FLAVOR EVALUATION FOR CROP SCIENTISTS: EXAMINING NEW METHODS FOR LOCAL FOOD MARKETS

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Abstract: The organic and local food sectors are becoming more important parts of the food system as shown by increasing sales and acreage. Eaters and buyers in these markets expect fruits, vegetables, and grains with superior eating and culinary qualities like flavor. In response, both farmers and agricultural researchers have increased interest in identifying varieties and breeding lines with exceptional sensory qualities. Historically, sensory science has utilized panels of highly trained, expert judges to evaluate and describe flavor properties, but traditional methods are not applicable for crop researchers working in organic and local food sectors for both logistical and scientific reasons. Traditional sensory analysis methods are overfit to industrial food contexts, and their ability to address the complexities underlying flavor development, perception, and preference seems questionable. The Seed to Kitchen Collaborative (SKC) is a joint research and Extension program at the University of Wisconsin-Madison. SKC is a participatory research network of seed companies, plant breeders, researchers, farmers, and local chefs that work to identify and develop high quality vegetable varieties for organic farms in the Upper Midwest. As part of their trialing process, SKC applies rapid sensory evaluation methods that eliminate formal training for tasters. The methods overall show good utility for applications in research and crop breeding and compare well with the established literature on correlations with crop preferences. But analysis of their internal reliability gives reason to reconsider sample collection protocols. Flavor, as a trait, is greater than the sum of its parts, and the same can be said about agriculture as a whole. This reckoning is impetus to critically look at the way Extension and Land Grant universities go about agricultural research, outreach, and education in general. In efforts to be valuable partners for organic growers now and in the future,

network-based tools and strategies like SKC are critical. They have the power to correct Extension's historic shortcomings, facilitate farmer learning, and identify important individuals.

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Chapter One

An Introduction to Flavor and its Evaluation for Plant Scientists – A Literature Review and a Case for New Methods

Introduction

In 1825, one of the world's original gastronomes Jean Anthelme Brillat-Savarin said, "smell and taste are in fact but a single composite sense, whose laboratory is the mouth and its chimney the nose." Brillat-Savarin provided one of the earliest definitions of flavor: a combination of taste and smell, and somewhat remarkably, modern scientists still use similar descriptions. Heymann et. al (1993) and other sensory scientists employ a psychophysical understanding of flavor defining it as the "biological response to chemical [stimuli] by the senses [that is] interpreted by the brain in the context of human experience." In truth, while chemical understanding of flavor has expanded tremendously since Brillat-Savarin, a complete and integrated comprehension of flavor development, perception, and preference still remains elusive (Bayarri & Costell, 2010; Roper & Chaudhari, 2017; Lahne, 2016).

Despite incomplete understanding of the complexities underlying flavor, there is still much interest in measuring the trait as part of the plant breeding and trialing process. Increasingly, breeding and research programs want to evaluate flavor and eating quality, but agreement on appropriate methods in crop sciences is lacking. Traditionally, sensory science uses a highly trained, expert panel of judges to assess and describe flavor qualities. In some cases, crop research programs have replaced these tasting experts with breeder experts instead (P. Simon, personal communication, February 6, 2020). Others have begun to apply rapid sensory evaluation methods, which rely on untrained or semi-trained tasters (ex: a field harvest crew) and/or professional end-users like local chefs, bakers, and brewers (Dawson & Healy, 2018; Healy et al., 2017; Brookfield et al., 2011). Appropriate and reliable methods for sensory evaluation that are applicable to plant breeding and agricultural research are still being debated and evaluated, and new approaches will likely emerge. Using humans to evaluate flavor in crops is inherently difficult due to the intricacies of the biological and psychological systems that underlie flavor development, perception, and preference. This review focuses on these particulars with hopes of providing baseline knowledge for plant scientists working to evaluate and improve sensory and culinary qualities in fruits, vegetables, and grains.

A Common Language: What is Flavor?

In everyday English, the terms taste and flavor are used interchangeably, but human physiologists would say the two are not the same. When someone asks, "does the food taste good?", the questioner is likely referring to flavor rather than taste, despite their use of the word. Taste, referred to by itself, implies the five basic tastes – sweet, sour, salty, bitter, and umami (the meaty or delicious sensation associated with mushrooms, soy sauce, and parmesan cheese) – which are perceived by specific receptor cells located in taste buds on the tongue (Roper & Chaudhari, 2017). Notably, the existence of additional tastes (ex: for fats and oils, calcium) is still being investigated and debated (Heymann, 2019). But when it comes to flavor, taste is only one part. Aroma is another critical component of flavor; in fact, volatile odor molecules are what give fruits and vegetables most of their distinctive flavors (Wang & Seymour, 2017). Others consider mouthfeel or a food's texture to be critical to flavor (Corollaro et el., 2014), and there is certainly some truth to eating with the eyes first, so appearance matters too (Bayarri & Costell, 2010; Oltman et al., 2014; Deliza & MacFie, 1996). While taste is one crucial component of flavor, the latter term encompasses much more of the eating experience.

When it comes to the quality of fruit and vegetables, flavor considers taste, appearance, smell, and texture, all of which are relevant to people's preferences. If plant breeders and researchers are going to evaluate flavor using human tasting panels, common terms and clear definitions are necessary. The previously mentioned definition by Heymann et al. (1993) provides a good starting point, but additional details on human taste physiology might be informative for plant scientists.

Whether evaluating a plain fruit, vegetable, or a formulated recipe, it is helpful to think of the tasting sample as a type of matrix. Consider a tomato (*Solanum lycopersicum*) fruit for example. Generally speaking, it is made of cells that contain sugars, acids, salts, aromas and other molecules that contribute to flavor. These are the chemical stimuli Heymann et al. (1993) refer to in their definition. Understanding food as a matrix is useful when considering different crops or plant organs and how they might develop and/or release flavor molecules differently (ex: tomato versus broccoli). In vegetables, most volatiles are synthesized after cells are damaged from cutting or chewing which exposes enzymes to their substrates (Goff & Klee, 2006; Bayarri & Costell, 2010).

When a slice of tomato is chewed, the tomato cells are crushed, spilling the contents into the mouth. Taste receptor cells are clustered in taste buds along the tongue's epithelium, and their membrane receptors bind the molecules involved in sweetness, sourness, umami, saltiness, and bitterness as they are released from the tomato tissue (Roper & Chaudhari, 2017). Saliva and the fruit's liquid create an aqueous solution that coats the tongue and taste receptors with their chemical stimuli (Fried, 2020). As the tomato tissue breaks down further, warm air circulating in the mouth and nose wafts the freed tomato aroma molecules (volatiles) so they bind to the receptors of olfactory cells lining the back of the throat and nasal cavity (Wang & Seymour, 2017; Olender et al., 2008). The tongue and mouth are also equipped with other types of nerve cells involved in flavor perception. The trigeminal nerve for example is responsible for sensing the cooling sensation of menthol in mint (*Mentha* spp.), the drying astringency of tannins in wine and tea, and the spicy burn from capsaicin in hot peppers (*Capsicum* sp.) and glucosinolates in brassicas (Bayarri & Costell, 2010; Roper & Chaudhari, 2017; Wieczorek et al., 2019; Meiselman, 1993; Fried, 2020). Some sensory nerves in the tongue and mouth are involved in tactile perception and assess texture and mouthfeel (Reed & Knaapila, 2010). Importantly, there is substantial variation in the taste and flavor-sensing machinery among humans which plant scientists should be aware of if they plan on using humans to evaluate flavor in their projects (Klee & Tieman, 2018; Meiselman, 1993; Reed & Knaapila, 2010).

The processing of taste and smell information is diagrammed in Figure 1.1. Multiple kinds of ligands can bind to the same receptor. For example, the membrane proteins of T1R2/T1R3 taste cells that perceive sweet stimuli can bind sucrose, fructose, glucose, sucralose, and a host of different sugars with varying affinities (Roper & Chaudhari, 2017). Odor molecules are the same way. The volatile safrole for instance was previously used to flavor root beer, toothpaste, and chewing gum because of its “candy shop” aroma (Kajiya et al, 2001; Amoore, 1952). Safrole actually binds to at least four different types of olfactory receptors simultaneously (Amoore, 1952) explaining its complex and enticing smell. Unfortunately, safrole was later found to be carcinogenic, and therefore was banned by the FDA as a product additive (Kajiya et al, 2001). Manufacturers had to reformulate using multiple aroma additives to maintain the same general flavor and smell (Kajiya et al, 2001).

