this method cannot stand on its own due to the relatively slow cooling rate and increasing ineffectiveness among lower layers of product (those farther from the ice source) (Cortbaoui, 2005).

Faster and more uniform than top-icing, package icing is characterized by an approximately uniform distribution of crushed ice throughout the packing container (Cortbaoui, 2005). Slush-icing, a modification of top-icing commonly used for sweetcorn, is a mixture of refrigerated water and ice. Due to its liquid nature, slush-ice is carried throughout produce-filled containers, aiding in ice distribution and conductive heat transfer (Talbot et al., 1991).

The advantages of ice cooling include relatively low equipment expense and a high humidity environment that prevents moisture loss. The disadvantages, however, are beginning to outweigh the benefits as newer technologies advance. The considerable additional weight afforded by the ice causes an increase in fuel cost. Another consideration is that standing water on the produce has the potential to become a breeding ground disease and rot.

Hydrocooling

The final precooling technique of significance in the case of sweetcorn is hydrocooling. In fact, it remains the most common means of precooling sweetcorn at the present time (Talbot et al., 1991). The effectiveness of hydrocooling is based on the principle that the heat transfer coefficient of produce-to-water is much higher than that of produce-to-air (ASHRAE, 2002). The result is a comparatively short cooling time. In this process, cold water released from the evaporator coils comes into direct contact

with freshly-harvested produce, which in the case of sweetcorn, has also been crated. The product surface-to-water contact results in conductive heat transfer. For this to be effective, the cooling water must be keep as close to 0°C as possible. A major advantage of water as the cooling medium is the virtual absence of mass (water) loss during cooling (Vigneaul et al., 2007).

In order to be suitable for hydrocooling, a product must be highly resistant to wetting and have a low vulnerability to water-induced surface wounds (Cortbaoui, 2005). Thus, citrus, grapes, and berries are not recommended. Leafy vegetables, sweetcorn, celery, radishes, and carrots, in addition to some fruits such as peaches and melons are well suited for hydrocooling (ASHRAE, 2002).

Water flow for hydrocooling may be administered in two distinct patterns – submersion and showering. In the case of submersion, warm produce is immersed in, and drawn through, a cold water bath. Further convection is accomplished by the water flow rate. As the name implies, submersion is best for those products that are denser than water such that they do not float above the surface. The average 7/8ths cooling time varies widely from product to product, with 45 minutes being the standard for sweetcorn packaged in wirebound wooden crates (Thompson et al., 2002).

With spray-type hydrocooling, cooling water is showered upon produce, packaged or individual, moving along a conveyor. The water passes through the individual pieces as it makes its way to the evaporator coils for re-cooling and recirculation (Vigneault et al., 2007). A schematic of this operation is depicted in Figure 2-4.

Transportation and Storage

Transportation and storage are the preceding steps to precooling in the post-harvest cold chain. As previously discussed, the precooling step is vital in controlling the final quality and shelf-life of a fresh product. If this process is omitted, the transportation and storage measures taken to maintain a proper cold chain will be ineffective. In the same way, if suitable precooling is achieved, but little care taken to transportation and storage, the precooling efforts were done in vain.

As with precooling, there are many factors that must be considered and controlled to ensure that the product of interest is of high quality when purchased by the consumer at the retail level. Requirements will vary based on the specific commodity and the intended marketing – short, medium, or long. Understandably, those items being shipped or stored for the medium and long term market will require tighter cold chain handling in order to arrive at their final destination at the appropriate level of quality (Eksteen, 1998).

Humidity

Most fruits and vegetables require a consistent high relative humidity (RH) of 90-95% for maximum shelf-life. In the case of sweetcorn an RH of 95-98% is considered optimal (Suslow & Cantwell, 2009). A low humidity environment leads to wilting, water loss, and even decay. Additional marketing loss, as a result of weight decrease, compounds the problem; particularly in produce that is sold by weight. Due to the lack of RH control in highway trailers, a common mode of transportation for fresh market produce, concerns must be combated by packaging. The uses of liners, bags, or plastic bags are all means to slow or prevent moisture loss (Vigneault et al., 2009). Sweetcorn

is generally protected from moisture loss as result of precooling that leaves residual water and/or ice on the product.

Temperature

Temperature is undoubtedly the most important factor affecting fresh produce; hence the extensive discussion of precooling (Vigneault et al., 2009). Once the field heat has been removed from a product and it has reached its optimal storage temperature (or as close to this value as possible), maintenance becomes critical. This is especially true for highly perishable products. Specialized temperature management practices apply to certain produce, but here the focus will be specifically on highly perishable items. The fundamental rule of perishable handling is that produce should be kept as cool as possible for as long as possible, even if there is potential for a break further down the cold chain (Vigneault et al., 2009).

Because transport units are not designed to cool, only sufficiently cool items may be loaded for transportation. Eksteen (1998) recommends that the pulp temperatures of any given product item upon loading for transportation should not be greater than 0.5°C above the recommended optimum storage temperature. Accordingly, the temperature control thermostat should be accurate to a maximum of ±0.5°C from the set point. Measures should be taken to ensure that both the control and recording of temperatures for the entire shipping duration be as accurate as possible. Such data is crucial if quality losses due to temperature are suspected later in the marketing chain (Eksteen, 1998).

The principles of temperature management for transportation of fresh produce extend to shipping. Again, products should be stored at the most optimum storage temperature feasible for as long as possible. Knowing the physiological age is also

important because it will help determine how long an item can be stored prior to distribution (Eksteen, 1998).

Store Management

The final step in the cold chain of a fresh horticultural product, just before reaching the hands of the consumer, is storage and display in the retail outlet. Storage in retail, back-store coolers should be handled much in the same way as in distribution center, or any other storage application prior to purchase by the consumer. The recommendation is to store fresh produce at the most optimum storage temperature, as required by the needs of the individual products (Eksteen, 1998).

The first challenge when a fresh product is placed for sale in the produce section of a retail outlet is location. Lack of knowledge and insufficient training of store employees often results in product misplacement. During peak seasons, high-selling perishable products often do not reach the refrigerated cases in which they are meant to be placed. For example, in-husk sweetcorn is frequently displayed in large unrefrigerated bins in mid-summer, exposing it to quality-lowering ambient temperatures. At the same time, items that are susceptible to chilling injury may be placed in improperly refrigerated cases because the “colder is better” mentality is difficult to disprove.

If products do make it to the appropriate display, further challenges ensue. Retail display cases are reputed to be the weakest link in the chain (Cortella, 2002). Even if a given case is set to the appropriate temperature for the commodities inside, maintaining this temperature throughout the case is difficult. Forced-air open display cabinets are the most common kind of refrigerated displays used in retail stores and must be designed to meet two dueling needs: 1) convince the customer to purchase the item,

and 2) maintain the item at the appropriate temperature. Keeping the products a safe distance away from the warm ambient environment but close enough to meet the eyes and reach of the consumer is a delicate balance. (Cortella, 2002). Various ever-changing and unpredictable factors have a large effect on the operation and efficiency of the case. These may include food temperature at loading, traffic flow, and seasonal climate changes. Given such variability, it is vital that retail cases be continuously monitored and controlled.

Nunes et al. (2009) studied the retail segment of the cold chain for a wide range of produce items to obtain a depiction of common humidity and temperature conditions. During the study, visual quality analysis and subsequent waste categorization provided an idea of the largest cause for product loss. It was found that display temperatures varied widely and often did not reflect the optimum storage temperature of the product being displayed. This observation was substantiated by the conclusion that 55% of observed product waste was a result of poor temperature management (Nunes et al., 2009).

Shelf-Life and Quality Modeling

The definition of shelf-life is difficult to establish in a universal sense because doing so would require an agreement between varied consumer tastes and mechanical deterioration. Consumers tend to define the end of shelf-life as being the point at which a product is no longer of satisfactory taste, while food industry standards must consider the extent of quality loss allowed prior to consumption as set by food companies (Fu & Labuza, 1993).

Appearance is the first and most important characteristic of a fresh horticultural product as judged by the common consumer. External quality attributes such as color,

size, shape, and percent of defect coverage can be easily determined. Appearance may be adversely affected by improper postharvest handling, enzymatic reactions, and water loss (Vankerschaver et al., 1996). The individual preferences will vary from consumer to consumer and may be influenced by regional and cultural differences.

The acceptable limits required by regulatory agencies and/or food companies to define the end of shelf-life often utilize different quality standards. When microbial standards are employed, they are usually at a low level and are defined in terms of legal requirements (Vankerschaver et al., 1996). For example, counts of mesophilic bacteria after minimal processing of fresh vegetables range from 10^3 to 10^9 cfu/g, but this may be considered acceptable in terms of quality depending on the product (Jacxsens et al., 2002). Quality degradation in terms of product breakdown (e.g. sugar to starch) can also be measured and equated to shelf-life. However, this is not regulated in the same way because it does not have the same safety implications as microbial growth does.

With a better understanding of shelf-life established, the next question becomes what purpose does modeling the quality degradation of a food product serve? In general, modeling in the scientific realm serves a three-fold function: understanding, prediction, and control. Kinetic modeling of changes in food aims to provide an understanding of the chemistry and physics behind such change. Prediction and control are tightly linked. A quantitative prediction of the future condition of a food product with specified parameters allows for later realization of a desired quality (van Boekel, 2008). With the intense complexity of food systems, reality may stray far from theory, but even so modeling still has the potential to be a powerful tool in many industries, namely retail. With knowledge of a few simple parameters, it may be possible for a retailer to predict

the future quality of a fresh product and make subsequent choices in regards to transportation and distribution that would result in reduced product loss and improved consumer satisfaction.

Microbial Growth Models

From a quantitative aspect, shelf-life has been modeled in various forms. Given that microbiological decay is one of the primary means of fresh food quality degradation (Fu & Labuza, 1993), predictive microbiology has been proven to be a useful tool in determining shelf-life (Corbo et al., 2005). The growth of microbiological organisms is translated to shelf-life by equating product age or end of shelf-life to the presence of a specific number of microorganisms. Countless models and methods exist to model and predict microbial growth. The exponential model, the square root model, the Gompertz equation, and the Arrhenius relationship are just a few among the many.

Square root model

The square root model has been shown to accurately detail the growth rate of many microbial organisms. It is a two-parameter equation based on temperature dependence, and as will be found with most other models, it works best in a specific temperature range (Fu & Labuza, 1993). Ratkowsky et al. (1982) proposed the formula as such:

$$\sqrt{k} = b(T - T_{min}) \tag{2-2}$$

where *k* is the specific growth rate, *b* is the is the slope of $k^{1/2}$ versus temperature, *T.*

Exponential model

The exponential model is a simple plot of specific growth rate as a function of temperature and takes the following form:

$$k = k_o \exp(sT) \tag{2-3}$$

where k is the specific growth rate a temperature T, in °C; k_o is the specific rate at 0°C; and s is the slope of the plot of ln k versus T. This model of lag phase microbial growth is limited to a maximum temperature of 30°C. In addition to lag phase growth, this model is said to be applicable to general shelf-life (Fu & Labuza, 1993).

Gompertz equation

The Gompertz equation, published in 1825 by Benjamin Gompertz, was originally created to illustrate age distribution in the human population. It was later applied as a model predicting growth rate as a function of exponential age and even touted as being more appropriately applied to biological work than to any other system (Zeide, 1993). A form of the modified Gompertz equation is the following:

$$\ln \frac{N}{N_o} = A_s exp\left\{-exp\left[\frac{\mu_{max}\, e}{A_s}(\lambda - t) + 1\right]\right\} \tag{2-4}$$

where N is the number of microorganisms, N_o is the number of organisms present at time zero, A_s is the asymptotic value of the maximum number of microorganisms possible, μ_{max} is the maximum growth rate, λ is the lag phase time in days, t is the time in days, and e is the value 2.718 (van Boekel, 2008). Note that the logarithm of the relative bacterial population size is plotted against time. The plot is done in this way because bacteria grow exponentially (Zweitering et al., 1990).

Using estimated parameters of the modified Gompertz equation, Corbo et al. (2006) calculated the shelf-life (SL) of minimally processed vegetables with the following equation:

$$SL = \lambda - \frac{A \cdot \left\{ln\left[-ln\left(\frac{\log 5 \cdot 10^{7} - N_o}{A}\right)\right] - 1\right\}}{\mu_{max} \cdot 2.7182} \tag{2-5}$$

where the limit of acceptability for the microbial population is 5 x 10^7. The drawback of using this approach is that there is much difficulty in calculating the confidence interval of the value obtained (Corbo et al., 2005).

Arrhenius model

The Arrhenius model may be used to predict temperature-dependent microbial growth and subsequent shelf-life based on overall activation energy and temperature, given that all other ecological factors are assumed constant. The equation must be kept within a limited temperature range and is as follows:

$$k = A \cdot \exp\left(\frac{-E_a}{RT}\right) \tag{2-6}$$

where *k* is the specific growth rate, *A* is the collision factor, *T* is the absolute temperature in Kelvin, *R* is the universal gas constant (8.314 $J \cdot mol^{-1} \cdot K^{-1}$), and E_A is the activation energy in J/mol. In terms of shelf-life, this relationship may be applied to the model of temperature dependence of the lag phase of microbial growth under differing temperatures (Fu & Labuza, 1993).

Non-microbial Growth Models

Non-microbial reactions, such as chemical and biochemical also occur during the life of a fresh product and contribute to quality degradation. A few examples of reactions that can occur throughout many of the key components of fresh products include hydrolysis, oxidation, and denaturation (van Boekel, 2008). Many models exist, however the lesser the number of parameters incorporated, the closer to reality the model performs (Fu & Labuza, 1993). Of particular interest are temperature-dependent (Arrhenius-like) models and empirical models.

Temperature dependent

Arrhenius' law, as previously described, is applicable to simple chemical reactions, in addition to microbial growth. Many Arrhenius-like equations, relating rate constant to absolute temperature have been proposed in literature. The following would perform equally as well as the Arrhenius equation:

$$k = A \cdot \exp\left(\frac{-B}{T}\right) \tag{2-7}$$

where *k* is the rate constant, *T* is the absolute temperature, and *A* and *B* are fit parameters that lack physical meaning (van Boekel, 2008). Equations of this form are most applicable to reactions in which activation energy is not necessary.

Empirical models

Given that the Arrhenius model (and those similar) was developed for simple, temperature-dependent reactions, the need for a way to study more complicated reactions pertaining to food science emerged. Accordingly, purely empirical models were developed. In such cases, activation energies are derived instead of using fundamental values. It is then interesting to compare the performance of empirical and semi-empirical models (van Boekel, 2008). Nunes et al. (2004) employed a similar method in the study of blueberry quality by producing curves from experimental and predicted quality data at varying temperatures. Predicted data was calculated used Q_{10} values from literature. The predicted shelf-life was found to be longer than the experimental at temperature below 5°C and shorter at temperatures above 5°C. Inconsistencies between the literature and experimental curves were attributed to varying environmental factors as low reliability of the correlation between quality and respiration rate (Nunes et al., 2004).