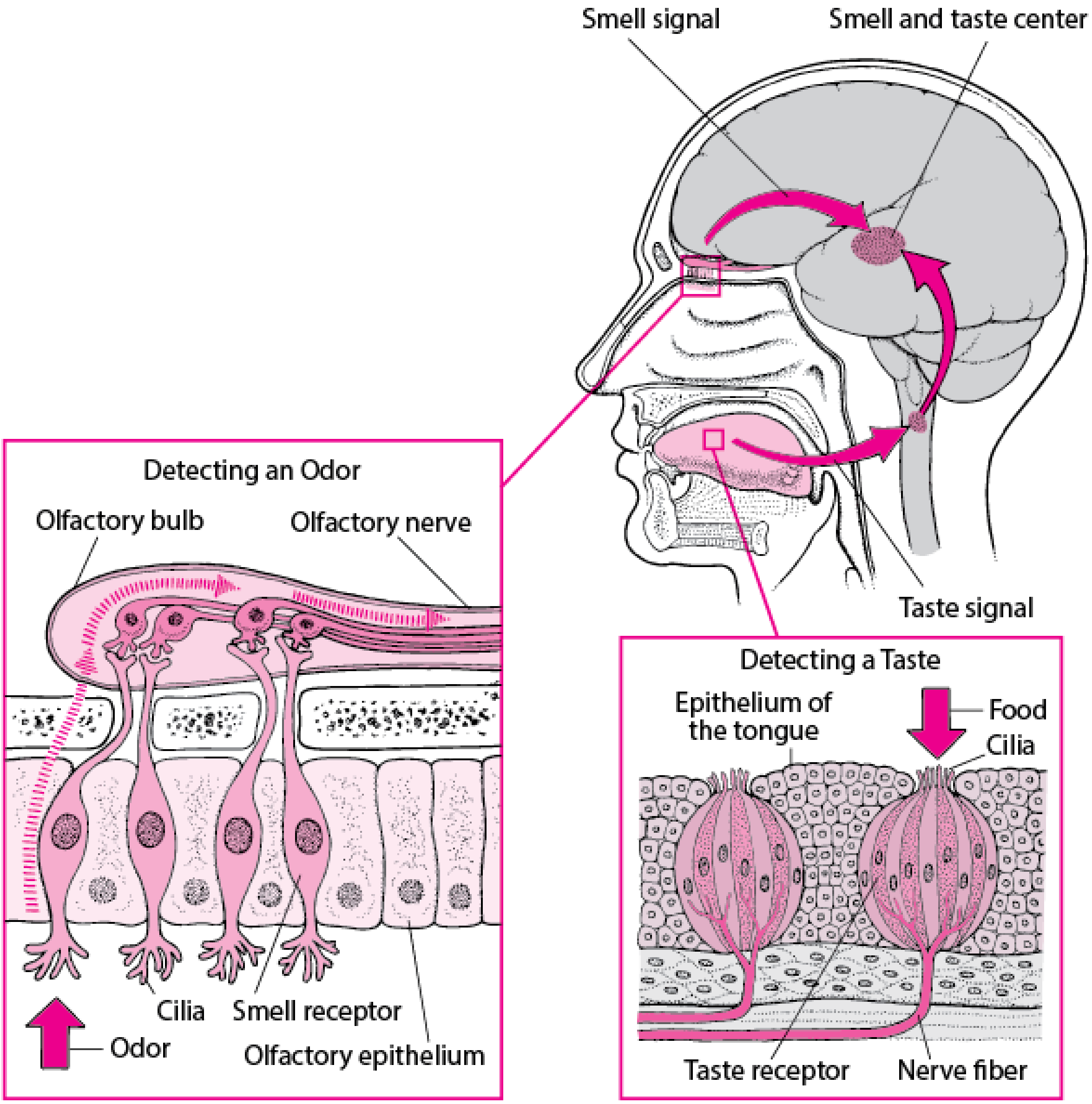

Figure 1.1 A diagram showing the general physiology behind smell and taste perception. Receptors in the mouth and nose perceive chemical stimuli in food before generating an electrical signal that travels to the brain for processing. (Fried, 2020).

The senses of taste and smell have evolutionary explanations. They give humans (and other animals) the ability to find nutrients and evaluate what they consume. For the most part, taste and odor receptors involved in flavor detection are G-protein coupled receptors (GPCRs), which when bound to an appropriate ligand, result in signal transduction and development of an action potential (Olender et al., 2008; Avau & Depoortere, 2016; Knaapila et al., 2007). This electrical signal then travels to the brain for processing. Sensory nerves lead to the brain's thalamus, which communicates with the frontal lobe – the brain's control panel – and, ultimately, this is where the psychological experience of flavor is created (Avau & Depoortere, 2016; Olender et al., 2008; Soudry et al., 2011). Olfactory nerves are wired slightly differently than taste and touch nerves. Unlike other sensory cells that lead directly to the thalamus, olfactory signals travel through the amygdala and hippocampus first (Soudry et al., 2011). This means smell signals activate parts of the brain that control memory and emotions before they are integrated with other sensory information like taste, appearance, and texture. The brain is responsible for "touching up the final percept" and integrating all the signals, so flavor is experienced as a unified sensation and not as individual, disparate parts (O'Mahony, 1991). In this way, flavor involves an interaction between both the brain and the mind. While this makes for an enjoyable experience as an eater, for researchers, the role of the brain-mind interaction complicates matters.

Altogether, the brain and the mind take information from the senses about food we consume and put it into context with the body's nutritional needs, cultural identity, past experiences and memories as well as the surrounding environment to come up with each individual's experience of flavor. To be clear, flavor perception and preference are not solely determined by any inherent quality about the food or eater themselves, but rather the amalgamation of sensory, biological, socio-cultural, historical, and environmental information. Since much of this information is unique to each individual's life experience and worldview, the same fruit or vegetables sample can evoke different impressions and responses. Understandably, this poses challenges for scientists using humans to investigate flavor qualities in fruits, vegetables and grains.

Evolutionary History of Flavor

While sometimes framed as part of the modern "Good Food Movement" in the United States (Finn, 2017), human interest and selection for flavor traits has been relevant since plant domestication. As human ancestors noticed and replanted desirable phenotypes of plants, they inevitably had an impact on flavor and its underlying genes. A typical feature of plant domestication syndrome is a reduction in secondary metabolites, particularly those perceived as toxic and/or bitter. Heiser (1988) proposes that there was very little intentional selection for the reduction of these bitter or harsh compounds and emphasizes that humans were quite adept at finding ways to reduce these unpalatable characteristics via cooking or processing. Examples include traditional practices to remove tannins from acorns (*Quercus* spp.) via grinding, washing, use of clay, or soaking, and the prolonged boiling or baking of taro (*Colocasia esculenta)* to denature the calcium oxalate crystals that irritate the mouth if eaten raw (Johns & Duquette, 1991; Denham, 2011). In fact, cooking, processing, and preserving can completely alter the building blocks of flavor, so it should not be assumed that early humans intentionally rogued bad-tasting individuals.

Intentional selection for other traits may have had indirect consequences on flavor because domestication's main features have all shown to have some relationship with various flavor-related components. The loss of natural dispersal mechanisms such as non-shattering seed and non-deciduous fruit has been linked to changes in fruit texture in both tomato and pepper (Paran & van der Knapp, 2007). More specifically, the *PG* (polygalacturonase) gene in tomato and its ortholog *S* (softness) gene in pepper affect the texture of cell walls and deciduousness of fruits during ripening (Rao & Paran, 2003). Recessive alleles at these loci promote ripe fruit remaining on the plant as well as increased pericarp firmness, a legacy that persists today in American preferences for firmer tomatoes and crisp sweet peppers (Rao & Paran, 2003; Oltman et al., 2014). Additionally, during domestication humans selected against plant mechanical protections like the prickles displayed by wild tomato and eggplant relatives (Heiser, 1988; Hurtado et al., 2014), which surely improved their mouthfeel.

Selection for larger plant tissues whether roots, tubers, fruit, leaves, or stems also had an effect on flavor. Declining tomato flavor can be traced back to the earliest stages of human intervention and selection for larger fruit (Klee & Tieman, 2018) due to the simple fact that chemical flavor components become increasingly diluted as plant organ size increases. Additionally, linkage drag associated with selection for alleles conferring larger fruit size significantly altered fruit metabolite profiles, including the regulation of many volatile compounds (Zhu et al., 2018; Gao et al., 2019). Intentional selection for culturally important aesthetic or visual traits has shown to have flavor side effects. Zhu et al. (2018) found that pink tomatoes (popular in Asia), which resulted from a single gene change, had over 100 significantly modified fruit metabolites, some of which are known flavor contributors. In beans (*Phaseolus* spp.), cultural preferences for white seeds over black and red seeds significantly reduced tannin levels, which are both astringent and anti-digestive (Powell et al., 1977). Furthermore, selection for traits unassociated with the plant organ of interest, like more even and rapid seed germination, could also have impacted flavor during the domestication process (Heiser, 1988). For example, many bitter-tasting and toxic compounds inhibit seed germination (Bewley et al., 2013), so as humans selected for earlier sprouting seeds, they may have effectively and unconsciously selected against more acrid flavor phenotypes.

Even though flavor has become a focus for many modern plant breeders, the history of crop flavor and humans is long. It is important to recognize flavor has a functional and evolutionary role for plants, too. Seed distribution is imperative to survival. Brightly colored and tasty fruits, or at least those more palatable, might have enticed more seed dispersing animals than poor or off-tasting counterparts. Evolution of volatiles and their receptors in animals would have allowed long range signaling of ripe fruit to seed dispersers (Wang & Seymour, 2017). Plant breeders should consider that evolutionary and natural selective forces have worked alongside humans and random chance to shape a vast genetic potential for flavor within crop species and their wild relatives (Goff & Klee, 2006). But while flavor diversity in plants was developed over millennia, it seems humans have done an incredible job of reducing that diversity in the last century, although for some crops more than others (Wang & Seymour, 2017). The growing consumer focus on eating qualities and subsequent breeding for better tasting fruits, vegetables, and grains is largely a response to this decline in flavor quality (Klee & Tieman, 2018).

Tomato acts as a posterchild for efforts aimed at improving flavor in fruits and vegetables because consumers are acutely aware of their poor flavor due to both genetics and the methods associated with industrial production (i.e. harvesting when green, cool storage, ethylene ripening) (Estabrook, 2012; Bergougnoux, 2014; Klee & Tieman, 2018). The story of tomato's flavor genetics starts with domestication, a process that is estimated to have begun 80,000 years ago (Bergougnoux, 2014; Estabrook, 2012). During domestication and subsequent improvement phases, tomato underwent several major bottleneck events (Goff & Klee, 2006). While the plant is native to coastal deserts of South America, domestication is believed to have occurred in modern-day Mexico after birds deposited seeds during seasonal migrations (Estabrook, 2012; Bergougnoux, 2014). As part of the Columbian Exchange, tomato seeds were brought to Europe in the 15^{th} Century (Laudan, 2015). Because they looked similar to their poisonous European relative Belladonna and were absent from the Bible, Europeans rarely ate tomatoes and used them mostly for landscaping (Estabrook, 2012). The Italian word for tomato, *pomodoro*, originates from a steward's description of them as "golden apples" (*pomi d'oro*) suggesting that varieties were likely yellow at the time (Estabrook, 2012). Tomato fruits were also reportedly "small and sour," but gradually gained eating popularity in Spain, Italy, and France as a way to flavor food without expensive spices (Bergougnoux, 2014; Laudan, 2015). Nonetheless settlers brought their own cultivars when they colonized the modern-day United States. Altogether considered, much genetic diversity has been lost from tomatoes as people (and birds) moved them around the world.

In the mid-1800s United States, Alexander Livingston was a farmer, scientist, and seedsman with an affinity for tomatoes (Bergougnoux, 2014). He began crossing varieties brought from Europe to wild tomatoes in the Americas and eventually developed some of the most popular varieties in the country that were notably larger and sweeter (Victory Horticultural Library, 2011). Livingston is credited with popularizing the persisting cultural ideals of what tomatoes should look and taste like in the United States (round, red and sweet) while also promoting their culinary use among the country's chefs (Victory Horticultural Library, 2011; Bergougnoux, 2014). He was a major instigator for the next century and a half of tomato breeding as the crop has become one of the most consumed vegetables across the globe. While tomatoes had undergone a massive narrowing of genetic diversity, Livingston began the process of reincorporating some of this diversity by making new crosses.

In Livingston's lifetime, before the rise of the global commodity market and the inventions of synthetic fertilizers and hybrid seed, the American food system was characterized by mostly small- and mid-scale farmers growing food consumed by local eaters. Today, large-scale operations dominate the market by growing incredible volumes of produce before transporting them around the world. Similarly, before the trans-global food system that rules today, farmers produced more seed on-farm, and they selected varieties that produced well and fit the eating quality expectations of their local customers (Estabrook, 2012). Many heirloom varieties in today's seed catalogs serve as a reminder of a pre-industrial time when good flavor was considered necessary for a variety's marketability. The rise of the global food system has indeed greatly changed breeding priorities around flavor.

Instead of looking for varieties that are locally well-adapted and tasty to local eaters, both breeders and growers have been forced to prioritize traits for the industrial food system. In tomatoes, marketable yield, disease resistance, shelf life, and ability to ship long distances have all been breeding goals (Bergougnoux, 2014; Estabrook, 2012). Perhaps unexpectedly, Gao et al. (2019) used a pan-genome to find that the genetic diversity in modern tomato varieties is larger than in heirlooms, so the regaining of genetic material started by Alexander Livingston in the 1800s has continued. A key difference, however, is that little genetic material related to flavor has been recovered. Introgression of genes for abiotic stress tolerance and disease resistance from wild relatives were hallmarks of tomato breeding throughout the 20th Century (Gao et al., 2019; Bergougnoux, 2014), which greatly benefited grower yields. But improving sensory qualities has largely been ignored until recently (Klee & Tieman, 2018; Gao et al., 2019; Wang & Seymour, 2017).

The story of tomato is not necessarily unique, and certainly all crops have their individual histories and challenges. Tomato flavor, or lack thereof, has become a top complaint of consumers (Klee & Tieman, 2018). But brassica breeding has resulted in stronger-tasting cauliflower cultivars, which has been linked to decreased consumption (Engel et al., 2002). For most domesticated food crops, the tradeoff is a narrowing of genetic diversity, but priorities in the industrial food system have exacerbated the loss in flavor because of over-focus on a few traits (Wang & Seymour, 2017; Estabrook, 2012). Additionally, the genetics underlying flavor remain somewhat forgotten and underexplored. Of course, better genetic understanding of flavor in crops means little if it is not integrated with insights about human flavor perception and preference, which is why more work is needed on approaches to flavor evaluation in the context of crop research.

The Short History of Formal Sensory Science

While flavor's evolutionary relationship between plants and people has gone on for millennia, formal sensory science is not yet a century old. Prior to the 1930s, the methods and technology to evaluate food and sensory qualities had not been standardized (Heymann, 2019). The first sensory science experiments looked at acceptance of military rations by enlisted troops with a goal to reduce the number of soldiers who skipped meals because they didn't like the food (Pangborn, 1964; Bartoshuk, 1978). By 1937, the American Chemical Society presented its first panel on "Flavor in Foods," and the field was poised for rapid expansion (Bartoshuk, 1978; Heymann, 2019).

Just like in agriculture and plant breeding, the early 20th Century was a time of rapid industrialization, segmentation, and specialization for the food industry. As economies of scale increased, sensory science emerged from business interests aimed at gaining larger market shares by consistently appealing to as many consumers as possible (Lahne, 2016; Heymann, 2019). An executive of a baking company, W. Platt in 1931 said, “all our millions of dollars worth of business depends on that little sensation which our products make upon the tongues of our customers” (Pangborn, 1964). According to Elaine Skinner in Lawless and Heymann (2010), sensory science is the “child of industry,” and its insight is to safeguard the “meeting of consumer expectations and a greater sense of marketplace success,” not to inform anything fundamentally true about food. In other words, the needs of the global food industry have driven both research topics and methods for sensory and flavor evaluation (as well as plant breeding). They have added much to the understanding of food properties but little applicable value for flavor evaluation in plant sciences and non-industrial contexts. Despite problems with sensory science’s origins, assumptions, and methodologies, their descriptive methods are still largely used as benchmarks of scientific validity and rigor for flavor evaluation.

Sensory science is a unique field because it has never concerned itself with developing a body of theoretical knowledge (Martens, 1999; Meiselman, 1993; Lahne, 2016), which typically plays a fundamental role in a scientific discipline. Instead, sensory science has historically borrowed existing theories from physiology and psychology that interpret human behavior and experiences as responses to an objective reality (Martens, 1999); it left little room for social and/or cultural influences. Likewise, sensory scientists were originally trained in vision and audition before applying equivalent research techniques to taste, touch, and smell (Pangborn, 1964; Lahne, 2016). Interestingly, in evaluating apple texture, Corollaro et al. (2014) mention a

0.98 correlation between using a texture analyzer and using acoustic measurements, and it is unclear if this is coincidence or not.

Formal sensory scientists understand that biochemical parts of food are stimuli that induce a psychological experience called flavor. But their paradigm has sought to bring the whole process under experimental control (Lahne, 2016). For example, tasters are isolated from one another or must evaluate samples under red light so they cannot be influenced by differences in appearance. Results are only considered meaningful if they are statistically significant and done in a controlled environment (Pangborn, 1964; Koster, 2009), which in effect means a flavor component only becomes tractable when it is somehow amenable to this type of experimentation. One has to wonder if this approach transfers well into real-life eating situations with much more complex stimulation. Formal sensory science assumes flavor and human perception can be reduced to its constitutive parts (Martens & Martens, 2007; Klee & Tieman, 2018), and these parts are separable from the eating context making them portable and predictable in others (Lahne, 2016). But in fact, it seems clear that flavor is an emergent phenomenon, where the whole is greater than the simple sum of its parts.

While formal sensory scientists typically hold that flavor is an intrinsic property of food and eaters are passive receivers of both these stimuli and the psychological experience of flavor (Lawless & Heymann, 2010), there are some social scientists who believe taste is a property inherent to eaters instead (Hennion, 2007). The reality is likely somewhere in between, as Lahne and Trubek (2014) write, there appears to be an "active and reflexive" process between objective properties of food, the way they are processed in each individual's brain, and extrinsic factors as well (Fernquist & Ekelund, 2014; Piqueras-Fiszman & Spence, 2015).

The socio-cultural factors that affect flavor perception and preference are considered biasing factors by formally trained sensory scientists. In fact, central to formal sensory science is attempting to separate the objective truths about food from the inner experiences of tasters and other “biasing” stimuli (Lawless & Heymann, 2010). Importantly then, the field makes two critical assumptions. First, their standard practices and methods are valid and robust for finding the sensory properties inherent and legitimate to the research question (Lahne, 2016). Recall that this assumption is without the guidance of a unique theoretical body of knowledge and methods that were adapted from studies of vision and audition. Second, sensory scientists assume that physical and chemical properties are sensorially relevant by default even though their correlations with perception might not be as strong as one might expect (Martens & Martens, 2007; Klee & Tieman, 2018; Tieman et al., 2012; Corollaro et al., 2014).

To their credit, sensory science has recognized some of its own shortcomings and begun to reflect on their assumptions. More recently, the field’s attention has turned to the ecological validity of sensory analysis and its link to consumer experiences (Piqueras-Fiszman & Spence, 2015). Much of this has been driven by a realized “mismatch [between] perceived requirements [for] rigorous sensory science research and empirical reality” (Lahne, 2016). As their popularity with consumers skyrockets, artisanal products like cheese and beer are examples of foods where application of traditional sensory methods appears to fall short. This is because artisanal products are not homogenous (in fact, variability in this context is valorized), and they have extrinsic values that are perceptible to eaters too (Lahne & Trubek, 2014; Piqueras-Fiszman & Spence, 2015). In Lahne and Trubek (2014), eaters said an artisanal Vermont cheddar tasted good partly because it was produced in small batches with a particular care for the livestock, people, and land. These factors are clearly influential in human discernments about flavor and preference

(Piqueras-Fiszman & Spence, 2015; Fernquist & Ekelund, 2014), but they are largely ignored by sensory scientists despite the embedded nature of producers, eaters, and food in society. These realizations have led some sensory scientists to compare formal sensory methodologies to an overfit statistical model. In other words, sensory science is so reliant on the information and imperatives imposed by the industrial food system that their application is not feasible in alternative contexts (Lahne, 2016).

These are relevant considerations for plant breeders and researchers looking at evaluating or improving flavor. Harker et al. (2009) note the natural heterogeneity of fruits and vegetables will often overwhelm detection of significant differences in triangle tests with trained sensory experts. Triangle tests present three samples to a taster, two of which are the same, and the assessor then has to determine which sample is different based on flavor (Bayarri & Costell, 2010). Admittedly, traditional methods may not be the best, but neither are they useless. Plant researchers should not be discouraged if formal sensory analysis is not feasible or doesn't reveal any significant results because they are only one tool in a toolbox. At the s
ame time, there appears immense opportunity for plant scientists to apply and develop new tools, particularly those geared toward non-industrialized contexts. Dawson and Healy (2018), for example, wrote a review for plant breeders on rapid sensory evaluation methods that eliminate or reduce training obligations, although rapid methods are often critiqued for not being rigorous enough. While research groups like the Seed to Kitchen Collaborative at the University of Wisconsin have started working with these tools to examine their utility and reliability, the tendency for plant scientists to try and mimic formal sensory analysis techniques still remains widespread.