Decay as a result of microbiological growth is not as great a concern as that from chemical kinetics for sweetcorn because they are generally moved quickly through the cold chain. However, chemical kinetics testing is not a realistic option in retail distribution decision making. It has been hypothesized that the use of an empirical model for the shelf-life of sweetcorn, based solely on initial global quality, time and temperature would be a sufficiently accurate means of predicting shelf-life and an aid in subsequent decision making.

Objectives

The aim of this project was to create a tool for the prediction of quality index and corresponding shelf-life of sweetcorn based on post-harvest time and temperature treatments. The specific objectives were the following:

1. Establish time-temperature profiles for the cold chain of fresh market sweetcorn by monitoring actual field-to-retail practices.
2. Study the effects storage temperatures on quality of freshly-harvested sweetcorn over time.
3. Develop and evaluate empirical and theoretical models for the prediction of sweetcorn quality deterioration, and produce a visual reference guide to aid in their use.
4. Validate prediction models using experimental data from field to store.

Table 2-1. Sweetcorn respiration rate based on temperature (Suslow & Cantwell, 2009)

Temperature (°C)	Respiration Rate (ml CO_2/kg·hr)
0	30-51
5	43-83
10	104-120
15	151-175
20	268-311
25	282-435

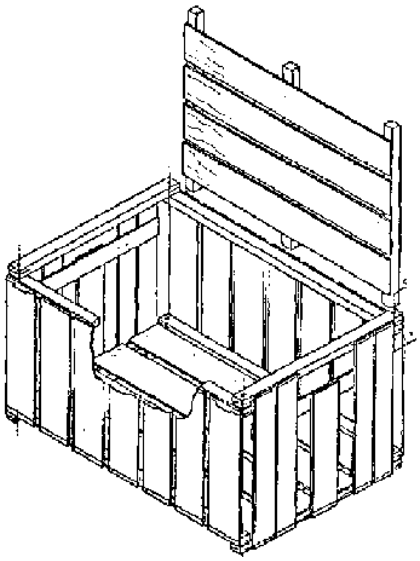

Figure 2-1. Collapsible wire-bound wooden crate (Harris, 1988)

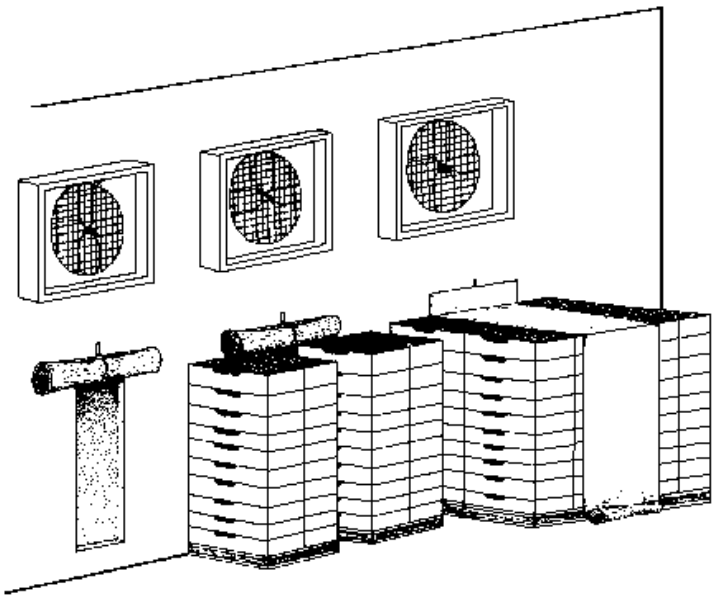

Figure 2-2. Cold wall vacuum cooler schematic (Boyette et al., 1996)

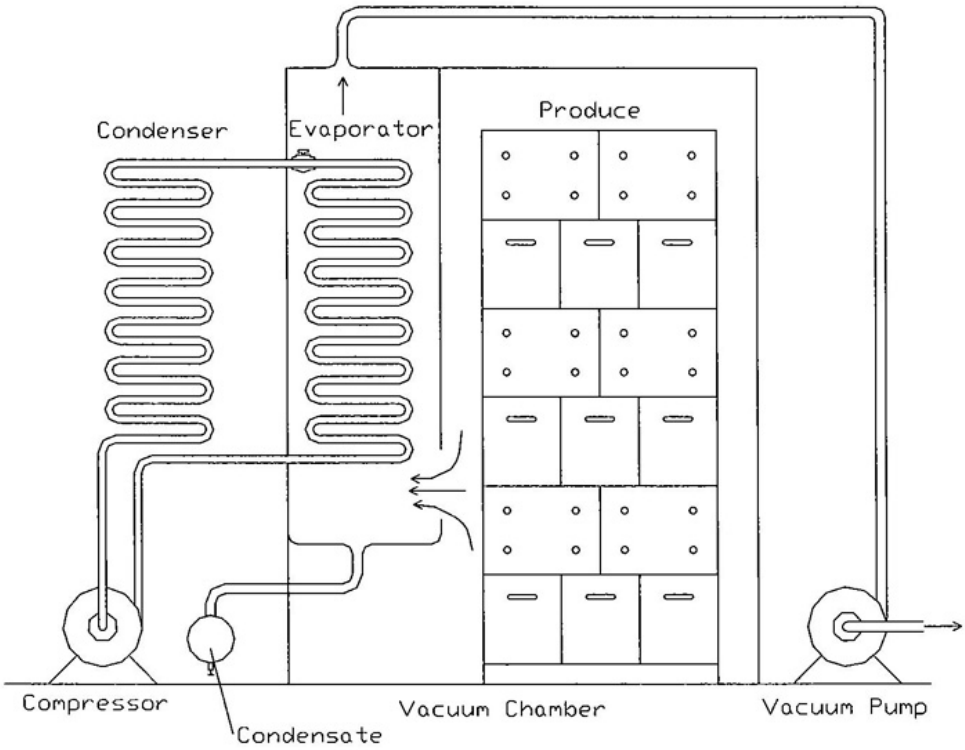

Figure 2-3. Vacuum cooler (Rennie, 1999)

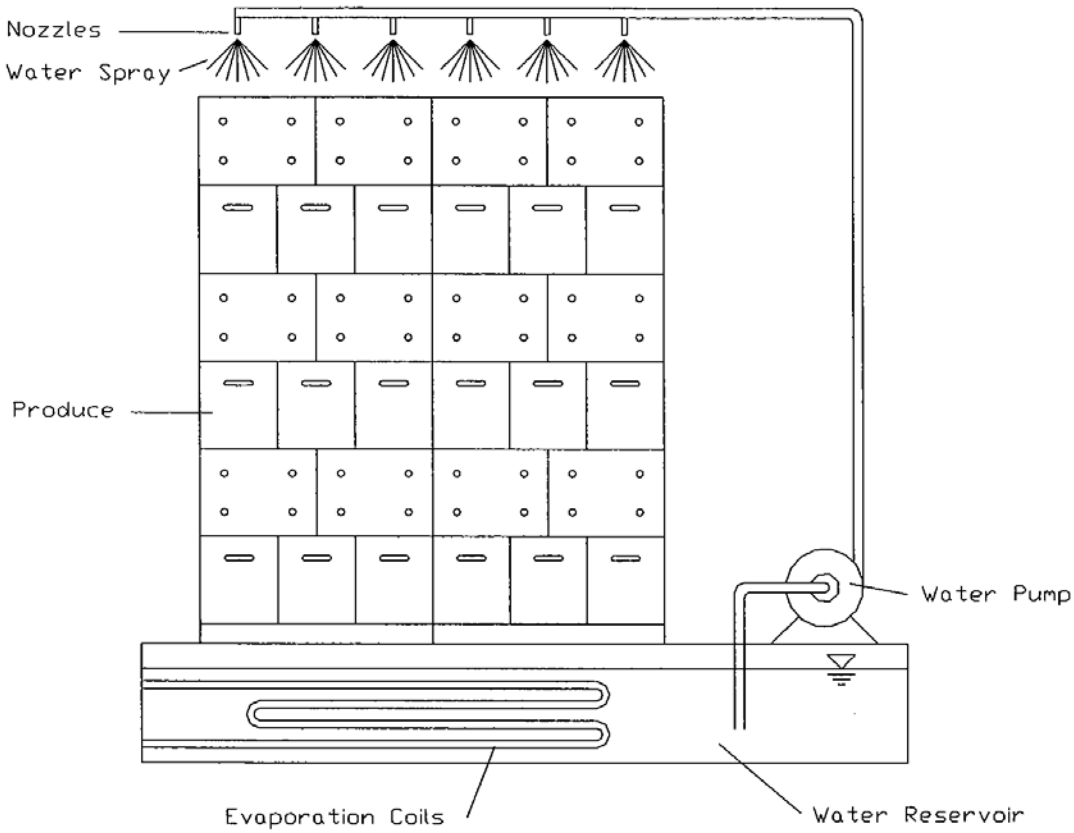

Figure 2-4. Spray-type hydrocooler cooler (Rennie, 1999)

CHAPTER 3
MATERIALS AND METHODS

Cold Chain Monitoring

In order to create and later validate the quality prediction modeling tool for fresh market sweetcorn, it was first necessary to produce sample time-temperature profiles of the cold chain of corn that would most accurately represent current handling conditions. This was accomplished by tracking actual shipments of sweetcorn from field harvest through to the point of consumer purchase. Included in the temperature tracking were precooling, transportation, storage, and retail display. Two trials were conducted in an identical manner: one at the peak of harvest (June 16th) and another at the end of harvest (June 30th) in Iron City, Georgia. Following data collection, temperature profiles for each harvest were produced.

Instrumentation

Sweetcorn (cv. 15752, yellow) was harvested by hand and packed into wood crates and reusable plastic containers (RPCs), with each crate holding approximately 42 and 48 ears, respectively. Sweet corn from both trials was harvested at approximately 9:00am. The freshly harvested corn was palletized and immediately sent by flatbed truck to a nearby precooling facility. Four pallets – two consisting of wood crates and two of RPCs – were instrumented with HOBO® Series H8 temperature loggers (Onset Computer Corporation, Bourne, USA). The loggers were oriented on a three-dimensional diagonal, with one located in a bottom corner crate, one in a middle center crate, and one in a top corner crate (Figure 3-1). Fitted for protection from water damage, the loggers were placed in the center of the selected crates with four TMC6-HD temperature probes attached. Two ears of corn were selected at random from each

crate, to which one probe was placed directly under the husk and another into the core. This allowed for temperature mapping of both corn pulp and surface throughout the pallet. An average of the values from these mappings was later used to develop time-temperature graphs. Data recording began just prior to precooling and was defined as time zero for profiling

Precooling

As discussed, many methods exist for precooling fresh vegetables; however, hydrocooling is the most common method of used to precool corn (Talbot, Sargent, & Brecht, 1991). For this reason, a facility employing this method was chosen for the sweetcorn cold chain study. The facility had a two-lane overhead spray-type cooler (Figure 3-2). Pallets were guided through on a continuous conveyor as water at approximately 1.5°C was dispensed from above.

The standard practice for this operation was a precooling time of roughly 50 minutes. To observe the affects of extended precooling time, two of the four experimental pallets (one wood crate, one RPC), were run through the cooling system a second time for a total of 100 minutes. The ears of corn from these pallets were denoted as “cooled optimum”.

Directly following precooling, the four pallets were moved to the facility’s cold storage room as they awaited pick-up for shipment to the retail distribution center – the next step in the cold chain. In addition, a sampling of corn from each pallet was reserved for quality observation in a food science laboratory at varying storage temperatures (see Quality Analysis).

Transportation and Storage

On the day following harvest, the pallets of instrumented sweetcorn were removed from refrigerated storage and loaded into a 16.2 meter refrigerated trailer (note: the lag time and subsequent warming of the corn between removal and loading is reflected in the time-temperature data). Shortly after leaving the precooling facility, the trailer stopped at a top-icing facility where slush ice was sprayed over the top of the entire load. The truck then proceeded to a retail distribution center (DC) in Atlanta, Georgia.

The cold storage area at this DC has a set-point of 1.1°C. Unloading at this location took place on the day following departure from the precooling facility. At the DC, the specific crates (both wood and RPC) from all four experimental pallets containing instrumented corn were repacked into a single pallet.

Following a short stay of four to six hours at the DC, the instrumented corn was again loaded into refrigerated 16.3 meter trailer for transportation to a retail supermarket outlet in Waycross, Georgia. Unloading occurred approximately 12 hours after unloading at the DC.

Retail

Upon arrival at the retail outlet, all corn crates were promptly unloaded and placed in the store's backroom produce cooler. Following a storage period of around 12 hours, the corn was retrieved from the store. The instrumented ears were discarded and the temperature data downloaded, while the remaining corn was set aside for quality testing. A total of 156 ears were reserved for this purpose.

To complete the temperature profile of the sweetcorn cold chain, additional temperature sensors were placed in the store's refrigerated and non-refrigerated sweetcorn displays over a period of six weeks. The goal was to gather an idea of the average display temperature. During pick-up of the experimental corn, a sample ear of displayed corn was chosen for a pulp temperature reading. This was achieved by inserting a T type thermocouple wire into the center of the ear. The temperature value was obtained by inserting the thermocouple wire into an Omega HH21A reader.

Temperature Profiling

Following the complete monitoring of fresh market sweetcorn from field to store, data were downloaded from the temperature loggers and imported into Microsoft®

Office Excel ® 2007(Microsoft Corporation, Redmond, Washington,1975-2010) . The temperature distributions for each pallet were combined to produce representative averages. Date and time values were converted into elapsed time, with time zero being assigned just prior to the start of precooling. Four separate profiles were produced for each harvest, corresponding to the four packaging/precooling treatment permutations. They were then compiled into a single comparative chart. By matching timing notes taken along the duration of each experiment with noticeable inflections in the charts, temperature profiles were produced. These were to be used later a tools for testing and validation of the quality prediction models.

Model Development

The procedure by which the quality prediction model was created was a multi-step process. It began with the collection of quality index data followed by the development of prediction curves as a function of time and temperature. For the purpose of comparison, two models were created, one empirical and the other theoretical. The empirical was based on data collected from a preliminary field study while the theoretical was based on the premise of exponential biological decay.