Flavor Development in the Plant

As alluded to already, a plant's genotype plays a fundamental role in the synthesis and accumulation of flavor-related compounds. Many studies have shown variety (genotype) has a significant effect on taste-related traits like amounts of sugar and titratable acidity, which are thought to be strongly correlated with perceived sweetness and acidity, respectively. In some species, specific genes involved in tastant (molecules that activate taste receptors) metabolism have been identified. In tomato, single nucleotide polymorphisms (SNPs) have been identified within an extracellular invertase gene that lead to significantly higher levels of sugar accumulation within the fruit (Klee & Tieman, 2018). Panthee et al. (2012) also found tomato cultivar to have a significant effect on soluble solids (a proxy for sugar content) and titratable acidity, however, there is no obvious genetic clustering of good versus bad-tasting cultivars, which underscores the complexity of untangling chemical stimuli and relating them to people's preferences (Tieman et al., 2012). In grafting studies of tomato, watermelon (*Citrullus lanatus)*, and cucumber (*Cucumis sativus*), rootstock genotype had a significant effect on fruit firmness as well as vitamin C and soluble solids (Rouphael et al., 2012). In broccoli (*Brassica oleracea*), genetic links have been found between low sugar levels and high glucosinolates, which humans perceive as bitter (Rouphael et al, 2012). Additionally, Bunning et al. (2010) found lettuce genotype had a significant effect on specific flavonols and phenolics that were correlated to perceived bitterness among tasters, so it seems quite apparent genotype plays a role in flavor across numerous crops.

Sugar content, while a seemingly straightforward way to approximate sweetness, is a quantitative trait itself (Tieman et al., 2012). It is impacted by other gene pathways and products, too, like those controlling pigment synthesis and storage. Pigments underlie important visual characteristics of fruits and vegetables that do influence people's preferences (see section on "Human Flavor Preferences"). They also function as antioxidants and in light transduction within the plant body (Paran & van der Knaap, 2007; Mustilli et al., 1999). The uniform ripening mutation (*u*) in tomato causes changes in the accumulation and distribution of fruit chloroplasts, which eliminates green shoulders but ultimately leads to lower sugar content than in non-mutants (Powell et al., 2012). On the other hand, green flesh (*gf*) and chlorophyll retainer (*cf*) tomato mutants retain their fruit chloroplasts, which give fruit a brown coloration and increased sugar levels (Paran & van der Knaap, 2007). High pigment (*hp1* and *hp2*) tomato mutants have significantly more total plastids, which leads to peculiar plant architecture but also more sugar, carotenoids, flavonoids and vitamins (Mustilli et al., 1999; Rouphael et al., 2012). Some pigment molecules, like anthocyanins in grape (*Vitis vinifera*) and bitter melons (*Momordica charantia*), have shown to be perceived as bitter (Paissoni et al., 2018). In fact, some anthocyanins are among a group of molecules that have the ability to bind to multiple types of sensory receptors including taste (bitter), trigeminal receptors (astringency), and odor receptors (Paissoni et al., 2018; Wieczorek et al., 2018; Reed & Knaapila, 2010).

For some, the prospect of increasing sugars or reducing bitter compounds in fruits and vegetables to improve their taste is enticing. Many breeders, however, recognize the fundamental metabolic tradeoffs between increasing sugar and decreasing yields, which is why so many breeders are focusing efforts on improving volatiles, especially in fruit crops like tomatoes (Wang & Seymour, 2017; Tieman et al., 2012). In attempts to predict consumer liking for fruits and vegetables, studies have found the most successful models utilize volatile measurements (Bayarri & Costell, 2010), but the resources needed to quantify volatiles in a breeding program are similarly cost prohibitive as employing formal sensory evaluation with trained tasters. Klee and Tieman (2018) say it is possible to identify genes regulating the synthesis of flavor volatiles as well as alleles of those genes that promote a more flavorful composition. While some researchers advocate strongly for genetic approaches to improving flavor, the process of relating chemical stimuli to human preferences and perceptions is awash with complexity (Klee & Tieman, 2018; Tieman et al., 2012; Wang & Seymour, 2017). Still, these types of key flavor genes and desirable alleles have been identified in tomato and strawberry (*Fragaria x* ananassa) as ones lost during domestication (Gao et al., 2019; Goff & Klee, 2006).

A rare allele in the promoter region of a tomato lipoxygenase gene (*TomLoxC*) that catalyzes the synthesis of 5- and 6-carbon volatiles (mostly “green leaf” aromas) was found in 91% of *Solanum pimpinellifolium* (tomato’s predecessor), but only 22% of domesticated heirloom varieties and 15% of modern hybrids (Gao et al., 2019). And the volatile profile of cultivated strawberry differs markedly from its wild relatives due to the loss of a single enzyme that synthesizes the volatile methyl anthranilate, which is responsible for fruity grapelike aromas (Goff & Klee, 2006). Even if relevant flavor genes and alleles can be identified, the flavor phenotype is still highly influenced by the environment. For some flavor-associated traits like titratable acidity in tomato, studies have calculated relatively high heritability (87%), while heritability estimates for other traits such as lycopene are much less (16%) (Goff & Klee, 2006; Panthee et al., 2012; Klee & Tieman, 2018). The ways in which growing environment can affect flavor-related chemicals in plants seem endless in the literature. Perhaps obviously, large amounts of water can dilute flavor of fruits and vegetables, but temperature and light both have tremendous impacts on organoleptic qualities, too. Higher light intensities have shown to increase levels of sugar, ascorbic acid, and dry matter in tomato, lettuce (*Lactuca sativa*), sweet pepper *(Capsicum annuum*), strawberry, and melon, while lower light intensities can promote production of antinutritive and bitter compounds like oxalates in Amaranthaceae crops (Budding et al., 2010; Rouphael et al., 2012). Colder growing temperatures affect the texture, taste and smell of tomatoes and also promote more bitterness in cucumbers and broccoli (Wieczorek et al., 2019; Rouphael et al., 2012).

The environment's effect on flavor includes cultural techniques used by the grower and field-specific factors like soil composition and nutrients. Tomatoes grown in glasshouses have lower levels of phenols compared to field-grown counterparts in the United Kingdom, whereas high tunnels increase overall quality of organically grown tomatoes in the Midwest United States (Rouphael et al., 2012; Healy et al., 2017). Increased levels of nitrate fertilizer led to reduced sugars and antioxidants but increased titratable acidity in tomatoes and habanero peppers (*Capsicum chinense*) (Benard et al., 2009; Nunez-Ramirez et al., 2011). The color of reflective mulches used to grow basil (*Ocimum basilicum*) significantly affected leaf succulence, aroma compounds, and total phenolics in the leaves (Loughrin & Kasperbauer, 2001). Banchio et al. (2009) found that presence of *Bacilus subtlis*, a plant growth promoting rhizobacteria, increased certain volatiles in basil leaves as well. Even plant stress responses can act to influence flavor-related chemicals as seen with leafhopper tea. When tea leaves (*Camellia sinensis*) are bitten by leafhoppers, it induces a stress response that produces a perceptible change in flavor once brewed (Scott et al., 2020). This flavor is highly prized for being both delicious and unique (Scott et al., 2020).

So even if researchers can identify key genes and alleles involved in flavor development, there still remains serious questions about the expression of those genes in various environments and under different growing conditions. Naturally, this is made more complicated by gene x environment (GxE) interactions. Mostafa et al. (2015) found a significant GxE effect on allicin content in 104 garlic (*Allium sativum*) accessions grown in Egypt and China. And in a diverse set of 42 tomato varieties grown in three locations, the GxE effect was significant on soluble solids, titratable acidity, and lycopene (Panthee et al., 2012). Clearly plant scientists have their work cut out for them in efforts to regain lost flavor in crops, since not only are the underlying genetics complex, their expression is highly mutable to a seemingly endless stream of environmental and horticultural factors.

Flavor Perception by Humans

While genetic, environmental, and horticultural factors can impact the production and accumulation of plant flavor compounds, human perception of these stimuli is not equal. In fact, Reed and Knaapila (2010) say, "perhaps no single human trait has as much person-to-person differences as abilities to taste and smell," and human genetic differences are at least partially responsible for differences in perception of the same tasting sample (Wieczorek, 2019). Each taste bud on the tongue is made up of 50-150 taste receptor cells, and each taste receptor cell bears one type of taste receptor (i.e. sweet, sour, umami, bitter, salty) (Roper & Chaudhari, 2017). Some receptor genes like those for umami are polyallelic meaning there is also within family variation of taste receptors; different alleles for umami receptor genes make some people unable to taste monosodium glutamate (MSG) for example (Reed & Knaapila, 2010). Roper and Chaudhari (2010) report that the number and distribution of taste buds and receptor cells within them, as well as variants of membrane receptors are all under genetic control. Such observations have led comparative physiologist to describe each person as living in their own "individual taste world" (Roper & Chaudhari, 2017). For example, taste and odor thresholds – the minimum amount of a stimulus to result in a perceptible sensation – vary widely from person-to-person, and the combinatory nature of receptors and ligands can easily elicit a response at sub-threshold levels (Klee & Tieman, 2018; Reed & Knaapila, 2010; Roper & Chaudhari, 2017). Formal sensory science seeks to mitigate this person-to-person variation with training (Lawless & Heymann, 2010), however, this reduces the ability to generalize results to untrained populations of everyday eaters (Pangborn, 1968; Lahne, 2016), which is the group crop researchers are most interested in.

The term "super taster" is ubiquitous in the sensory science literature, and in fact, further stratification can be found that differentiates tasters, non-tasters, medium tasters, and super tasters (Bartoshuk, 1978; Klee & Tieman, 2018; Wieczorek, 2019). Super tasters are so named because of their high sensitivity to two bitter compounds – 6-n-propylthiouracil (PROP) and phenylthiocarbamide (PTC) – neither of which are found naturally in food (Reed & Knaapila, 2010; Wieczorek, 2019). The sensitivity to these two chemicals lies in the *TAS2R38* gene (a bitter taste receptor), which is one of at least 25 in the *TAS2R* gene family (Avau & Depoortere, 2016). This family of bitter receptors is activated by many different molecules, and some of these molecules can bind to multiple types of TAS2R receptors (Avau & Depoortere, 2016; Wieczorek, 2019). The relationship between PROP, PTC and *TAS2R38* has been intensely studied; PTC in particular is unique because it exclusively binds to the *TAS2R38* receptor (Reed and Knaapila, 2010). Altogether considered, these studies give relatively little insight into the impact of genetics on final bitter sensitivity, as the "nontaster" form of *TAS2R38* still might be able to taste other bitters (Ava & Depoortere, 2016). Likewise, there is much more to know about bitter tastants themselves. Wieczorek et al. (2019) say trained sensory panels differentially perceive and describe bitterness from different glucosinolates in broccoli. These may be important insights for plant breeders and researchers looking at the chemical building blocks of flavor within plants, but many questions still remain about the implications this has for using humans to evaluate flavor in crop research.

For perception of other tastes, like sweetness, there is a better sense of the role of genetics. For example, alleles in the promoter-region of sweet receptor gene *Tas1r3* have shown good ability to predict a person's sensitivity to sweet stimuli, but it is known other genes like those involving secondary messengers (ex: gustducin) are also involved (Robino et al., 2019; Reed & Knaapila, 2010). There is evidence that sour perception also has a genetic component, but little research has sought to investigate specifics, and scientists have yet to untangle the physiological machinery of salt perception let alone any potential underlying genetics (Roper & Chaudhari, 2017; Reed & Knaapila, 2010; Robino et al., 2019).

Both sweetness and bitterness perception can be enhanced or mitigated by the presence of certain volatiles (Wieczorek et al., 2019; Baldwin et al., 2008; Wang & Seymour, 2017), but this requires appropriate odor receptors to be present in the taster's nose and throat. In the human genome, the family of olfactory receptor (*OR*) genes is one of the largest and has shown to contribute to variation in the ability to smell certain odorants. There are nearly 400 functional *OR* genes in humans along with an equivalent number of pseudogenes, and about 60 others that have been found with both functional and nonfunctional variants (Klee & Tieman, 2018; Olender et al., 2008). *OR* genes can be found on the X sex chromosome and all somatic chromosomes except 20 (Olender et al., 2008). As described earlier with safrole, ORs work combinatorially and for the most part they are broadly tuned to respond to a wide range of volatile ligands (Klee & Tieman, 2018; Tesileanu et al., 2019). The relatively small effect of an allele change in a human *OR* gene highlights the complicated nature of the sense of smell (Olender et al., 2008).

Using 26 families in Finland, Knaapila et al. (2007) came to interesting conclusions when they examined the heritability of olfactory-related traits. Unlike taste traits, they estimated very low heritability for the ability to perceive lemon and chocolate aromas, but high heritability for pleasant responses to cinnamon smells, which they mapped to chromosome 4 (Knaapila et al., 2007). Just like with plants and their synthesis of flavor molecules, genetics do not explain the entirety of human flavor perception. Age, education, occupation, socio-economic level, health and smoking history are some of the many characteristics that can modify responses to sensory stimuli (Pangborn et al., 1988; Deliza & MacFie, 1996; Fernquist & Ekelund, 2014). Children appear to have more intense bitter and sweetness responses compared to adults (Wieczorek et al., 2019), and overall taste and smell sensitivity declines as people get older (Pangborn et al., 1988; Reed & Knaapila, 2010). Education can dictate which and how many words a person uses to describe and understand a food and its properties, while the language itself can have bearing too. In Japanese, there are more than 400 words used to describe food texture, while only about 100 in English (Nishinari et al., 2008). It is estimated that on average humans can differentiate over 1 trillion smells, but surely there are not enough words in any language to distinguish each one separately!

Differences in perception are also attributed to seemingly benign factors such as rates of respiration while eating, or how hard and fast someone chews before swallowing, or slight differences in anatomy of the mouth, nose, and throat (Bayarri & Costell, 2010; Heymann et al., 1993). Taste perception and trigeminal nerve response are influenced by a multitude of factors including the food's temperature, altitude, background noise, or what vessel samples are presented in (Roper & Chaudhari, 2017; Spence et al., 2014; Piqueras-Fiszman & Spence, 2015). Sensitivity to bitterness in cauliflower has been linked to consumption amount (Wieczorek et al., 2019), and plant-based foods enhance the expression of bitter receptor genes (Medawar et al., 2019). In fact, nerve cells, especially olfactory receptor cells, are regularly replaced in the mouth, nose and throat. The types and distribution of receptor cells can change in orders of several magnitude over time (Tesileanu et al., 2019; Fried, 2020). Recently Tesileanu et al. (2019) have proposed that this is an adaptive mechanism for responding to changing chemosensory environments. In other words, human gene expression changes in response to chemical signals from the environment – including in food – to alter the types and distribution of sensory cells. This explains why systematic and repeated exposure to odorants can increase sensitivity to them (Tesileanu et al., 2019; Reed & Knaapila, 2010; Baldwin et al., 2008).

If the cellular machinery involved in flavor perception changes regularly, then surely this has implications for its evaluation in crops. It also gives rise to more questions about formal sensory analysis training and calibration protocols. The training of panelists in sensory science is supposed to reduce the amount of variation attributable to differences in taste perception, but few studies have been published on the effect of training, and some have shown inconsistencies of professional tasters over time (Lahne, 2016; Corollaro et al., 2014). Even with the use of trained sensory experts, the effect of taster is still frequently statistically significant, and convention has been to place blame on the abilities of tasters rather than the methods (Corollaro et al., 2014; Meiselman, 1993; Pangborn, 1968). This is all the more reason for researchers in the plant sciences to explore and describe new approaches to flavor evaluation in contexts other than industrial food production.

Human Flavor Preferences

Ultimately, improving flavor in crops is fundamentally related to human preferences, so understanding how preferences are formed will be helpful for plant scientists in these endeavors. Perhaps unexpectedly, there are genetic components to human smell and flavor preferences, some of which are related to receptor variation (Robino et al., 2019; Knaapila et al., 2007). For example, two SNPs in the *OR7D4* gene are responsible for different perceptions of androstenone, a volatile found in male pig meat: individuals with one gene variant describe the aroma as "foul" and "sweaty," while people with another report "pleasant floral" aromas (Robino et al., 2019). Likewise, variation in the *OR6A2* gene has been correlated to dislike of cilantro (*Coriandrum sativum*) because of perceived soapiness (Robino et al., 2019). There are a wide range of influences that affect human preferences and aversions, and the historic approach of using averages and consensus metrics in sensory science can belie the importance of different preference criteria (Pangborn et al., 1988; Meiselman, 1993; Bayarri & Cowell, 2010).

Preference development has been shown to begin *in utero* as nutrients and volatiles from a mother's food are passed to the baby (Goff & Klee, 2006), but overall, humans are born with relatively few innate preferences (Pangborn et al., 1988). Newborns show a preference for both sweet and fatty stimuli as well as mildly salty solutions, but they show aversions for bitter and sour tastes (Reed & Knaapila, 2010). This makes sense because taste has evolved as a way to evaluate the composition of foods; fats and sugars communicate energy-richness, and salt is important for electrolyte balance, while bitterness and sourness can indicate the presence of toxins or food spoilage (Reed & Knaapila, 2010; Roper & Chaudhari, 2017). But preferences and aversions retain a great deal of plasticity throughout lifespans because they are sensitive to modification from lived experiences, which sometimes work unconsciously (Myers & Sclafani, 2006). Natural preferences are shaped over time by nutritional factors and various social and cultural constructions that have been elaborated over generations.

The volatile compounds that give fruits and vegetables many of their distinct sensory characteristics are largely derived from essential nutrients like fatty acids, amino acids, and antioxidants like glucosinolates and carotenoids that are beneficial for human health (Bayarri & Costell, 2010; Wang & Seymour, 2017). In that sense, Goff and Klee (2006) say plant volatiles can be thought of as "positive nutrient signals that communicate health benefits." Perhaps surprisingly, taste and odor receptors are not only located in the mouth, nose, and throat. They have been found in the lining of the gastrointestinal tract, in respiratory system epithelia, on the surface of the brain, and even in male testes (Avau & Depoortere, 2016; Roper & Chaudhari, 2017). While not completely figured out yet, there appears to be a type of "back door" communication between the body and brain about nutrients that are consumed in food, and this can be a mechanism by which the brain learns to prefer certain foods and flavors over others (Goff & Klee, 2006). Myers and Sclafani (2006) refer to this as "flavor-nutrient conditioning," which is sensed post-ingestion. In fact, there are plenty of documented instances where animals seemingly learn to recognize and select more nutrient dense foods over others (Sclafani & Ackroff, 2012). The relationship with flavor, however, is at this point unclear.

Food preferences can be affected by a variety of learning mechanisms and environmental factors like dietary habits, personal experiences, culture, religion, and physiology (Wieczorek et al., 2019; Wright et al., 2001; Pangborn et al., 1988; Deliza & MacFie, 1996; Fernquist & Ekelund, 2014; Piqueras-Fiszman & Spence, 2015). Numerous studies have pointed out an exposure effect – the more times a person has encountered a food or flavor is positively correlated to acceptance and liking (Myers & Sclafani, 2006; Deliza & MacFie, 1996). Generally speaking, humans exhibit innate neophobia, although openness to new things has been linked to both geography and culture (Meiselman, 1993; Wright et al., 2001). Many encounters are required for a person to develop a preference compared to the small amount of exposure necessary to develop a strong aversion (Goff & Klee, 2006). Preferences and aversions can also arise from other associations and conditioning besides nutrients. For example, rewarding or distracting children with candy can give rise to preferences for particular flavorings and more intense sweetness (Cervellon & Dabe, 2005; Robino et al., 2019). Likewise, an aversion can easily develop from a bout of food poisoning or toxicity (Myers & Sclafani, 2006).