Data Collection

Model development began with a laboratory controlled evaluation of sweetcorn (cv. 15752, yellow) quality index as a function of time and temperature. Early harvest (late-May) sweetcorn was obtained from Iron City, Georgia immediately following precooling. It was received by food science laboratory in Gainesville, Florida within four hours of harvest. A total of 90 ears of sweetcorn were selected based on uniform color, size, and defect coverage. They were disbursed among five temperature-controlled

rooms held at 2, 5, 10, 15, and 20°C at a relative humidity of 80-90% (Nunes, 2008; unpublished data).

Quality evaluations fell into three categories: subjective, quantitative, and compositional. Subjective quality evaluations consisted of those that were obtained by visual inspection. The subjective evaluations were carried on always by the same trained person(s) as the exact interpretation of visual quality varies from one individual to another. Visual assessments of external features such as the leaves, flags, husks, and silks; in addition to internal features such as kernel appearance, composed the subjective quality evaluation. The visual rating scale detailed in Table 3-1 was used to rate the external and internal visual quality of sweetcorn. Instrumental surface color measurements (L*a*b*) and kernel firmness composed the quantitative section. Finally, compositional analysis consisted of weight loss, moisture content and total sugar content of sweetcorn kernels (Nunes, 2008; unpublished data).

Limiting Factor Determination

While overall quality is a function of all the before mentioned quality attributes, a limiting quality factor was needed for practical usage. For the purpose of quality determination as a function of temperature, it was necessary to plot subjective quality attributes against temperature. The scaling method taken by Nunes (2008; unpublished data) was to set a maximum acceptable quality value and the first attribute to reach that threshold for a given storage temperature was considered the limiting quality factor. The corresponding quality index (QI) ratings at given time intervals for that limiting quality factor were then inputted into the final table used for modeling. Considerations and

accommodations to account for non-continuity throughout the tested temperature range will be discussed in Chapter 4.

Empirical Model

The empirical model began with evaluation of the quality curves resulting from early harvest (June 16th) quality analysis. In order to aid in curve-fitting, an additional higher temperature (30°C) data set was added. The quality values for this temperature were predicted using the same method employed for the theoretical model (detailed in Theoretical Model).

A quality equation for each 24-hour time step (from 0 to 10 days) was created by plotting temperature versus observed quality and performing a linear regression. Many types of regressions were tried; however, a second-order polynomial fit best in all cases. In effect a two-variable system was produced by creating a formula for each day based on temperature.

For the derived equations to be useful, it was necessary to link them in such a way that, given three known parameters: initial quality value, a storage temperature, and a duration for which the product will be held at that temperature; the ensuing quality could be predicted. It was also desired that this be a dynamic as opposed to static system; that is instead of assuming a constant temperature for the duration of storage, transportation, display, etc., the final quality could take into account temperature fluctuations. Expectedly, the result will be closer to reality than those predicted by earlier methods. To achieve this objective, the derived equations were integrated into a task automating system called a macro which was run in Microsoft® Visual Basic (Microsoft Corporation, Redmond, Washington, 1975-2010). An iterative effect was created by

producing a new set of QI values for each temperature and corresponding duration experienced by a given shipment of sweetcorn. The user can then choose to model an entire cold chain or just specific segments.

In addition to final quality, the macro was programmed in a way such that the remaining shelf-life could be estimated by looking at the equivalent elapsed time (to be discussed further in Chapter 4).

Theoretical Model

For the intent of comparison, it was desired to create a second model for sweetcorn quality prediction based on theoretical data. Observations from the empirical results and the assumption of exponential decay were the bases for this model. The knowledge of respiration rate at specific temperatures was the starting point. Based on existing storage recommendations for sweet and supersweet varieties of fresh corn, it was decided that the end of shelf-life for sweetcorn should occur at a QI of 2.0 and at no more than 14 days. Note that 2.0 is lower than the threshold chosen for limiting quality factor determination. A lower value was selected in order to more closely match actual retail product rejection standards. The goal, therefore, was to create a curve for QI at 0°C that would degrade to a QI value of 2.0 close to day 14. The target day for the end of shelf-life (DSL) for the remaining temperature values – 5, 10, 15, and 20°C – were then calculated with following equation:

$$DSL_n = \frac{R_{n-1}}{R_n} \times DSL_{n-1} \tag{3-1}$$

where R_{n-1} is the respiration rate of the next lowest temperature, R_n is the respiration rate of temperature of interest, and DSL_{n-1} is the end shelf-life for the next lowest temperature.

With the end of shelf-life days known, a trial and error approach was taken to find exponential equations to achieve a value of 2.0. The final equation chosen to create the theoretical values for QI based on time and temperature was as follows:

$$QI = -\ln\left[\left(1 + \frac{T}{5}\right) \times t\right] + 5 \qquad (3\text{-}2)$$

where *T* is the temperature and *t* is the time in days. The end result of applying this equation was a set of quality values at varying temperatures over time.

As with the empirical data, again equations for quality based on temperature were produced for each day and transcribed into Microsoft® Visual Basic by programming a macro (Refer back to the Empirical Method section, page 45, for further details).

Comparative Quality Analysis

Data Collection

Quality analysis of sweetcorn samples collected from two positions in the cold - chain (after precooling and after arrival at retail) was completed by a food science laboratory team. Subjective quality evaluations included leaf, flag, silk, and husk appearance in addition to kernel denting and decay. Quantitative analysis involved measurement of weight loss, moisture content, and total sugar content. The resulting limiting values were of interest for the later development of the shelf-life prediction modeling tool. The sweetcorn were separated by precooling treatment and subjected to varying storage temperature conditions.

From field

Quality analysis of sweetcorn (cv. 15752, yellow) was conducted on two sets of samples, corresponding in timing with the two cold chain temperature monitoring

experiments previously detailed. The first came from the from peak harvest (mid-June) and the second from late harvest (late-June) in Iron City, Georgia.

Within hours of precooling, a representative sampling of sweetcorn ears from different precooling and packaging treatments were collected and transported to Gainesville, Florida. Immediately upon arrival, 10 ears were chosen for initial quality measurements. Following initial evaluation, the remaining ears were separated into the following categories: optimum cooling, wood crate top, wood crate center, wood crate bottom, RPC top, RPC center, and RPC bottom. They were stored in temperature-controlled rooms for a total of eight days at 0°C to represent optimum handling and storage temperature conditions for sweetcorn. Quality analysis was performed again at the end of the storage period (Nunes, 2009; unpublished data). The averaged external appearance quality index values would later be used for validation of the prediction models.

From store

Similar to the field tests, quality analysis of fresh sweetcorn pulled from the cold chain at the retail level was conducted twice. Again, these tests corresponded with the two cold chain monitoring experiments and the selected corn came directly from crates off the experimental pallets.

Upon arrival at the store level (approximately four days following harvest), a representative sampling of sweetcorn ears from varying precooling and packing treatments was collected and immediately transported to a food science laboratory in Gainesville, Florida. Ten ears were selected for initial quality measurements. A total of 156 ears were stored for four days in temperature-controlled chambers held at 0, 5, and

20°C, at a relative humidity of 90%. The three temperatures were chosen to simulate optimum, refrigerated, and non-refrigerated storage and handling conditions; all of which could be experienced by fresh market sweetcorn as it passes through commercial operations (Nunes, 2009; unpublished data). Quality analysis was performed once more on day four, and again the quality index values that would later be used to test and validate the prediction models were based on those that proved to be quality limiting.

Model Validation

The validation step is where cohesion amongst all parts of the project occurred, with the goal being to take observed quality data and compare it to data predicted by the empirical models. Doing so would indicate the successful performance of one model over the other, direct possible industry use, and suggest further research and modifications. A two-fold approach was taken for validation, comparing first field then retail data.

Field comparison

The comparison of data from the field with simulated data required a simple, single iteration within the theoretical and empirical models. Because the experimental corn obtained from the field was obtained directly after precooling and maintained at 0°C for the duration of transportation and storage treatment, each model was run for that same duration (8 days) at 0°C. The initial QI for the experimental corn was 5.0; subsequently this value was used for the model initial QI. Finally, the resulting final QI from each of the two prediction methods was compared to observed values as well as to each other. Comparison included percentage difference calculation between the observed and model values using the following formula:

$$\% \, difference = \frac{QI_{observed} - QI_{model}}{\left(QI_{observed} + QI_{model} / 2\right)} \times 100 \quad (3\text{-}3)$$

The percentage difference acted as a measure of the accuracy in prediction by each model. This same procedure was carried out for each of the two experimental harvests.

Store comparison

The comparison of model-predicted QI to observed QI from sweetcorn obtained at the store level is where the cold chain temperature profiling was utilized. Unlike the field comparison, the experimental sweetcorn experienced temperature fluctuation. The temperatures and corresponding durations for the individual segments of the cold chain were entered into each model, with an assumed initial quality of 5.0. Upon arrival at the food science laboratory where analysis took place, samples from the four packaging/cooling treatments were subjected to three different temperature treatments and monitored. This was to represent “store display”. This step in the chain was also included in the model. Again, the resulting final QIs were compared to the observed QIs at the end of storage (“store display”) period using equation (3-3). This procedure was carried out for each of the two experimental harvests.

Visual Referencing

For practical usage of the sweetcorn cold chain simulator, it was important to create visual quality references. To do so, two sets of yellow sweetcorn ears were obtained at the retail level. One set (A) was stored at 4°C and the other set (B) at 19°C. In the case of set (A), pictures were taken of each whole corn ear (with husk) at consistent intervals. Set (B) ears were also photographed daily, however the husks were pulled back to capture kernel condition. By running the simulator at each of the specified temperatures, QI values were assigned to each day. The result was a

reference chart by which an individual using the simulator could determine the initial quality of a sample ear of corn.

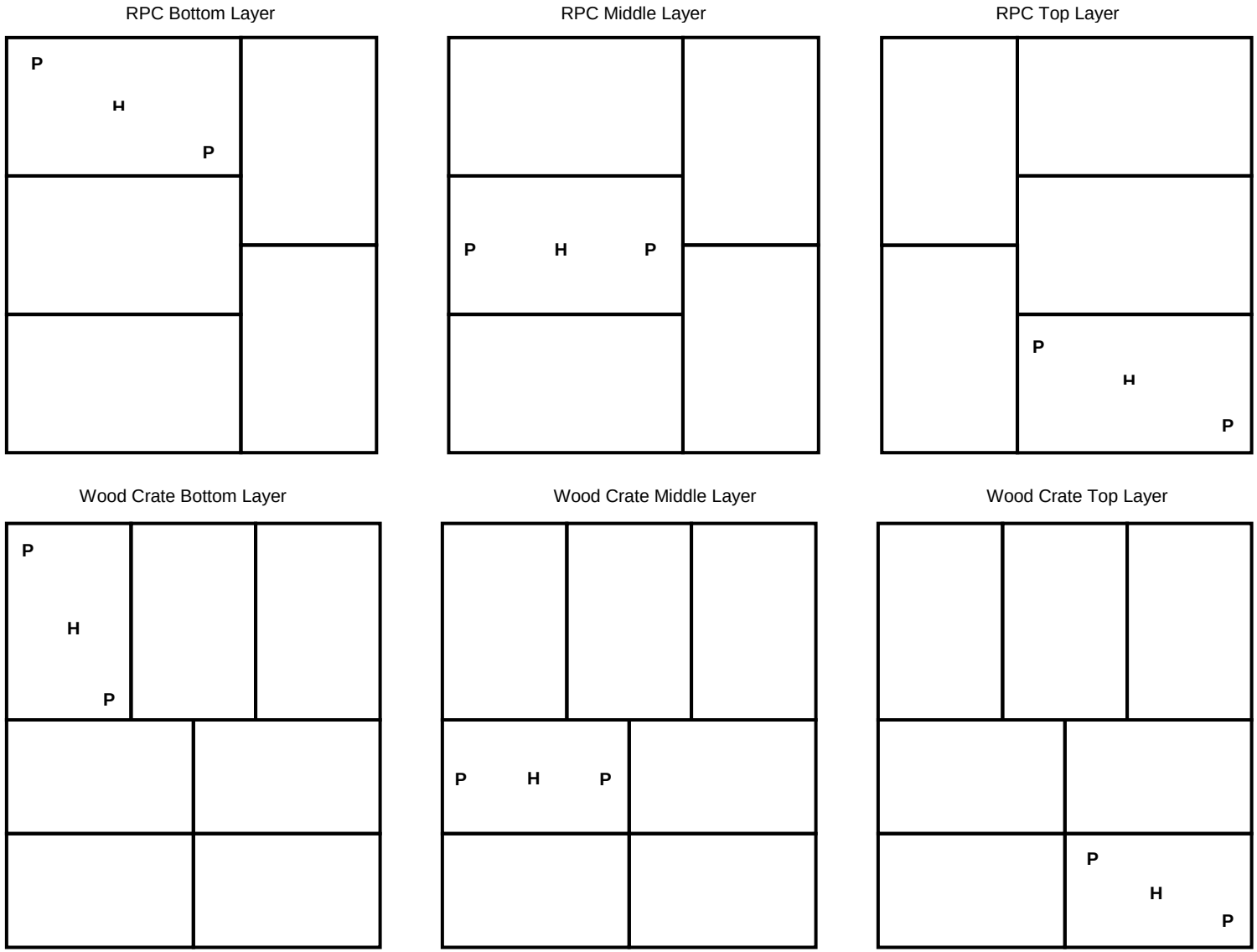

Figure 3-1. Temperature sensor layout (H: Hobo, P: Probe)


Figure 3-2. Precooling operation

Table 3-1. Visual quality ratings and descriptors for sweetcorn (adapted from Nunes 2008; unpublished data)

	Characteristics	
QI Rating	External Appearance	Internal Appearance
5	- fresh, bright green flags - tight, green husk - shiny, fresh silk	- kernels are bright and shiny - no sign of kernel denting
4	- minor flag wilting - loss of bright green color - slightly dry but shiny silk	- kernels are bright and less shiny - slight signs of kernel denting
3	- evident flag and silk wilting - dry and less bright husks	- kernels lose bright, shiny Appearance - evident kernel denting
2	- dry and moderately brown flags and husk - dry and brown silk	- dull kernels - severe kernel denting
1	- extremely dry and brown flags, husks and silks	- dull, discolored kernels - extremely dented and dry Kernels

CHAPTER 4
RESULTS AND DISCUSSION

Time-Temperature Profiles

Two shipments of sweetcorn were followed for the duration of their cold chain handling from field to store. For each trial, four pallets distinguished by crate material and cooling time were instrumented with temperature sensors. Figures 4-1 and 4-2 detail the temperature profiles of the first and second harvest, respectively. The designation of wood crate/RPC indicates packaging type, while standard/optimum is the cooling time. The elapsed time was designated just before the start of precooling. The curves in Figures 4-1 and 4-2 are broken down into separate cold chain steps identified by duration and average temperature in Tables 4-1 and 4-2. The step number designations are as follows: 1) precooling and storage at precooling facility, 2) transportation to retail DC, 3) storage at DC and transportation to retail, 4) retail backroom cooler storage, and 5) transportation to laboratory. Note that in practical application step 5 would likely be retail display.