Another factor affecting liking is whether a food meets expectations, which also relates to a person's history of use and experience (Meiselman, 1993; Deliza & MacFie, 1996; Piqueras-Fiszman & Spence, 2015). This is largely where novel colors, shapes, and the appearance of fruits and vegetables can drive eaters to reject them. For example, in a roundtable at the 2019 Organic Vegetable Production Conference (Madison, WI), organic farmers lamented that many customers complained about tomato flavor but were also unwilling to buy any non-red tomatoes because their unfamiliar color. This seems to be a popular preference in the United States. Preference mapping is a way to segment a population into smaller groups that share common determinants of preference to better understand their buying and eating decisions (Greenhoff & MacFie, 1994). Using preference mapping of tomato consumers, Oltman et al. (2014) identified the largest consumer segment had very strong priorities for red tomatoes and rejected soft textures, but their preferences were not determined by other sensory qualities. The next largest group's preferred firm, crisp tomatoes with few seeds but showed no preferences related to color or external appearance.

American partialities for red and firmer tomatoes are one example of how culture can affect food preferences in subtle ways. While the senses have evolved for humans to assess their environments, food and flavor are about more than just biology; food is also a way that humans indulge themselves, connect to others, and search for identity through consumption (Wright et al., 2001; Hennion, 2007; Fernquist & Ekelund, 2014). Individual and cultural food preferences are inextricably linked to art, design, media, and marketing that all signal what food should look and taste like (Piqueras-Fiszman & Spence, 2015). Additionally, art and media have not only historically implied what food should look like, but they also portrayed who should be eating it. Beginning in the 1980s, French sociologist Bourdieu wrote several papers on how food was used to advertise class and social standing throughout history (Wright et al., 2001), and Margot Finn (2017) has extended this idea to the modern "Good Food Movement" in the United States. She and others argue that the development of connoisseurship is a way that people attempt to assert class and status without money or political power (Finn, 2017). As Bourdieu famously said, "taste classifies, and it classifies the classifier" (Wright et al., 2001). Food preferences have been used as a way to characterize people in different social strata, too. For example, throughout the 19th Century in Britain, having a sweet tooth was associated with the working class because they did not possess the prowess to elevate their tastes beyond the visceral pleasures of sugar (Wright et al., 2001). In a more modern example, the rise of vegetarianism in women has been explained as an unconscious expression of control over her own body (Medawar et al., 2019). Indeed, at least part of the impetus for current breeding work that prioritizes better flavor is socially based, so clearly more than just physical and chemical properties of plant parts are involved.

In her book *Cuisine and Empire*, Rachel Laudan (2015) retells world history from the perspective of cuisine, and how food has been used to assert power and dominion over others as various empires set out to conquer the world. She writes much about religion and how it has shaped regional cuisines and cultural food preferences. For example, the rise of Protestantism in Britain created widespread disavowal of sensual pleasures including from food, which led to the relatively unadorned boils and roasts that characterize much of British cuisine (Laudan, 2015; Wright et al., 2001). And the arrival of Buddhism in Japan created an emphasis on simple, mildly flavored and vegetable-focused dishes (Laudan, 2015). Even though this is ancient history, these factors still influence people's food preferences and their liking of different crop cultivars. Historical events have helped form the traditions and foodways that at least partially inform individual identities. As new foods – or new crop cultivars – are tasted, the interaction between brain and mind cannot help but compare them to past memories and experiences which inevitably tug on emotions. Anecdotally for example, at a public tomato tasting event in 2019 (Farm to Flavor, Madison, WI), one taster pointed out their favorite variety and explained it was because the texture reminded them of tomatoes in their home country of Brazil. This poses a problem for understanding flavor as an objective measurement for plant scientists because it appears there may be no such thing.

Pangborn et al. (1988) were some of the first to study differences in aroma preferences across the globe. Perhaps expectedly, they found that different geographic areas had preferences for some smells over others, and the preferred smells differed distinctly by region (Pangborn et al., 1988). The researchers were unable to determine if preferences fell along geographic or cultural lines, and follow-up studies have had similar difficulty in cleaving the distinction. Geographic determinants would be more specific to a physical place such as native flora and fauna, whereas cultural determinants would include things like foodways, and obviously there is much overlap between the two (Pangborn et al, 1988; Wright et al., 2001).

Advancements in science and nutrition have further complicated understanding how people develop preferences (Piqueras-Fiszman & Spence, 2015). In a meta-analysis of studies looking at consumer liking in kiwifruit, Harker et al. (2009) found preference differences for eaters in Japan versus those in New Zealand, who were overall more accepting of soft fruit. The authors found an interesting subsection of New Zealand consumers who preferred blander and less sweet kiwifruits whom they hypothesized ate the fruit for its health benefits rather than its sensory properties (Harker et al., 2009). Cervellon and Dabe (2005) found similar results in their comparisons of food and flavor preferences between French and Chinese eaters. While both cultures have a strong emphasis on food, French preferences were almost entirely driven by affective reasoning, or in other words, they were driven mostly by "sensations, feelings, and emotions" (Cervellon & Dabe, 2005). The results for Chinese eaters indicated that preferences and food choices were based on a balancing of affective and cognitive reasons such as health benefits that reflected important Chinese cultural principles of equilibrium (Cervellon & Dabe, 2005).

Altogether, there are a wide variety of factors that inform which foods and flavors are preferred. While these are surely relevant considerations for plant breeders and researchers, their implications on flavor evaluation methods remain unknown. Food preferences may be described as highly flexible, but plant breeders should consider that some of the determinants of preference are deeply rooted and sensitive topics. For example, when tomato cultivars are geared toward American preferences for firmness and sweetness, this is another way in which immigrants, refugees, and other marginalized groups are forced to assimilate. Meaningful plant breeding and efforts to evaluate flavor must take these factors into account as methods are introduced, improved, and discussed.

Conclusion

The quest to recover and maintain better flavor and sensory qualities in crops is undoubtedly a daunting task for breeders and researchers. While genetics play a role in laying the foundation for good flavor, the growing environment and cultural techniques have a big impact on their manifestation (Klee & Tieman, 2018). Human perception of flavor is fickle. As genetically unique individuals, everyone's sensory machinery is different and constantly changing in response to the environment (Reed & Knaapila, 2010; Tesileanu et al., 2019). And still neither of these tells the full story. While sensory and plant scientists alike describe flavor as the "sum of [sensory] inputs that informs the brain what we are eating," (Klee & Tieman, 2018) it is clearly more than that. Reflexively and unavoidably, everything tasted is put into the context of past experiences, expectations, histories, and identities. Flavor doesn't just tell us what we're eating, it reminds us about who we are and where we come from, too.

Yet somehow, in spite of all that makes studying flavor so complex, it has been assumed that the formal sensory science methods are the best. Certainly these traditional sensory methods have value and a continue place in flavor research, but the inability to mimic descriptive analyses with professionally trained panelist is often lamented by plant scientists. Attempts are made to proxy their methodologies with the use of expert breeders, while rapid sensory methods and alternatives that utilize professional end-users are automatically relegated as inferior. It seems unlikely that the approaches in traditional sensory evaluation are objectively better at coping with the realistic complexities of assessing flavor especially in non-industrial contexts where food also has extrinsic value (Piqueras-Fiszman & Spence, 2015). With sensory evaluation being the "child of industry" (Lawless & Heymann, 2010), their methodologies have not been described, critiqued, and refined in the same way as other scientific disciplines. In fact, studies investigating the impact of training on reducing taster variability or its effect over time are practically absent in the literature (Lahne, 2016; Harker et al., 2009; Meiselman, 1993). Presumably some of this information exists, but it is outside the public domain and proprietarily owned by major food companies who use formal sensory science to guard market shares. Likewise, it can easily become problematic when one group of people (trained sensory panelists) is making decisions about what they think is best for others (all eaters), especially when the group in power doesn't accurately reflect the people they are making decisions for. With these things considered, plant scientists should be wary of valorizing traditional methods, and room needs to be made for discourse that recognizes the historic shortcomings of applied flavor research. Instead, plant scientists must see the situation as an opportunity to go back to the drawing board and come up with new approaches that are better suited to non-industrial and agricultural contexts. This should be the future of plant science that works on improving flavor.

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Chapter Two

Assessing the Utility and Reliability of Rapid Sensory Evaluation Methods as Part of Organic Vegetable Variety Trials with the Seed to Kitchen Collaborative in Madison, Wisconsin

Abstract

Agricultural researchers and plant breeders have become increasingly interested in flavor and its evaluation due to growing consumer demand for better flavor and sensory qualities in fruit, vegetable, and grain cultivars. This is especially true in the organic and local food sectors, which continue to grow in importance. Traditional sensory analysis techniques that utilize trained panelists are out of reach for most plant breeding and research programs. As alternatives, the Seed to Kitchen Collaborative employs rapid sensory methods and a participatory approach to flavor evaluation as part of their organic vegetable variety trials. The results from their 2019 crew tastings were analyzed to assess their overall utility and reliability. A series of ANOVA tests for different flavor variables revealed many cases of significant differences between varieties across crops and market classes. The results helped in variety characterization and to identify both standout and poor performing varieties for sensory characteristics. Flavor variable correlations with taster overall preference were compared to ones established in the literature and showed very good agreement. The internal reliability of SKC's crew tasting methods were assessed with repeated internal checks and analyzed with k-means clustering, which showed 29 out of the 37 check pairs clustered together. These results may have implications to reconsider taste sample collection protocols.

Background and Introduction

The Seed to Kitchen Collaborative (SKC) is a participatory research network based out of the Urban and Regional Food Systems Lab in the Horticulture Department at the University of Wisconsin – Madison. They use data generated from a diverse network of stakeholders including regional farmers and gardeners, local chefs, plant breeders, and seed companies to identify suitable vegetable varieties for organic farms in the Upper Midwest. The farmer participants in SKC are mostly small-scale, diversified, direct-market vegetable operations. They require vegetable varieties that grow and produce well on their organic farms and also possess the quality and flavor characteristics demanded by customers in their markets. While there is continued growth in demand for locally and organically produced food, buyers in these market sectors have higher expectations when it comes to eating quality (ex: flavor, texture, culinary attributes) (Yiridoe et al., 2005; Tropp, 2014; Organic Trade Association, 2019).

With flavor becoming more important for eaters and end-users (ex: chefs, bakers, brewers), sensory traits have become more relevant for growers and likewise for plant breeders and agricultural researchers (Dawson & Healy, 2018). Breeders and researchers are increasingly interested in the main drivers of consumer preference for example, but evaluating flavor is not necessarily a straight-forward process. Flavor is an inherently complex trait particularly when measured with human tasters (Klee and Tieman, 2018). For this reason, it has historically been considered sufficient for breeders to ensure cultivar flavor is acceptable, rather than selecting for improvement. Similarly, the traditional model of sensory analysis has made participation in flavor evaluation inaccessible for many relevant stakeholders like chefs and everyday eaters.

Formal sensory analysis traditionally uses an expert panel of highly trained judges to obtain precise measurements of flavor and its components (Lawless and Heymann, 2010).

Creating and maintaining a trained sensory panel is neither possible nor practical because of time and financial costs for the majority of crop researchers and breeders, especially those focused on small- and mid-scale, organic vegetable farmers (Dawson & Healy, 2018). Likewise, by relying on expert tasting panels, the eventual eaters and users of the vegetables are excluded from participating and giving their opinions (Varela & Ares, 2012). Considering the ultimate goal is to achieve better flavor in vegetables as perceived by the people buying them regularly, then it makes sense these stakeholders should be directly involved in the flavor evaluation process. In short, the traditional paradigm of flavor evaluation is not necessarily appropriate in plant breeding and agricultural research especially in local and organic market sectors.

The number of plant breeding and research programs interested in assessing flavor is growing, but development of appropriate methods is lagging. This interest reflects the rising economic and cultural attention to organic and locally produced food where good flavor is expected and prioritized (Tropp, 2014; Organic Trade Association, 2019). Many breeding programs currently rely on the flavor evaluation of one or two highly experienced breeders rather than a panel of highly trained tasters (P. Simon, personal communication, February 6, 2020). This seems an attempt to create analogous sensory evaluation procedures by replacing the expert tasting panel with breeder experts instead. It is true that longtime breeders will have likely tasted the full gambit of possible flavors within a crop, and they are presumably attuned to the needs of their regional stakeholders, so experienced breeders clearly have valuable contributions in the quest for better flavor in fruits and vegetables. Nevertheless, every individual has biologically imposed limitations as a taster, and this approach similarly ignores the eventual end-users and eaters (Varela & Ares, 2012). So, the question remains how plant breeders and agricultural researchers can best assess flavor and use that information to make decisions and recommendations.

The need for inclusive, accessible, flexible, and faster sensory evaluation methods has not gone unnoticed. Dawson and Healy (2018) describe an array of rapid sensory evaluation methods and explain how they can be applied to plant breeding efforts aimed at improving flavor, however, they avoid prescriptive recommendations in favor of presenting a useful set of potential tools. Rapid sensory methods severely reduce or eliminate the need for a formal training process, while still providing qualitative and quantitative information (Frost et al., 2015; Dawson & Healy, 2018). They emerged as a response to the inherent problems and challenges posed by formal sensory analysis protocols. Overall, rapid sensory methods have shown to be consistent over time and reflective of conventional analyses with trained judges (Varela & Ares, 2012; Dawson & Healy, 2018). It is not necessarily the goal, however, for plant scientists to mimic the results of a trained expert panel even though this comparison is often used to defend the legitimacy of rapid sensory methods in the face of criticism that they are not rigorous enough. However, while trained experts may have calibrated abilities to detect particular aromas or specific components of flavor, they do not necessarily represent the flavor preferences, perceptions, nor culinary expectations of local chefs, bakers, and eaters (Varela & Ares, 2012; Frost et al., 2015).

This paper describes a more in-depth look at the rapid sensory evaluation methods used by SKC and examines their overall utility and reliability. The methods were used as part of SKC's annual organic variety trials as well as a participatory tomato breeding project. They tap into a network of research station field workers and UW students. Overall, rapid sensory evaluation methods that use diverse groups of stakeholders to assess flavor in crops appear to be viable alternatives to the standard approaches used by sensory scientists (trained panels) and plant breeders (single expert). But there may be considerations for altering sampling protocols based on k-means clustering that assessed the internal reliability of checks. These rapid sensory methods are capable of producing useful information about breeding populations, varieties and crops, and underscore the importance of engaging in local participatory networks.

Methods and Materials

SKC has been working to develop appropriate participatory methods to evaluate flavor with a diverse group of stakeholders since 2013. Through that process, three general surveys have been developed: one for public tastings, one for crew tastings, and one for chef tastings. Since its beginning, SKC has used an iterative process to refine various aspects of the surveys including appropriate questions/traits, language and terms clarification, visualizations, and interface. For all 2019 tastings, paper ballots were made available, however, tasters were strongly encouraged to use the electronic version of the survey made with Qualtrics software, version 2019.6 (SAP, Provo, UT). A sample survey can be found in Appendix A.

This paper focuses on the methods and results from using SKC's crew tasting survey during their 2019 trial season. Crew tastings were open to any interested participants, but mostly consisted of graduate students and field/lab workers that were employed at the research station. Participants were apprised of tastings and activities through a listserv at least 48 hours ahead of time. This type of network and communication is critical to the usefulness of data derived from crew tastings because assessors gain experience and familiarity with the process over time, and it allows for a more consistent group of tasters to help reduce variation introduced by differences in taste perception. So, in addition to the logistical benefit of having most assessors centrally located, it can also diminish the error introduced by the effect of taster. Tapping into a network of interested plant scientists also helps achieve higher numbers of tasters, which is sometimes a point of contention when using untrained panelists (Lawless & Heymann, 2010; Dawson & Healy, 2018).

At the beginning of the season, available crew members went through a brief exploratory training exercise and a walkthrough of the survey to clarify terms and answer any questions. The activity (seen in Appendix B) involved tasting three different concentrations of sugar (sweetness), citric acid (sourness), cinchona bark (bitterness), table salt (saltiness), and Bragg's liquid aminos (umami) in plain water and then again in tomato juice. The tomato juice exercise provides a more accurate reflection of the flavor complexity present in raw fruit and vegetables as well as the difficulties identifying which component is responsible for changes in perception. Crew members were tasked with recognizing the flavor component they were tasting and the concentrations for each (low, medium, or high). This can be quite difficult for some tasters, but there is clear growth in people's perceptual abilities by the end. Traditional sensory methodologies use these trainings to qualify capable tasters (Lawless & Heymann, 2010), but SKC uses the activity as a learning exercise. For many who are new to the program, this is the first time they have thought about flavor as having separate and identifiable components. Attending the training was not a requirement to participate in tastings throughout the season, but the surveys did include a question asking whether or not the taster participated in the activity for 2019. On average, there were eight tasters per tasting and five of those tasters had attended the pre-season training/learning activity.

Sample Collection

All tasting samples were grown as part of SKC's organic variety trials at West Madison ARS (Verona, WI), although some winter squash samples were used from the SKC trials at Spooner ARS (Spooner, WI) due to disease pressure, high field mortality and storage difficulties at the Madison site. Horticultural methods followed what local farmers recommended for each individual crop. In 2019, nine different crop species were evaluated for flavor with multiple market classes and varieties for each (see summary table in Appendix C). Crew tastings typically occurred once to twice weekly throughout the growing season and once to twice monthly for fall storage crops (i.e. winter squash, carrots, potatoes). During the growing season, tastings were scheduled to coincide with harvest for the different crops, and usually happened the day after, so as to streamline field and flavor data collection.

Varieties were planted in at least two different field plots as part of an augmented design with multiple checks. Tasting samples were collected from every plot of the variety and bulked for presenting to tasters to minimize flavor differences attributable to field location. Samples were collected at maturity to mirror how they would be harvested and sold by direct-market farmers. For fruit and root crops, 3-4 whole samples were taken per plot while 1-2 whole plants were collected for lettuce.

Constructing Tasting Sets

Tasting sets were limited to six or seven varieties, if possible, to avoid inducing palate fatigue and minimize the time commitment for assessors (Dawson & Healy, 2018). The smallest tasting sets had three samples, whereas the largest contained nine. In total, 52 different tasting sets were evaluated with the field crew surveys. To help give insight into the internal reliability of SKC's tasting methods, 37 of these tasting sets contained a repeated check within the samples. Varieties were grouped based on their market class and similarity in appearance. For example, red slicing tomatoes were tasted separately from pink slicing tomatoes, as were yellow and orange slicing tomatoes. The data can be analyzed and compared by tasting set, market class, or crop depending on the research goals. The grouping process was more difficult with the tomato breeding project due to the phenotypic variation still present in many families (F2 – F5 generations). Tasting samples for breeding lines were prepared so that each sample corresponded to a single field plot of three plants.

In some cases, time and availability of participants necessitated preparing and presenting up to three different tasting sets at the same time. Tasters were asked to avoid giving partial answers and complete as many sets as their schedule allowed.

Sample Preparation

After collecting from the field, samples were washed and prepped for tasting. The preparation process was somewhat crop-specific, but in general, vegetables were cut into bite-size pieces that allowed for the best representation of the whole. As an example, tomatoes were sliced into wedges where each piece contained pericarp tissue as well as the internal gel and seeds. Additionally, one sample was left whole and displayed for tasters to consider in their appearance rating. All crops were tasted raw except potatoes and winter squash, which were steamed in countertop roasting ovens at 400°F. Perforated aluminum trays (4" x 6") were filled with 1" cubes of potatoes or squash and placed on wire racks in preheated roasters (Hamilton Beach Mo. 32229) with 1" of water in the bottom. Samples were pierced with a fork to test for doneness after 30 minutes and removed once tender. Some varieties of squash took longer to cook than others (up to 40 minutes), but all potatoes were done after half an hour.

Crew Tasting

Figure 2.1: A prepared tasting set of yellow potatoes. Potatoes in the containers are steamed and displayed alongside an uncut, whole sample. Not shown: fronts of containers are labeled with random 3-letter codes (ex: EIC, XKA, CYK). See Appendix A for sample survey.