Little difference was noted between the two harvests and amongst the different pallet types. However, considering all eight individual profiles, corn packed in RPCs and cooled for the optimum time of 100 minutes maintained a cold chain closest to the recommended cold chain for sweetcorn.

Also included in the temperature profiling was a monitor of retail conditions. Table 4-3 provides information gathered about the average dry display ambient temperature over a period of six weeks. In addition, samples of sweetcorn were pulled from wet and dry displays and their pulp temperature recorded. The dry display ambient and corn pulp temperatures are consistent, while the misted display corn is higher. This is likely a

result of improper misting water temperature. In general, however, all three values are above the recommended storage temperature for sweetcorn of 0°C. The affect on quality of storage at 5°C, the average dry retail display temperature is reported later in Chapter 4.

Model Development

Empirical Curves

Limiting quality values observed for early harvest sweetcorn were obtained from Nunes (2009; unpublished data) and combined with predicted values for 30°C (Table 4-4). It was found that external appearance (composed of leaf, flag, husk, and silk) was the first quality attribute to reach the threshold QI for sweetcorn stored at 2 and 5°C, while kernel appearance was found to be the limiting factor for sweetcorn stored at 15 and 20°C. These values were translated into curves shown in Figure 4-3. It was observed from this figure that the degradation of sweetcorn, as expected, followed the theory of exponential decay at all storage temperatures tested.

It should be noted that, in addition to 2, 5, 15, and 20°C, a set of sweetcorn was also stored at 10°C as detailed in Chapter 3. The corn was monitored for quality loss and originally intended for inclusion into the process by which daily value prediction equations were created. However, this temperature range was decidedly omitted from the final results due to inconsistency.

Theoretical Curves

Given the exponential decay illustrated by the empirical curves shown in Figure 4-3 and the recurring presence of exponential decay throughout all biological systems, it was decided that the theoretical data should take the same form. Table 4-5 details the

values obtained by applying exponential decay as function of time for each temperature point of interest. They were translated into curves in Figure 4-4. Looking at the curves, it appears as though an ear of sweetcorn stored at 0°C may not reach a quality index of 2.0 for a long period of time – well past the 14 day cutoff. An important note is that while the sweetcorn may be deemed acceptable by appearance, various other factors comprise the overall quality, many of which cannot be perceived by visual inspection. The sugar content, for example, may degrade at a much more rapid pace. This is why both age and quality acceptability cutoffs are to be employed.

Comparing the empirical and theoretical curves, one can see that the theoretical are clearly smoother and more uniform. This occurred because the theoretical values for each temperature were produced by the same equation, with time being the only variable. The result was a continuous curve for each temperature. It should also be noted that while the empirical data goes through day 10, the theoretical data extends through day 14. Empirical data was collected only until day 10, therefore limiting the prediction model. Given that the theoretical data was produced by the use of exponential formulation and assuming that quality decay would continue to follow the same exponential pattern, the model was extended it to 14 days. This time period was chosen based to the supposition that, on average, sweetcorn will last no longer than two weeks even under optimal storage conditions. Therefore, information regarding quality past this point is irrelevant.

Equation Fitting

For both the empirical and theoretical data, the QI value was plotted against temperature in a separate graph. The line of best fit was found by regression, as shown

in Figure 4-5 and 4-6. The same curve-fitting procedure was carried out for each day and the resulting equations are shown in Tables 4-6 and 4-7. Also displayed in these tables is the R-squared, or coefficient of determination for each trendline. The coefficient of determination is a measure of closeness between predicted outcomes (produced by the trendline equation) and actual observed outcomes (those that make up the original curves). It is the portion of the variance explained by the regression equation. The coefficient of determination varies from 0 to 1.0, where the closer the R-squared value is to 1.0, the stronger the correlation. Polynomial trendlines were chosen for both modeling methods because they resulted in the strongest correlations. However, greater variation in correlation was observed among the empirical equations than the theoretical. This variation may be explained by the fact that empirical QI values are, in reality, affected by more than just temperature.

Macro Development

With the curve equations determined, the next step was translation into a Macro-Enabled Excel ® worksheet. The first version of each model was programmed to output a single final QI in addition to the equivalent elapsed time. The equations shown in Tables 4-6 and 4-7 were embedded into their respective model worksheets. The necessary inputs included initial QI, holding temperature, and time in minutes. The program progresses by first laying out the QI by day based on the temperature input. Then the time starting point is determined based on where the initial QI falls. This is where the duration begins. Finally, the macros were written such that the resulting QI would be calculated using the formula for the day in which the duration ended. Figures 4-7 and 4-8 depict examples of a trial scenario with and initial QI of 5.0, a holding

temperature of 7°C, and a duration of 1440 minutes (i.e. one day). Comparison between the actual QI output values obtained will be discussed later in the Chapter 4.

The preliminary versions, while effective in achieving the desired outputs, could only be applied to a product held at a static temperature. The aim of this project, however, was to predict quality at specific points, from beginning to end, throughout a dynamic cold chain. That is, to predict quality changes with a cold chain that is imperfect and where temperature fluctuations will occur. Hence, it became necessary to advance the system to accommodate several time/temperature steps in journey from field to store. This was done by duplicating the existing worksheet arrangements and extending macro codes accordingly. Subsequently, time and temperature inputs for each were needed, in addition to the initial QI value, for a successful run of the prediction model. Examples of the completed models are shown in Figure 4-8 for the empirical and Figure 4-9 for the theoretical model. The highlighted cells represent the final QI following all imputed cold chain steps and, again, the equivalent elapsed time is based on the conditions at the end of the time step.

Validation and Comparison

The validation and comparison of the two sweetcorn quality prediction models was accomplished by evaluating observed quality data obtained at two points in the cold chain.

From Field

Quality results from the field study are shown in Tables 4-8 and 4-9. Overall, it appeared that the empirical model results matched the observed data more closely than the theoretical model based on percent difference comparison. This may be explained by the fact that exponential decay is a simple formula and only partially encompasses

the factors that contribute to the decrease in sweetcorn quality over time. The percentage difference between the observed and model QIs following the 8-day storage period ranged from 0 to 28.8%. The differences observed by use of the theoretical were almost double, ranging from 24.1 to 49.4%.

Further examination of data shown in Tables 4-8 and 4-9 reveals a disparity between the two harvests. Both models appear to fit the observed data from the late harvest much closer than the first harvest. This may be explained by the closeness in environmental conditions on the days during which data was collected. This also suggests that it might be appropriate to create several empirical models corresponding to different harvest times – early, peak, and late.

Figure 4-11 shows the average percent difference for each model separated by harvest. Overall, it was found from the field study that the most accurate model application was the empirical model applied to the late harvest.

From Store

Quality results from the store study are shown in Tables 4-10 through 4-13, separated by model and harvest. An important modification was done to the original observed data for the purpose of consistency. The point of discrepancy was an incoming QI of 5.0 for all corn samples pulled from the cold chain at the store level. Such a QI is unlikely given that the corn was four days post harvest and optimum temperatures had not been maintained up to that point. It was therefore assumed that the initial QI as well as the subsequent QI after an additional four days of storage should be reduced by a constant value. The value chosen was 1.5, based on the predicted QI upon store collection. For example, an ear of corn with an initial QI of 5.0 then became

3.5, and an ear of corn having a 4-day QI of 3.7 was reduced to 2.2. The original quality rating values can be found in Appendix B.

An additional issue arose specifically when generating the empirical model QI values after four days of storage at 0°C. The model began to overshoot due to the 10-day constraint. Consequently, the final QI output defaulted to 1.0. Extrapolation was used to accommodate the problem for this study. A plot of time versus QI at 0°C was generated as well as a polynomial best fit equation. The time at which the final QI was calculated by use of this equation was found by locating the QI and corresponding day on the Day/QI display and then adding 4 days. A more practical solution to this issue is proposed and discussed in Chapter 5.

For the purpose of comparison, the observed QIs from sample of sweetcorn analyzed upon reception and again after four days of storage were grouped and averaged based on model and harvest. The percent differences between the model and observed final QI values after the storage period are shown in Figure 4-12. Similar to the field test, the empirical model produced final QI values that were closer to the observed than were the theoretical model values for the first harvest. However, the store test differed from the field test in that the second harvest was modeled more closely by the theoretical model. Comparing the different storage temperatures, there appears to be no correlation between closeness of fit between model and observed values based on storage temperature. In other words, it cannot be said whether either model provides more accurate results when run within specific temperature ranges.

Additional examination of data shown in Tables 4-10 through 4-13 as well as Figure 4-12 fails to affirm the observation from the field study indicating that both

models fit the second harvest more closely than the first. The result of the store study was, in fact, just the opposite. The correction factor used may contributed to this result. Overall, it was found that the most accurate model application was the empirical model applied to the peak harvest.

Visual Referencing

The reference color chart was created as an additional visual aid to be used simultaneously with the shelf life predicting models (Figure 4.13). For practical usage, and in order to determine the QI of an ear or sweetcorn, it was recognized that an individual would benefit from a visual color chart depicting the different quality ratings (5=best; 1=worst) for sweetcorn. This is to be used in addition to the visual quality descriptors provided in Table 3-1. Based on results from quality testing that led to the creation of the empirical model, it was found that, in general, the external appearance of fresh sweetcorn degrades quicker than the internal appearance (i.e. kernel) at storage temperatures below 10°C. However, at storage temperatures above 10°C, the opposite affect was observed. In other words, a sample of sweetcorn might appear to have a quality rating of 4.0 (minor flag wilting, loss of bright green color) based on the appearance of the husk, but when husked would actually be classified as having a quality rating of 5.0 (fresh from the field; kernels are bright and shiny with no signs of denting). Therefore, a single quality attribute would not be sufficient for determining QI. Accommodations were made by including in the color chart both external and kernel pictures of how and ear of sweetcorn with different quality ratings will look. A user would then be instructed to determine two ratings for a sample ear of sweetcorn. The lower of the two would then be used for the initial QI input value.

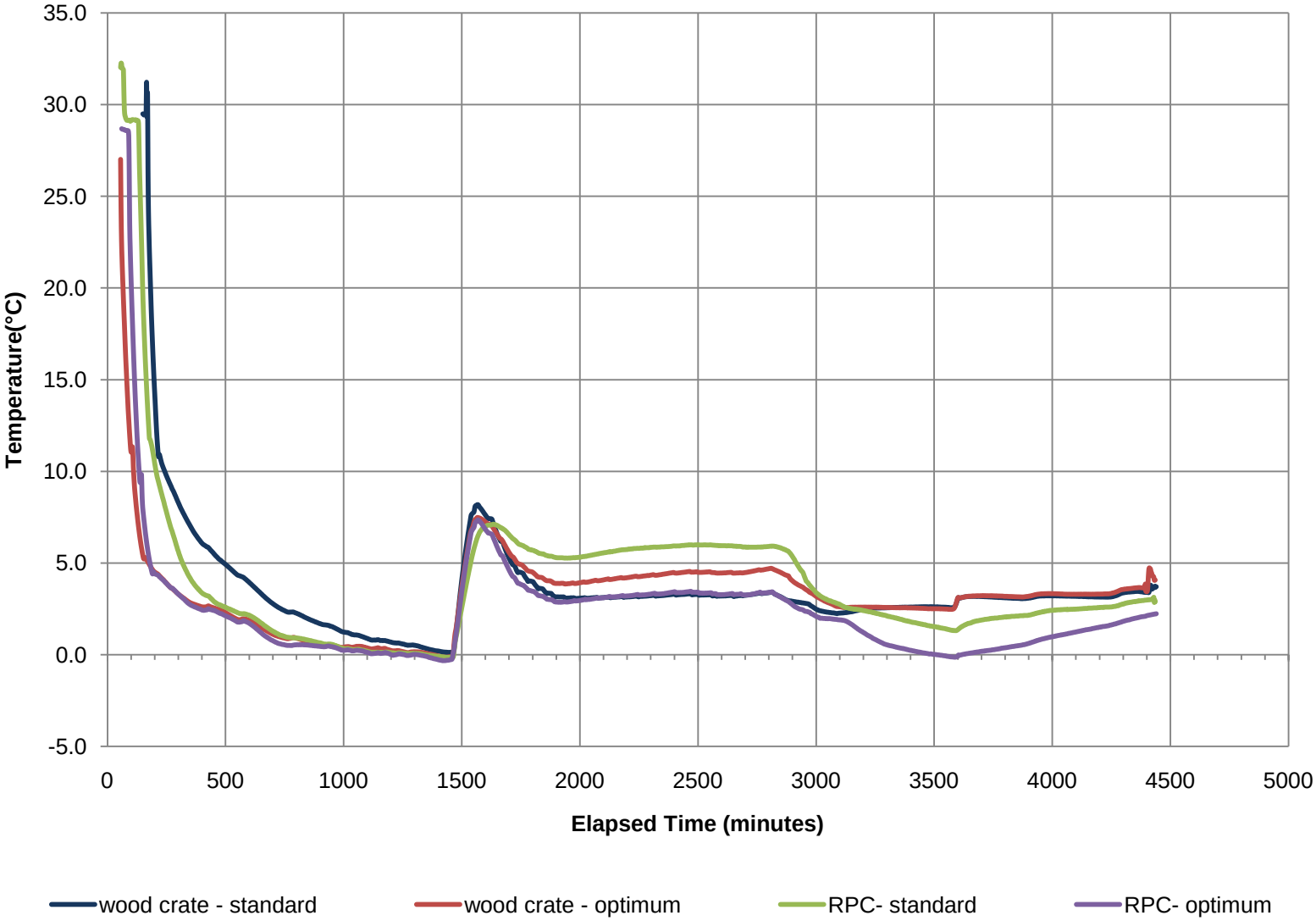

Figure 4-1. Cold chain temperature monitoring separated by crate type and cooling time - first harvest

Table 4-1. Time/temperature profile averages - first harvest

		Packaging/Precooling Treatment			
Step	Variable	Wood crate/ standard	Wood crate/ optimum	RPC/ standard	RPC/ optimum
1	Avg. Temp (°C)	3.5	2.1	3.1	2.4
	Duration (min)	1300	1300	1300	1300
2	Avg. Temp (°C)	3.9	4.7	5.8	3.7
	Duration (min)	1300	1300	1300	1300
3	Avg. Temp (°C)	2.6	3.0	3.1	1.5
	Duration (min)	700	700	700	700
4	Avg. Temp (°C)	3.1	3.2	2.2	0.9
	Duration (min)	900	900	900	900
5	Avg. Temp (°C)	7*	7*	7*	7*
	Duration (min)	240	240	240	240

* Estimated value

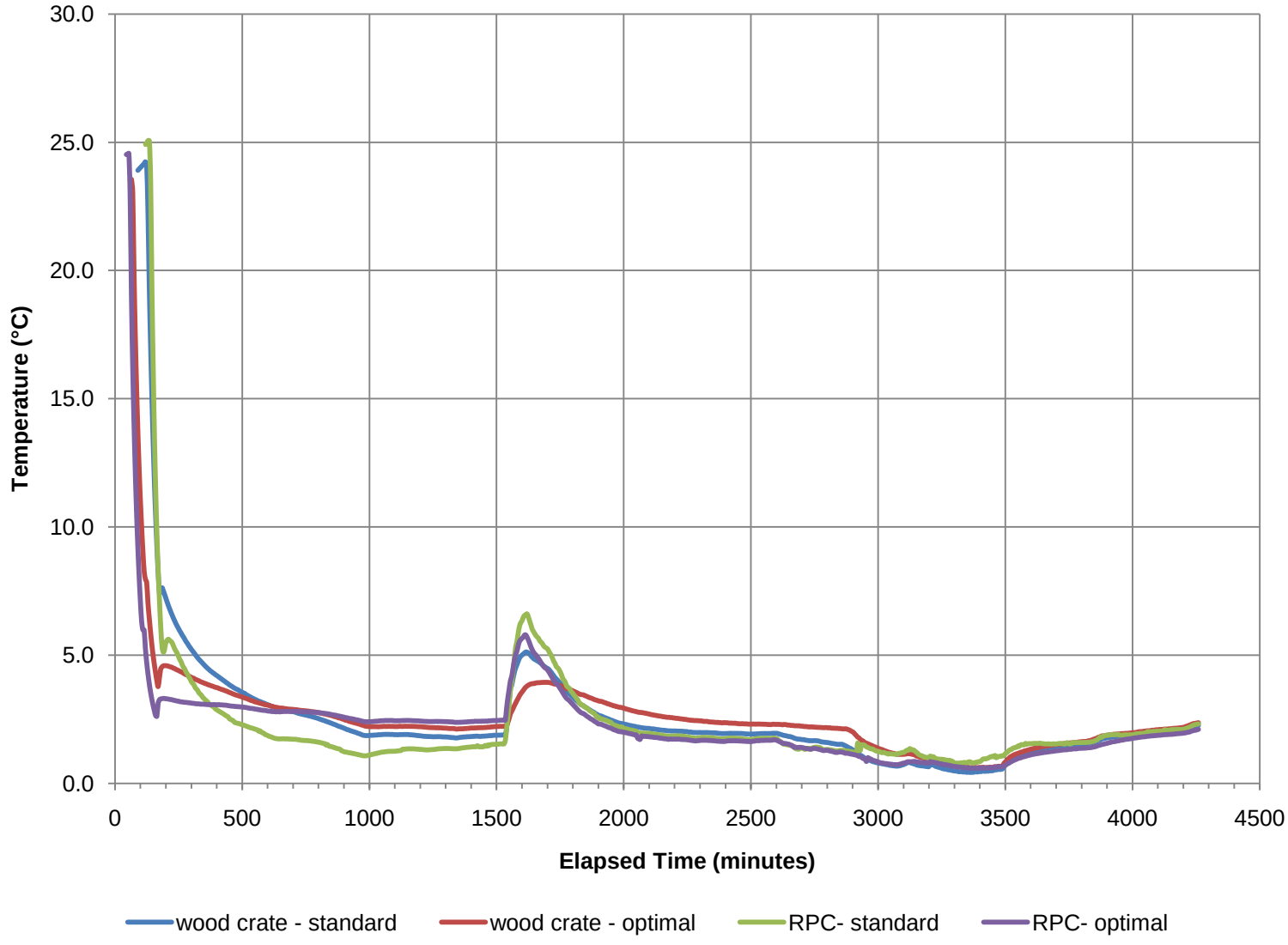

Figure 4-2. Cold chain temperature monitoring separated by crate type and cooling time - second harvest

Table 4-2. Time/temperature profile averages - second harvest

		Packaging/Precooling Treatment			
Step	Variable	Wood crate/ standard	Wood crate/ optimum	RPC/ standard	RPC/ optimum
1	Avg. Temp (°C)	3.8	3.6	2.7	3.3
	Duration (min)	1350	1350	1350	1350
2	Avg. Temp (°C)	2.6	2.8	2.6	2.4
	Duration (min)	1200	1200	1200	1200
3	Avg. Temp (°C)	0.9	1.3	1.1	0.9
	Duration (min)	800	800	800	800
4	Avg. Temp (°C)	1.6	1.7	1.7	1.5
	Duration (min)	700	700	700	700
5	Avg. Temp (°C)	7*	7*	7*	7*
	Duration (min)	240	240	240	240

Table 4-3. Empirical QI values based on quality limiting factors

Location	Average Temperature (°C)
Dry display - ambient air	4.8
Dry display - internal corn	4.8
Wet display - internal corn	6.1

Table 4-4. Empirical QI values based on quality limiting factors (adapted from Nunes 2009, unpublished data)

	Quality Index (5-1)				
Time (Days)	2°C	5°C	15°C	20°C	30°C
0	5.0	5.0	5.0	5.0	5.0*
1	5.0	4.5	3.2	3.0	3.1*
2	4.3	4.1	2.8	2.5	2.4*
3	4.0	3.9	2.4	2.2	2.0*
4	4.0	3.6	2.3	2.1	1.7*
5	4.0	3.6	2.1	2.0	1.4*
6	3.5	3.6	2.0	1.9	1.3*
7	3.5	3.2	1.9	1.8	1.1*
8	3.4	3.1	1.9	1.8	1.0*
9	3.3	3.0	1.8	1.8	-
10	3.3	2.9	1.8	1.6	-

*Predicted value

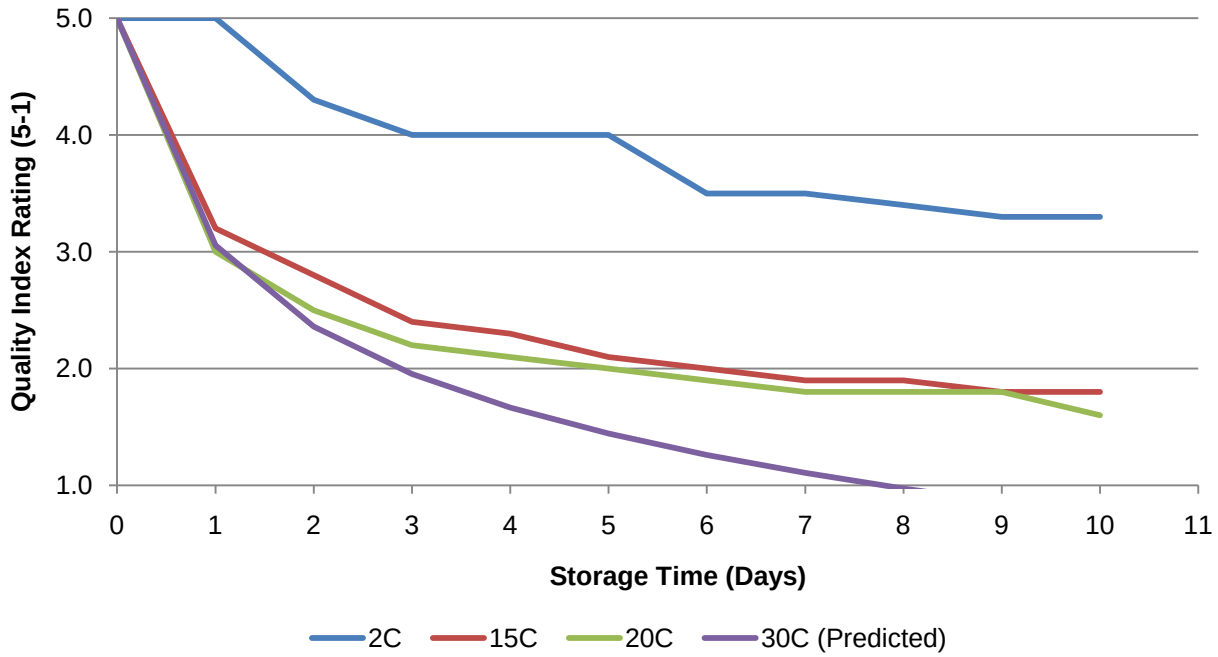

Figure 4-3. Empirical curves of QI as a function of time

Table 4-5. Theoretical QI values based on exponential decay

	Quality Index (5-1)					
Time (Days)	0°C	5°C	10°C	15°C	20°C	25°C
0	5.0	5.0	5.0	5.0	5.0	5.0
1	5.0	4.3	4.1	3.6	3.4	3.2
2	4.3	3.6	3.2	2.9	2.7	2.5
3	3.9	3.2	2.8	2.5	2.3	2.1
4	3.6	2.9	2.5	2.2	2.0	1.8
5	3.4	2.7	2.3	2.0	1.8	1.6
6	3.2	2.5	2.1	1.8	1.6	1.4
7	3.1	2.4	2.0	1.7	1.4	1.3
8	2.9	2.2	1.8	1.5	1.3	1.1
9	2.8	2.1	1.7	1.4	1.2	1.0
10	2.7	2.0	1.6	1.3	1.1	-
11	2.6	1.9	1.5	1.2	1.0	-
12	2.5	1.8	1.4	1.1	-	-
13	2.4	1.7	1.3	1.0	-	-
14	2.4	1.7	1.3	1.0	-	-

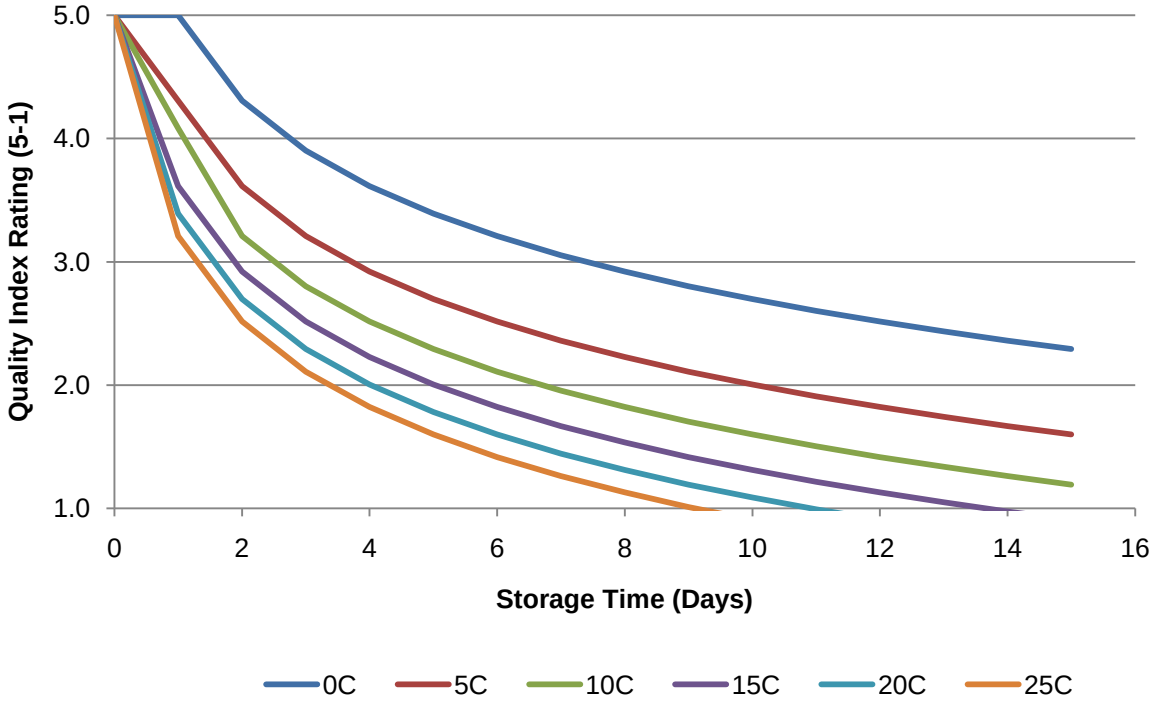

Figure 4-4. Theoretical curves of QI as a function of time

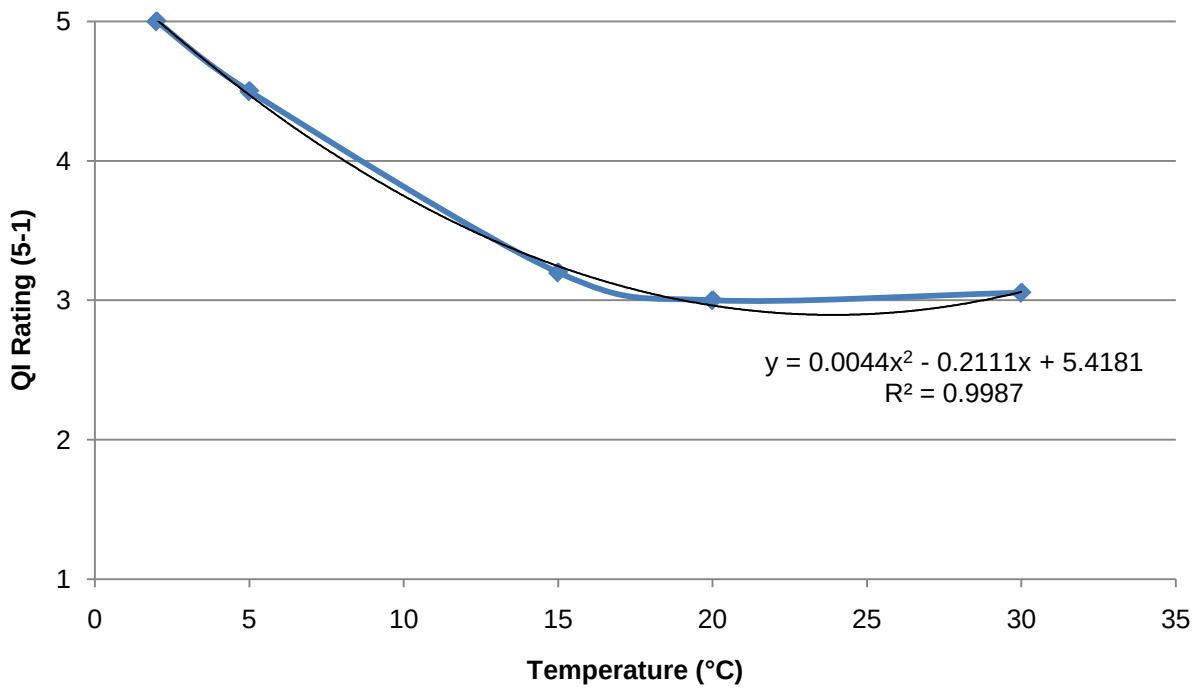

Figure 4-5. Example empirical equation determination (day 1)

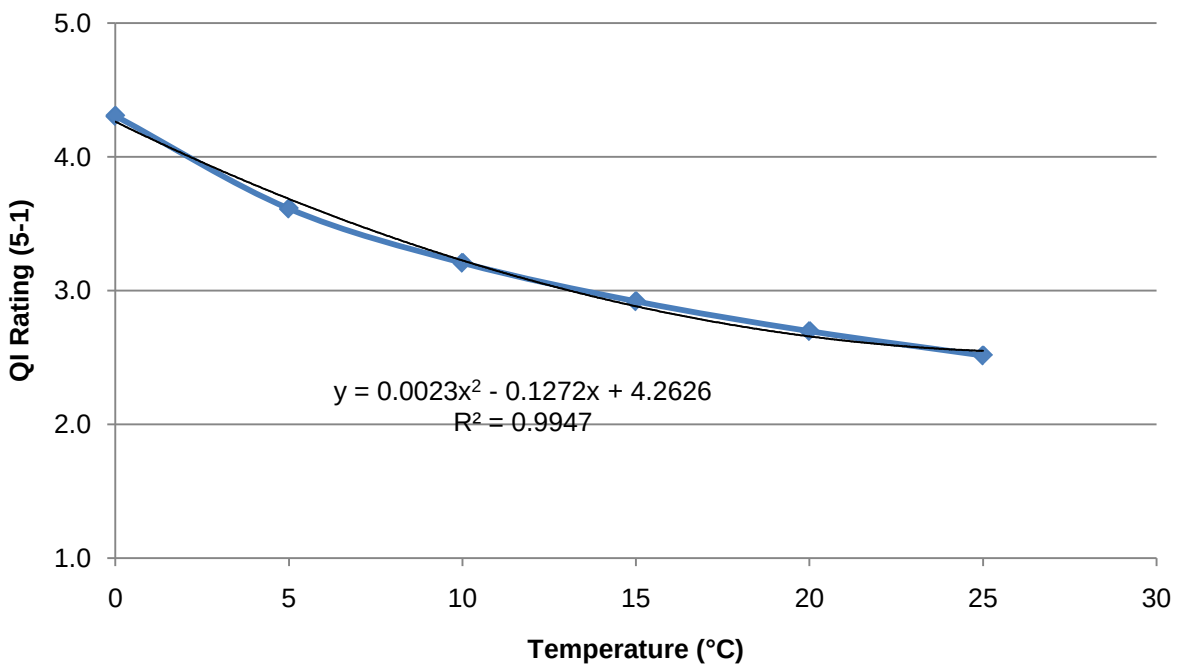

Figure 4-6. Example theoretical equation determination (day 2)

Table 4-6. Derived daily quality equations, empirical

Day	QI Equation	R-squared Correlation
0	$QI=5.00$	1
1	$QI=0.003t^2-0.183t+5.00$	0.998
2	$QI=0.003t^2-0.173t+5.00$	0.989
3	$QI=0.003t^2-0.179t+4.93$	0.977
4	$QI=0.002t^2-0.172t+4.35$	0.995
5	$QI=0.003t^2-0.185t+4.30$	0.998
6	$QI=0.001t^2-0.145t+3.98$	0.957
7	$QI=0.001t^2-0.144t+3.81$	0.987
8	$QI=0.001t^2-0.124t+3.65$	0.987
9	$QI=0.001t^2-0.114t+3.52$	0.977
10	$QI=0.001t^2-0.122t+3.51$	0.993

Table 4-7. Derived daily quality equations, theoretical

Day	QI Equation	R-squared Correlation
0	$QI=5.00$	1
1	$QI=0.001t^2-0.115t+4.96$	0.988
2	$QI=0.002t^2-0.127t+4.26$	0.994
3	$QI=0.002t^2-0.127t+4.86$	0.994
4	$QI=0.002t^2-0.127t+3.57$	0.994
5	$QI=0.002t^2-0.127t+3.35$	0.994
6	$QI=0.002t^2-0.127t+3.16$	0.994
7	$QI=0.002t^2-0.127t+3.01$	0.994
8	$QI=0.002t^2-0.127t+2.88$	0.994
9	$QI=0.002t^2-0.127t+2.76$	0.994
10	$QI=0.002t^2-0.127t+2.65$	0.994
11	$QI=0.002t^2-0.127t+2.56$	0.994
12	$QI=0.002t^2-0.127t+2.47$	0.994
13	$QI=0.002t^2-0.127t+3.39$	0.994
14	$QI=0.002t^2-0.127t+2.32$	0.994

Initial Quality		5	-
Initial Temperature		7	°C
Duration		1440	minutes
	Day	**QI**	
	0	5.00	
	1	3.87	
	2	3.68	
	3	3.39	
	4	3.24	
	5	3.15	
	6	3.01	
	7	2.85	
	8	2.83	
	9	2.72	
	10	2.66	
	Final Quality	3.87	-

Figure 4-7. Empirical model output example – single cold chain step

Initial Quality		5	-
Initial Temperature		7	°C
Duration		1440	minutes
	Day	**QI**	
	0	5.00	
	1	4.20	
	2	3.49	
	3	3.07	
	4	2.78	
	5	2.56	
	6	2.37	
	7	2.22	
	8	2.09	
	9	1.97	
	10	1.86	
	11	1.77	
	12	1.68	
	13	1.60	
	14	1.53	
	Final Quality	4.20	-

Figure 4-8. Theoretical model output example –single cold chain step

STEP 1			STEP 2			STEP 3			STEP 4			STEP 5		
Initial Quality	3.9	-	Initial Quality	2.30	-	Initial Quality	3.81	-	Initial Quality	3.69	-	Initial Quality	3.65	-
Initial Temperature	25	°C	Initial Temperature	5	°C	Initial Temperature	2	°C	Initial Temperature	1	°C	Initial Temperature	2	°C
Duration	1300	minutes	Duration	300	minutes	Duration	720	minutes	Duration	300	minutes	Duration	1440	minutes
Day	**QI**		**Day**	**QI**		**Day**	**QI**		**Day**	**QI**		**Day**	**QI**	
0	5.00		**0**	5.00		**0**	5.00		**0**	5.00		**0**	5.00	
1	2.30		**1**	4.16		**1**	4.65		**1**	4.82		**1**	4.65	
2	2.29		**2**	3.95		**2**	4.41		**2**	4.57		**2**	4.41	
3	1.89		**3**	3.67		**3**	4.15		**3**	4.32		**3**	4.15	
4	1.30		**4**	3.54		**4**	4.01		**4**	4.18		**4**	4.01	
5	1.55		**5**	3.45		**5**	3.94		**5**	4.12		**5**	3.94	
6	0.98		**6**	3.28		**6**	3.69		**6**	3.83		**6**	3.69	
7	0.83		**7**	3.11		**7**	3.52		**7**	3.67		**7**	3.52	
8	1.18		**8**	3.06		**8**	3.41		**8**	3.53		**8**	3.41	
9	0.73		**9**	2.95		**9**	3.29		**9**	3.40		**9**	3.29	
10	0.52		**10**	2.90		**10**	3.27		**10**	3.39		**10**	3.27	
Final Quality	2.30	-	**Final Quality**	3.81	-	**Final Quality**	3.69	-	**Final Quality**	3.65	-	**Final Quality**	3.50	-

Figure 4-9. Complete empirical model view. The highlighted cell represents the final QI following all cold chain steps.

STEP 1			STEP 2			STEP 3			STEP 4			STEP 5		
Initial Quality	3.6	-	Initial Quality	3.17	-	Initial Quality	3.11	-	Initial Quality	3.02	-	Initial Quality	2.99	-
Initial Temperature	7	°C	Initial Temperature	5	°C	Initial Temperature	2	°C	Initial Temperature	1	°C	Initial Temperature	2	°C
Duration	1300	minutes	Duration	300	minutes	Duration	720	minutes	Duration	300	minutes	Duration	1440	minutes
Day	**QI**		**Day**	**QI**		**Day**	**QI**		**Day**	**QI**		**Day**	**QI**	
0	5.00		**0**	5.00		**0**	5.00		**0**	5.00		**0**	5.00	
1	4.20		**1**	4.41		**1**	4.73		**1**	4.84		**1**	4.73	
2	3.49		**2**	3.68		**2**	4.02		**2**	4.14		**2**	4.02	
3	3.07		**3**	3.27		**3**	3.61		**3**	3.73		**3**	3.61	
4	2.78		**4**	2.99		**4**	3.32		**4**	3.45		**4**	3.32	
5	2.56		**5**	2.76		**5**	3.10		**5**	3.22		**5**	3.10	
6	2.37		**6**	2.58		**6**	2.92		**6**	3.04		**6**	2.92	
7	2.22		**7**	2.43		**7**	2.76		**7**	2.89		**7**	2.76	
8	2.09		**8**	2.29		**8**	2.63		**8**	2.75		**8**	2.63	
9	1.97		**9**	2.17		**9**	2.51		**9**	2.63		**9**	2.51	
10	1.86		**10**	2.07		**10**	2.41		**10**	2.53		**10**	2.41	
11	1.77		**11**	1.97		**11**	2.31		**11**	2.43		**11**	2.31	
12	1.68		**12**	1.89		**12**	2.23		**12**	2.35		**12**	2.23	
13	1.60		**13**	1.81		**13**	2.15		**13**	2.27		**13**	2.15	
14	1.53		**14**	1.73		**14**	2.07		**14**	2.19		**14**	2.07	
Final Quality	3.17	-	**Final Quality**	3.11	-	**Final Quality**	3.02	-	**Final Quality**	2.99	-	**Final Quality**	2.82	-

Figure 4-10. Complete theoretical model view. The highlighted cell represents the final QI following all cold chain steps.

Table 4-8. Observed QI vs. empirical model comparison after 8 days in 0°C storage

		QI		
Harvest	Precooling Treatment/Packaging	Observed	Empirical	% Difference
Peak	Optimum-RPC	4.7	3.6	26.5
	Standard - RPC	4.7	3.6	26.5
	Standard - wood crate	4.8	3.6	28.6
Late	Optimum-RPC	3.6	3.6	0.0
	Standard - RPC	4.0	3.6	10.5
	Standard - wood crate	3.7	3.6	2.7

Table 4-9. Observed QI vs. theoretical model comparison after 8 days in 0°C storage

		QI		
Harvest	Precooling Treatment/Packaging	Observed	Theoretical	% Difference
Peak	Optimum-RPC	4.7	2.9	47.4
	Standard - RPC	4.7	2.9	47.4
	Standard - wood crate	4.8	2.9	49.4
Late	Optimum-RPC	3.6	2.9	21.5
	Standard - RPC	4.0	2.9	31.9
	Standard - wood crate	3.7	2.9	24.2

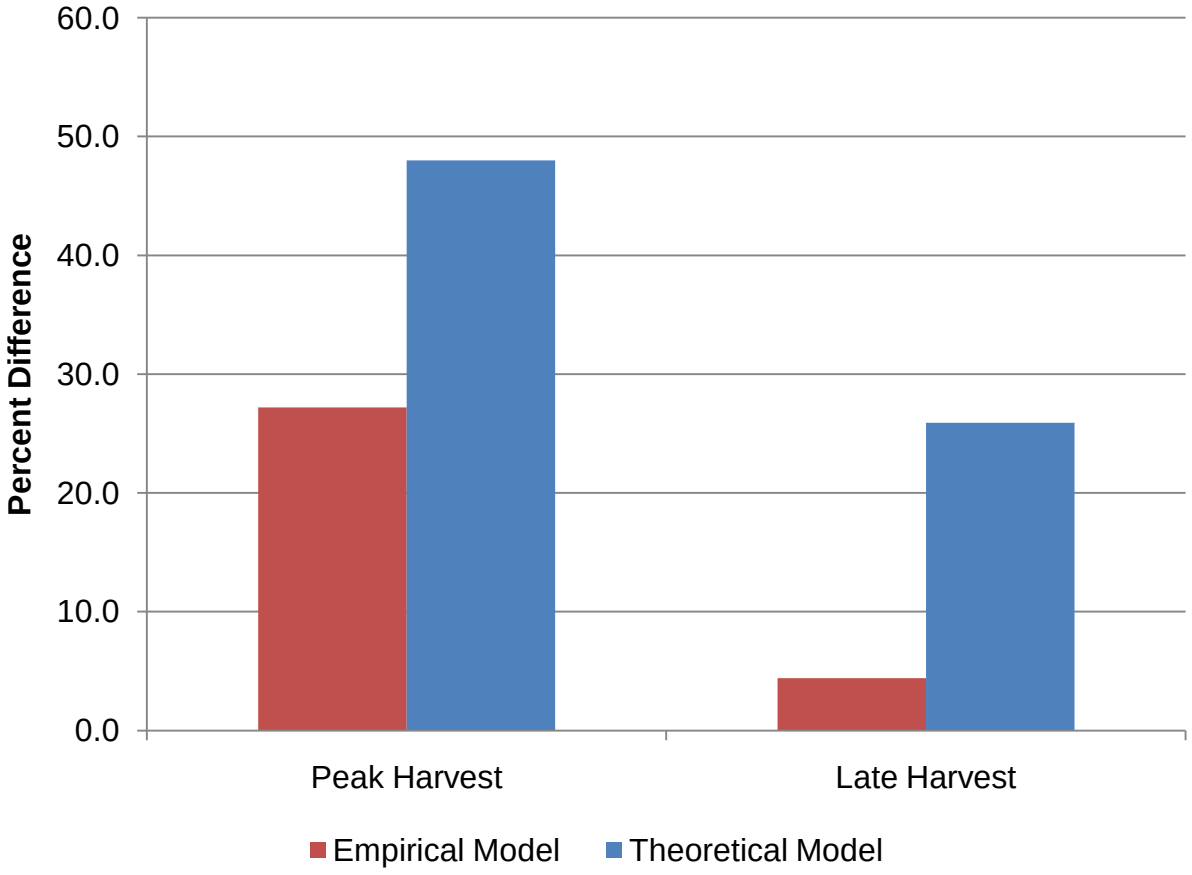

Figure 4-11. Average percent difference comparison – from field

Table 4-10. Observed QI vs. empirical model comparison from store – first harvest

Treatment	Storage Temperature (°C)	Store arrival QI Observed	Store arrival QI Empirical	Store arrival % Difference	4 days QI Observed	4 days QI Empirical	4 days % Difference
Wood crate - standard	0	3.5	3.9	10.8	3.1	3.3*	6.2
	5	3.5	3.9	10.8	2.9	3.1	6.7
	20	3.5	3.9	10.8	2.0	1.8	10.5
Wood crate - optimum	0	3.5	3.9	10.8	2.9	3.3*	12.9
	5	3.5	3.9	10.8	3.0	3.1	3.3
	20	3.5	3.9	10.8	1.9	1.8	5.4
RPC - standard	0	3.5	3.7	5.6	3.2	3.3*	3.1
	5	3.5	3.7	5.6	3.0	3.1	3.3
	20	3.5	3.7	5.6	2.4	1.8	28.6
RPC - optimum	0	3.5	4.0	13.3	3.4	3.3*	3.0
	5	3.5	4.0	13.3	2.7	3.3	20.0
	20	3.5	4.0	13.3	1.7	1.8	5.7

* Extrapolated values

Table 4-11. Observed QI vs. empirical model comparison from store – second harvest

Treatment	Storage Temperature (°C)	Store arrival QI Observed	Store arrival QI Empirical	Store arrival % Difference	4 days QI Observed	4 days QI Empirical	4 days % Difference
Wood crate - standard	0	3.5	3.9	10.8	2.2	3.3*	40.0
	5	3.5	3.9	10.8	2.0	3.1	43.1
	20	3.5	3.9	10.8	1.4	1.8	25.0
Wood crate - optimum	0	3.5	3.9	10.8	2.3	3.3*	35.7
	5	3.5	3.9	10.8	2.0	3.1	43.1
	20	3.5	3.9	10.8	1.1	1.8	48.3
RPC - standard	0	3.5	4.0	13.3	2.2	3.3*	40.0
	5	3.5	4.0	13.3	2.4	3.3	31.6
	20	3.5	4.0	13.3	1.6	1.8	11.8
RPC - optimum	0	3.5	3.9	10.8	2.3	3.3*	35.7
	5	3.5	3.9	10.8	2.4	3.1	25.5
	20	3.5	3.9	10.8	1.6	1.8	11.8

* Extrapolated values

Table 4-12. Observed QI vs. theoretical model comparison from store – first harvest

Treatment	Storage Temperature (°C)	Store arrival QI Observed	Store arrival QI Theoretical	Store arrival % Difference	4 days QI Observed	4 days QI Theoretical	4 days % Difference
Wood crate - standard	0	3.5	3.5	0.0	3.1	2.8	10.2
	5	3.5	3.5	0.0	2.9	2.5	14.8
	20	3.5	3.5	0.0	2.0	1.7	16.2
Wood crate - optimum	0	3.5	3.5	0.0	2.9	2.8	3.5
	5	3.5	3.5	0.0	3.0	2.5	18.2
	20	3.5	3.5	0.0	1.9	1.7	11.1
RPC - standard	0	3.5	3.4	2.9	3.2	2.8	13.3
	5	3.5	3.4	2.9	3.0	2.5	18.2
	20	3.5	3.4	2.9	2.4	1.7	34.1
RPC - optimum	0	3.5	3.6	2.8	3.4	2.9	15.9
	5	3.5	3.6	2.8	2.7	2.6	3.8
	20	3.5	3.6	2.8	1.7	1.7	0.0

Table 4-13. Observed QI vs. theoretical model comparison from store – second harvest

Treatment	Storage Temperature (°C)	Store arrival QI Observed	Store arrival QI Theoretical	Store arrival % Difference	4 days QI Observed	4 days QI Theoretical	4 days % Difference
Wood crate - standard	0	3.5	3.5	0.0	2.2	2.8	24.0
	5	3.5	3.5	0.0	2.0	2.5	22.2
	20	3.5	3.5	0.0	1.4	1.7	19.4
Wood crate - optimum	0	3.5	3.5	0.0	2.3	2.8	19.6
	5	3.5	3.5	0.0	2.0	2.5	22.2
	20	3.5	3.5	0.0	1.1	1.7	42.9
RPC - standard	0	3.5	3.6	2.8	2.2	2.9	27.5
	5	3.5	3.6	2.8	2.4	2.6	8.0
	20	3.5	3.6	2.8	1.6	1.7	6.1
RPC - optimum	0	3.5	3.5	0.0	2.3	2.8	19.6
	5	3.5	3.5	0.0	2.4	2.5	4.1
	20	3.5	3.5	0.0	1.6	1.7	6.1

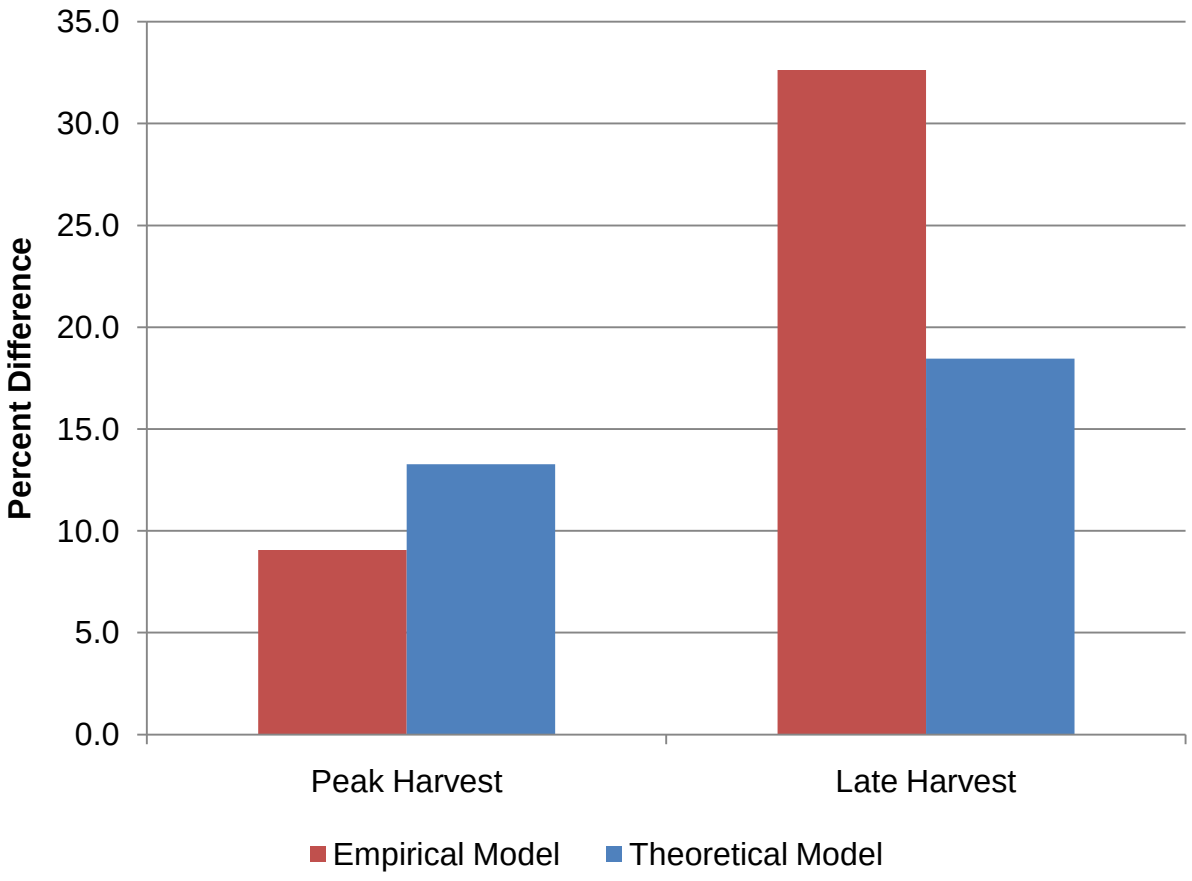

Figure 4-12. Average percent difference comparison – from store

Figure 4-13. Visual reference color chart where 5 = best quality and 1 = worst quality

CHAPTER 5
SUMMARY AND CONCLUSIONS

The objective of this study was to develop a model-based simulation for the distribution cold chain of fresh market sweetcorn. This was achieved through several sub-objectives. Time-temperature monitoring of sweetcorn cold chain operations from field to retail during the peak and late harvest seasons was done to establish this base of research. Four pallets of sweetcorn differing in crate type and precooling time were instrumented with temperature-recording devices and followed to retail. The time-temperature data were translated into complete graphical profiles and then separated into individual cold chain steps. The temperature for each step was averaged and a specific duration determined. Comparison of these profiles revealed that the sweetcorn packed in RPCs and precooled for an optimum time of 100 minutes maintained temperatures closest to the optimum temperature of 0°C.

The second part of this study was to examine the effects of storage temperature on sweetcorn quality as a function of time. Quality evaluations were performed immediately following sample collection and again after an eight day storage period in temperature controlled chambers set to 2, 5, 10, 15, and 20°C at a relative humidity of 80-90%. The limiting quality factor was found to be external appearance when sweetcorn was stored at temperatures below 10°C and kernel appearance when stored at temperatures above 10°C. Following data collection, curves of QI versus temperature were produced. From analysis of these curves it was determined that the sweetcorn exhibited exponential decay at every storage temperature.

The third part of this study required that the quality curves comprised of empirical quality data be utilized for the construction of a prediction model for sweetcorn. In addition to empirical curves, theoretical curves were created based on the theory exponential decay in combination with respiration rate information obtained from literature. Accordingly, two separate models were constructed. Linear regression analysis of the quality curves allowed for the production quality equations at 24-hour time steps as a function of temperature. The equations were coded into a computer program that would output a final QI based upon an initial QI and the input of time and temperature for up to five cold chain steps. This allowed for an iterative prediction effect. The final product was a set of two simulation programs, one based on experimental data collected from actual quality evaluation of samples of sweetcorn and another based on theoretical data predicted by exponential decay. A comparison would follow. To aid in practical use of the simulator, a visual reference guide was created with external and internal views of sweetcorn at different QI values of 5 (best quality) though 1 (worst quality).

The final step in this study was to validate and compare the created prediction models. This process was carried out by again collecting sweetcorn samples; this time from two points in the cold chain – directly after precooling and following transportation to retail. Initial quality was recorded and then evaluated again after specified storage times. The time-temperature profiles corresponding to latter of the two collection points were used as inputs for the models. Each model was run a total of 30 times. There was significant variation between the results of the two models. Considering percent difference measurements from all 30 trials, on average, the values predicted by the

empirical model fit the observed data more closely than did those from the theoretical model. The overall average percent difference was 18.3% as opposed to 26.4%.

The empirical model created in this study proved to be the best fit, on average, for the prediction of sweetcorn quality based on time and temperature. There are, however, many potential sources of error whose effects may be reduced by using sets of data multiple times. Most apparent among the potential errors is inconsistency in quality rating. Appearance is subjective and variability will occur even with the aid of a reference color chart. Environmental factors and time of harvest likely play a large role as well. It is possible that several models for sweetcorn based on different aspects such as variety and time of year would be necessary for more accurate prediction.

An accurate simulation program for the prediction of quality based on treatment in preceding cold chain steps has the potential to transform the fresh sweetcorn retail market in two key areas. First, prediction can drive the transition from a *First In, First Out* (FIFO) to a *First Expired, First Out* (FEFO) product flow strategy. With the ability to predict the quality of different sweetcorn shipments at distribution center, one could determine which load would likely have a shorter shelf-life and hence should be transported to retail sooner. This decision would then be independent of the time the product was received. This same decision-making process could be utilized by produce managers at the store level as well. The result will be less product waste, which equates to higher sales and satisfied customers. The second foreseen impact of an accurate prediction model is the ability to reinforce better cold chain management. By simulating different time-temperature scenarios, the importance of maintaining optimum temperature conditions can be quantitatively assessed. In addition, this could allow

retailers to decide where to make improvements in their cold chain based on where maximum benefit could be achieved.

As we consider the future potential a cold chain simulation has for improving the market of fresh sweetcorn, the potential of other cold chain technologies may also be highlighted. Prediction of future effect based on past treatment would not be possible without temperature information. For that we must look to temperature logging equipment. Currently, radio frequency identification (RFID) is at the forefront of innovation for temperature logging Using real time RFID data available, decision-making based on temperature tracking could eventually become computer-automated. In addition, quality modeling using the same concept applied here to sweetcorn could be extended to the entire produce section.

APPENDIX A
MACRO CODING

Empirical Model

```
Public Sub empiricalcoldchain()

'precooling

Dim piQI, piTemp, pdt, pQIx, pQI1, pQI2, ptx, pt1, pt2 As Double

piQI = Cells(2, 2)    'iQI is the initial quality index
piTemp = Cells(3, 2)
pdt = Cells(4, 2) / (24 * 60)

Dim n1 As Integer

n1 = 1

Do

    If Cells(6 + n1, 2) < piQI Then
        pQI1 = Cells(6 + n1 - 1, 2)
        pQI2 = Cells(6 + n1, 2)
        pt1 = Cells(6 + n1 - 1, 1)
        pt2 = Cells(6 + n1, 1)

        ptx = (pt2 - pt1) / (pQI2 - pQI1) * (piQI - pQI1) + pt1
        ptx = ptx + pdt


        Do Until ptx < pt2
            pt1 = pt2
            pt2 = pt1 + 1
            pQI1 = pQI2
            pQI2 = Cells(6 + n1 + 1, 2)
            n1 = n1 + 1
        Loop

        If pt2 < Cells(16, 1) Then pQIx = (pQI2 - pQI1) / (pt2 - pt1) * (ptx - pt1) + pQI1 Else
pQIx = 0
        If pQIx < 1 Then pQIx = 1


        Cells(18, 2) = pQIx
        Cells(19, 2) = ptx


        Exit Do
    End If

    n1 = n1 + 1

    If Cells(6 + n1, 2) < 0 Then
        Exit Do
    End If


Loop Until Cells(6 + n1, 2) = ""


'transportation to DC

Dim tiQI, tiTemp, tdt, tQIx, tQI1, tQI2, ttx, tt1, tt2 As Double

tiQI = Cells(2, 5)
tiTemp = Cells(3, 5)
tdt = Cells(4, 5) / (24 * 60)

Dim n2 As Integer

n2 = 1

Do

    If Cells(6 + n2, 5) < tiQI Then
        tQI1 = Cells(6 + n2 - 1, 5)
```

```
        tQI2 = Cells(6 + n2, 5)
        tt1 = Cells(6 + n2 - 1, 4)
        tt2 = Cells(6 + n2, 4)

        ttx = (tt2 - tt1) / (tQI2 - tQI1) * (tiQI - tQI1) + tt1
        ttx = ttx + tdt


        Do Until ttx < tt2
            tt1 = tt2
            tt2 = tt1 + 1
            tQI1 = tQI2
            tQI2 = Cells(6 + n2 + 1, 5)
            n2 = n2 + 1
        Loop

        If tt2 < Cells(16, 4) Then tQIx = (tQI2 - tQI1) / (tt2 - tt1) * (ttx - tt1) + tQI1 Else
tQIx = 0
        If tQIx < 1 Then tQIx = 1


        Cells(18, 5) = tQIx
        Cells(19, 5) = ttx


        Exit Do
    End If

    n2 = n2 + 1

    If Cells(6 + n2, 5) < 0 Then
        Exit Do
    End If

Loop Until Cells(6 + n2, 5) = ""


'DC storage

Dim DiQI, DiTemp, Ddt, DQIx, DQI1, DQI2, Dtx, Dt1, Dt2 As Double

DiQI = Cells(2, 8)    'iQI is the initial quality index
DiTemp = Cells(3, 8)
Ddt = Cells(4, 8) / (24 * 60)

Dim n3 As Integer

n3 = 1

Do

    If Cells(6 + n3, 8) < DiQI Then
        DQI1 = Cells(6 + n3 - 1, 8)
        DQI2 = Cells(6 + n3, 8)
        Dt1 = Cells(6 + n3 - 1, 7)
        Dt2 = Cells(6 + n3, 7)

        Dtx = (Dt2 - Dt1) / (DQI2 - DQI1) * (DiQI - DQI1) + Dt1
        Dtx = Dtx + Ddt


        Do Until Dtx < Dt2
            Dt1 = Dt2
            Dt2 = Dt1 + 1
            DQI1 = DQI2
            DQI2 = Cells(6 + n3 + 1, 8)
            n3 = n3 + 1
        Loop

        If Dt2 < Cells(16, 7) Then DQIx = (DQI2 - DQI1) / (Dt2 - Dt1) * (Dtx - Dt1) + DQI1 Else
DQIx = 0
        If DQIx < 1 Then DQIx = 1


        Cells(18, 8) = DQIx
        Cells(19, 8) = Dtx


        Exit Do
    End If
```

```
    n3 = n3 + 1

    If Cells(6 + n3, 8) < 0 Then
        Exit Do
    End If


Loop Until Cells(6 + n3, 8) = ""


'transportation to retail

Dim siQI, siTemp, sdt, sQIx, sQI1, sQI2, stx, st1, st2 As Double

siQI = Cells(2, 11)    'iQI is the initial quality index
siTemp = Cells(3, 11)
sdt = Cells(4, 11) / (24 * 60)

Dim n4 As Integer

n4 = 1

Do

    If Cells(6 + n4, 11) < siQI Then
        sQI1 = Cells(6 + n4 - 1, 11)
        sQI2 = Cells(6 + n4, 11)
        st1 = Cells(6 + n4 - 1, 10)
        st2 = Cells(6 + n4, 10)

        stx = (st2 - st1) / (sQI2 - sQI1) * (siQI - sQI1) + st1
        stx = stx + sdt


        Do Until stx < st2
            st1 = st2
            st2 = st1 + 1
            sQI1 = sQI2
            sQI2 = Cells(6 + n4 + 1, 11)
            n4 = n4 + 1
        Loop

        If st2 < Cells(16, 10) Then sQIx = (sQI2 - sQI1) / (st2 - st1) * (stx - st1) + sQI1 Else
sQIx = 0
        If sQIx < 1 Then sQIx = 1


        Cells(18, 11) = sQIx
        Cells(19, 11) = stx


        Exit Do
    End If

    n4 = n4 + 1

    If Cells(6 + n4, 11) < 0 Then
        Exit Do
    End If


Loop Until Cells(6 + n4, 11) = ""


'retail

Dim riQI, riTemp, rdt, rQIx, rQI1, rQI2, rtx, rt1, rt2 As Double

riQI = Cells(2, 14)   'iQI is the initial quality index
riTemp = Cells(3, 14)
rdt = Cells(4, 14) / (24 * 60)

Dim n5 As Integer

n5 = 1

Do

    If Cells(6 + n5, 14) < riQI Then
        rQI1 = Cells(6 + n5 - 1, 14)
        rQI2 = Cells(6 + n5, 14)
```

```
        rt1 = Cells(6 + n5 - 1, 13)
        rt2 = Cells(6 + n5, 13)

        rtx = (rt2 - rt1) / (rQI2 - rQI1) * (riQI - rQI1) + rt1
        rtx = rtx + rdt


        Do Until rtx < rt2
            rt1 = rt2
            rt2 = rt1 + 1
            rQI1 = rQI2
            rQI2 = Cells(6 + n5 + 1, 14)
            n5 = n5 + 1
        Loop

        If rt2 < Cells(16, 13) Then rQIx = (rQI2 - rQI1) / (rt2 - rt1) * (rtx - rt1) + rQI1 Else
rQIx = 0
        If rQIx < 1 Then rQIx = 1


        Cells(18, 14) = rQIx
        Cells(19, 14) = rtx


        Exit Do
    End If

    n5 = n5 + 1

    If Cells(6 + n5, 14) < 0 Then
        Exit Do
    End If


Loop Until Cells(6 + n5, 14) = ""

End Sub
```

Theoretical Model

```
Public Sub theoreticalcoldchain()
'precooling

Dim piQI, piTemp, pdt, pQIx, pQI1, pQI2, ptx, pt1, pt2 As Double

piQI = Cells(2, 2)
piTemp = Cells(3, 2)
pdt = Cells(4, 2) / (24 * 60)

Dim n1 As Integer

n1 = 1

Do

    If Cells(6 + n1, 2) < piQI Then
        pQI1 = Cells(6 + n1 - 1, 2)
        pQI2 = Cells(6 + n1, 2)
        pt1 = Cells(6 + n1 - 1, 1)
        pt2 = Cells(6 + n1, 1)

        ptx = (pt2 - pt1) / (pQI2 - pQI1) * (piQI - pQI1) + pt1
        ptx = ptx + pdt


        Do Until ptx < pt2
            pt1 = pt2
            pt2 = pt1 + 1
            pQI1 = pQI2
            pQI2 = Cells(6 + n1 + 1, 2)
            n1 = n1 + 1
        Loop

        If pt2 < Cells(20, 1) Then pQIx = (pQI2 - pQI1) / (pt2 - pt1) * (ptx - pt1) + pQI1 Else
pQIx = 0
        If pQIx < 1 Then pQIx = 1
```

```
        Cells(22, 2) = pQIx
        Cells(23, 2) = ptx


        Exit Do
    End If

    n1 = n1 + 1

    If Cells(6 + n1, 2) < 0 Then
        Exit Do
    End If


Loop Until Cells(6 + n1, 2) = ""


'transportation to DC

Dim tiQI, tiTemp, tdt, tQIx, tQI1, tQI2, ttx, tt1, tt2 As Double

tiQI = Cells(2, 5)
tiTemp = Cells(3, 5)
tdt = Cells(4, 5) / (24 * 60)

Dim n2 As Integer

n2 = 1

Do

    If Cells(6 + n2, 5) < tiQI Then
        tQI1 = Cells(6 + n2 - 1, 5)
        tQI2 = Cells(6 + n2, 5)
        tt1 = Cells(6 + n2 - 1, 4)
        tt2 = Cells(6 + n2, 4)

        ttx = (tt2 - tt1) / (tQI2 - tQI1) * (tiQI - tQI1) + tt1
        ttx = ttx + tdt


        Do Until ttx < tt2
            tt1 = tt2
            tt2 = tt1 + 1
            tQI1 = tQI2
            tQI2 = Cells(6 + n2 + 1, 5)
            n2 = n2 + 1
        Loop

        If tt2 < Cells(20, 4) Then tQIx = (tQI2 - tQI1) / (tt2 - tt1) * (ttx - tt1) + tQI1 Else
tQIx = 0
        If tQIx < 1 Then tQIx = 1


        Cells(22, 5) = tQIx
        Cells(23, 5) = ttx


        Exit Do
    End If

    n2 = n2 + 1

    If Cells(6 + n2, 5) < 0 Then
        Exit Do
    End If

Loop Until Cells(6 + n2, 5) = ""


'DC storage

Dim DiQI, DiTemp, Ddt, DQIx, DQI1, DQI2, Dtx, Dt1, Dt2 As Double

DiQI = Cells(2, 8)    'iQI is the initial quality index
DiTemp = Cells(3, 8)
Ddt = Cells(4, 8) / (24 * 60)

Dim n3 As Integer
```

```
n3 = 1

Do

    If Cells(6 + n3, 8) < DiQI Then
        DQI1 = Cells(6 + n3 - 1, 8)
        DQI2 = Cells(6 + n3, 8)
        Dt1 = Cells(6 + n3 - 1, 7)
        Dt2 = Cells(6 + n3, 7)

        Dtx = (Dt2 - Dt1) / (DQI2 - DQI1) * (DiQI - DQI1) + Dt1
        Dtx = Dtx + Ddt


        Do Until Dtx < Dt2
            Dt1 = Dt2
            Dt2 = Dt1 + 1
            DQI1 = DQI2
            DQI2 = Cells(6 + n3 + 1, 8)
            n3 = n3 + 1
        Loop

        If Dt2 < Cells(20, 7) Then DQIx = (DQI2 - DQI1) / (Dt2 - Dt1) * (Dtx - Dt1) + DQI1 Else
DQIx = 0
        If DQIx < 1 Then DQIx = 1


        Cells(22, 8) = DQIx
        Cells(23, 8) = Dtx


        Exit Do
    End If

    n3 = n3 + 1

    If Cells(6 + n3, 8) < 0 Then
        Exit Do
    End If


Loop Until Cells(6 + n3, 8) = ""


'transportation to retail

Dim siQI, siTemp, sdt, sQIx, sQI1, sQI2, stx, st1, st2 As Double

siQI = Cells(2, 11)    'iQI is the initial quality index
siTemp = Cells(3, 11)
sdt = Cells(4, 11) / (24 * 60)

Dim n4 As Integer

n4 = 1

Do

    If Cells(6 + n4, 11) < siQI Then
        sQI1 = Cells(6 + n4 - 1, 11)
        sQI2 = Cells(6 + n4, 11)
        st1 = Cells(6 + n4 - 1, 10)
        st2 = Cells(6 + n4, 10)

        stx = (st2 - st1) / (sQI2 - sQI1) * (siQI - sQI1) + st1
        stx = stx + sdt


        Do Until stx < st2
            st1 = st2
            st2 = st1 + 1
            sQI1 = sQI2
            sQI2 = Cells(6 + n4 + 1, 11)
            n4 = n4 + 1
        Loop

        If st2 < Cells(20, 10) Then sQIx = (sQI2 - sQI1) / (st2 - st1) * (stx - st1) + sQI1 Else
sQIx = 0
        If sQIx < 1 Then sQIx = 1
```

```
        Cells(22, 11) = sQIx
        Cells(23, 11) = stx


        Exit Do
    End If

    n4 = n4 + 1

    If Cells(6 + n4, 11) < 0 Then
        Exit Do
    End If


Loop Until Cells(6 + n4, 11) = ""


'retail

Dim riQI, riTemp, rdt, rQIx, rQI1, rQI2, rtx, rt1, rt2 As Double

riQI = Cells(2, 14)   'iQI is the initial quality index
riTemp = Cells(3, 14)
rdt = Cells(4, 14) / (24 * 60)

Dim n5 As Integer

n5 = 1

Do

    If Cells(6 + n5, 14) < riQI Then
        rQI1 = Cells(6 + n5 - 1, 14)
        rQI2 = Cells(6 + n5, 14)
        rt1 = Cells(6 + n5 - 1, 13)
        rt2 = Cells(6 + n5, 13)

        rtx = (rt2 - rt1) / (rQI2 - rQI1) * (riQI - rQI1) + rt1
        rtx = rtx + rdt


        Do Until rtx < rt2
            rt1 = rt2
            rt2 = rt1 + 1
            rQI1 = rQI2
            rQI2 = Cells(6 + n5 + 1, 14)
            n5 = n5 + 1
        Loop

        If rt2 < Cells(20, 13) Then rQIx = (rQI2 - rQI1) / (rt2 - rt1) * (rtx - rt1) + rQI1 Else
rQIx = 0
        If rQIx < 1 Then rQIx = 1


        Cells(22, 14) = rQIx
        Cells(23, 14) = rtx


        Exit Do
    End If

    n5 = n5 + 1

    If Cells(6 + n5, 14) < 0 Then
        Exit Do
    End If


Loop Until Cells(6 + n5, 14) = ""

End Sub
```

APPENDIX B
QI DATA FROM STORE

Unmodified QI data from store - first harvest

Treatment	Storage Temperature (°C)	External Appearance	
		Initial	4 days
RPC cooled standard	0	5	4.7
RPC cooled standard	5	5	4.5
RPC cooled standard	20	5	3.9
RPC cooled optimum	0	5	4.9
RPC cooled optimum	5	5	4.2
RPC cooled optimum	20	5	3.2
Wood cooled standard	0	5	4.6
Wood cooled standard	5	5	4.4
Wood cooled standard	20	5	3.5
Wood cooled optimum	0	5	4.4
Wood cooled optimum	5	5	4.5
Wood cooled optimum	20	5	3.4

Unmodified QI data from store - second harvest

Treatment	Storage Temperature (°C)	External Appearance	
		Initial	4 days
RPC cooled standard	0	5	3.7
RPC cooled standard	5	5	3.9
RPC cooled standard	20	5	3.1
RPC cooled optimum	0	5	3.8
RPC cooled optimum	5	5	3.9
RPC cooled optimum	20	5	3.1
Wood cooled standard	0	5	3.7
Wood cooled standard	5	5	3.5
Wood cooled standard	20	5	2.9
Wood cooled optimum	0	5	3.8
Wood cooled optimum	5	5	3.5
Wood cooled optimum	20	5	2.6

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BIOGRAPHICAL SKETCH

Kristina Anderson was born and raised in Dublin, Ohio. At the age of 15 she moved to Bradenton, Florida where she graduated from high school in 2005. She was accepted to the University of Florida that same year, and completed her Bachelor of Science degree in agricultural and biological engineering in 2009.

Encouraged by her experience as a student research assistant in the Post Harvest division of the UF/IFAS Center for Food Distribution and Retailing, Kristina decided to remain at the University of Florida in the Department of Agricultural and Biological Engineering to pursue her ME in the area of food engineering. She graduated with a master's degree in May 2010.