Once a tasting set had been put together, each variety was assigned a random three-letter code to disguise variety names. Experience with specific varieties as well as evocative language in cultivar names can induce bias for tasters (Wansink et al., 2005; Piqueras-Fiszman & Spence, 2015). Matching containers were labeled with the tasting code, filled with the corresponding sample, and placed alongside a whole, uncut sample for appearance ratings. This was done for each variety in the tasting set and displayed side-by-side on a table as seen in Figure 2.1.

Participants were asked to refrain from talking throughout the tasting process unless they had a question for the facilitator. This reduces bias caused by comments from other assessors and allows each person to focus on the task at hand. Tasters scanned a QR code with their smart phones or tablets that linked to the crew survey, which combined several different rapid sensory methods. For hedonic ratings of appearance, texture, and overall preference, a 1-5 scale was used where 1 corresponded to “poor” or “do not like” and 5 meant “excellent” or “extreme like.” Similarly, intensity scales from 1 (low) – 5 (high) were used to rate perceived sweetness, acidity, bitterness (harshness in carrots), and flavor intensity. For some crops (potatoes and tomatoes), tasters were also asked to rate umami (the “delicious” or “savory sensation” associated with products like meat, soy sauce, parmesan cheese, and mushrooms) (Marcus, 2005). Assessors were asked to rate each flavor trait - sweetness, acidity, bitterness (harshness), umami, and overall flavor intensity - objectively. In other words, they are asked “on a scale of 1-5 (1=low, 5=high), how sweet is this variety?” This is different than asking for hedonic ratings (ie: “On a scale of 1-5, how much do you like the sweetness of this variety?”).

In the survey, tasters first provided a hedonic rating for each variety’s market appeal/appearance. Each variety was then tasted and rated one at a time. The survey was programmed to present varieties in a randomized sequence to reduce the effect of tasting order (Muir & Hunter, 1992). A hedonic rating for texture and objective ratings on the intensity scales for each variety made up the bulk of the survey. Following the intensity scales, a type of open-ended evaluation allowed tasters to give qualitative feedback such as any unique or novel attributes they perceived about the variety (Frost et al., 2015; Drake & Civille, 2006).

At the end of the survey, assessors were asked to taste all the varieties again and give an overall hedonic preference score for each one. To palate cleanse between varieties or between tasting sets, plain crackers and filtered, room temperature water were provided.

Statistical Methodology

Statistical analysis was performed using a combination of Microsoft Excel (2016), R (3.1.0), and RStudio (1.2.5033). Data was analyzed at various levels of grouping (ie: tasting set, market class, breeding lines only, etc.). Notably, there is not an inherently correct way to group varieties for analysis. Researchers should consider what questions they are interested in asking and use those as a guide.

Mixed-Model ANOVA

The following mixed-effects model was used to evaluate the effect of variety on each survey response variable (appearance, sweetness, acidity, etc.):

$$Y_{ijl} = \mu + variety_i + taster_j + date_l + e_{ijl}$$

The lmer function in the lme4 R package (Bates et al., 2015) was used for the analysis with taster and date as random effects and variety as fixed. Additionally, the R packages lmerTest (Kuznetsova et al., 2017) and emmeans (Lenth, 2020) were used to approximate the degrees of freedom for formal F-tests via Satterthwaite's method (lmerTest) and perform post-hoc analysis with Tukey's HSD using estimated marginal means (emmeans). Estimated marginal means are equivalent to least squares means but are applied to unbalanced designs, which occurs when the number of tasters changes between tasting events or a taster mistakenly leaves a question blank (Kuzetsova et al., 2017). For some crops (ex: squash and potatoes), varieties within a market class are tasted on the same day. For others, like tomatoes, logistical reasons like fruit maturity necessitate tasting varieties over a period of a few weeks. For every date, each assessor tastes each variety, but not every variety nor every assessor is present on each date. So, the assumption is made that no variety by date, variety by taster, nor variety by date by taster interactions exist. While this may not be ideal from a statistical standpoint, it makes tasting all varieties and all crops logistically possible. This method is equivalent to treating tasters as replicates and date as a blocking factor in an incomplete block design.

Correlation Matrices

To examine the main drivers of taster's overall preference, correlation matrices were created in R's basic stat package. Correlation coefficients and their significance levels were examined for both the raw data and variety means, although only correlations using variety means will be presented and discussed.

k-means Clustering

The k-means clustering algorithm was used in R to evaluate if repeated checks within tasting sets grouped together. Each crop was analyzed individually with all market classes combined and all variables considered. As a multivariate technique with testable hypotheses, k-means clustering offers a more desirable alternative to univariate pairwise t-tests. This is especially true when varieties are similar to each other, and there is no particular standout in the set (Simon et al., 1980; Varming et al., 2004). However, as an iterative process that begins with a random draw, it can be difficult to produce repeatable results; this was mitigated with other functions and attention to certain arguments in R's kmeans function such as increasing the number of iterations and setting the initial seed (Everitt & Hothorn, 2011).

First, the ideal number of clusters was determined by plotting the within group sum of squares as cluster number increased (see Appendix G). R's built-in kmeans function was then applied to a data frame of variety means, which assigned each variety to a cluster. Finally, the cluster package (Maechler et al., 2019) was used to project the final groupings on a graph with axes representing the first two principal components.

Results

Mixed-Model ANOVA

The series of F-tests indicated that variety had a significant effect on many of the variables impacting flavor in most of SKC's trials. These results are summarized in Table 2.1A, which shows the p-values for F-tests across all market classes and crops in 2019. P-values less than 0.10 were considered significant and warranted further analysis with Tukey's HSD using emmeans. The pairwise comparisons are summarized in Table 2.1B, which shows the number of significance groupings after this follow-up analysis.

Table 2.1A: P-values of F-tests for fixed-effect of Variety using Satterthwaite's Method for the 2019 SKC Organic Vegetable Trials

	Appearance	Texture	Sweetness	Acidity	Bitterness*	Umami	Intensity	Overall preference
Mini Butternut Squash	<0.001	<0.001	<0.001	0.22	0.055	NA	<0.001	<0.001
Large Butternut Squash	<0.001	<0.001	0.0025	0.34	0.086	NA	0.0013	<0.001
Purple Carrots	0.020	<0.001	<0.001	0.84	0.50	NA	0.18	0.0012
Red Carrots	<0.001	0.15	<0.001	0.81	<0.001	NA	0.16	<0.001
Orange Carrots	<0.001	0.65	<0.001	0.057	<0.001	NA	0.022	<0.001
Asian Cucumbers	<0.001	0.023	0.10	0.90	0.0040	NA	0.69	0.054
Mini Cucumbers	0.061	0.16	0.29	0.76	0.35	NA	0.92	0.39
Pickling Cucumbers	0.061	0.48	0.18	0.44	0.020	NA	0.39	0.50
Butterhead Lettuce	0.012	0.18	0.28	0.83	0.10	NA	0.30	0.65
Little Gem Lettuce	0.065	0.38	0.96	0.32	0.14	NA	0.80	0.016
Green One-Cut Lettuce	0.0070	0.16	0.23	0.85	0.010	NA	0.16	0.42
Red One-Cut Lettuce	<0.001	0.015	0.88	0.32	0.012	NA	0.011	0.0080
Blue Green *maxima* Squash	0.023	<0.001	<0.001	0.99	0.61	NA	<0.001	<0.001
Red Pink *maxima* Squash	0.023	0.18	<0.001	0.95	0.56	NA	<0.001	0.0010
Orange-Fleshed Melons	0.012	<0.001	<0.001	0.056	0.021	NA	<0.001	<0.001
Galia Melons	0.74	<0.001	0.95	0.94	0.80	NA	0.078	0.23
Red Bell Peppers	<0.001	0.018	0.018	0.23	0.0061	NA	0.88	0.0072
Yellow Orange Bell Peppers	0.0025	<0.001	0.018	0.76	0.96	NA	0.011	<0.001
Red Corno di Toro Peppers	<0.001	0.24	0.89	0.20	0.29	NA	0.21	0.98
Orange Yellow Corno di Toro Peppers	0.52	0.22	0.51	0.70	0.66	NA	1.0	0.19
Multi-Colored Potatoes	0.37	0.10	0.57	0.30	0.17	0.14	0.36	0.18
Red Potatoes	0.046	0.45	0.63	0.56	0.33	0.59	0.025	0.75
Yellow Potatoes	0.78	0.59	0.48	0.59	0.037	0.50	0.32	0.96
Cherry Tomatoes	0.28	0.25	0.31	0.94	0.58	0.21	0.026	0.054
Cocktail Tomatoes	0.0024	0.54	0.36	0.0033	0.52	0.93	0.34	0.10
Orange Yellow Tomatoes (Field)	0.31	0.33	0.017	0.30	0.71	0.48	0.43	0.066
Pink Tomatoes (Field)	0.022	0.54	0.074	0.27	0.0025	0.029	0.41	0.063
Red Tomatoes (Field)	<0.001	0.17	0.017	0.010	0.11	0.051	0.079	0.36
Pink Tomatoes (High Tunnel)	0.30	0.0064	0.47	0.045	<0.001	0.0020	0.0086	0.017
Red Tomatoes (High Tunnel)	0.015	0.042	0.091	0.021	0.69	0.038	0.18	0.039
Breeding Tomatoes	0.078	0.19	<0.001	0.40	0.92	0.57	0.0038	0.0035

Table 2.1A: This table shows the p-values for each F-test of variety's fixed-effect on each response variable across all crops and market classes in SKC's 2019 trials. P-values <0.10 were considered significant and warranted further analysis using Tukey's HSD with estimated marginal means. *In carrots, the term harshness was used instead of bitterness since it better describes the chemical compounds present. NA: Trait not evaluated for that crop.

Table 2.1B: Number of Significance Groupings after Pairwise Comparisons using emmeans								
	Appearance	Texture	Sweetness	Acidity	Bitterness*	Umami	Intensity	Overall preference
Mini Butternut Squash	2	3	2	NS	*ND*	NA	4	3
Large Butternut Squash	3	2	2	NS	2	NA	2	2
Purple Carrots	3	6	4	NS	NS	NA	NS	2
Red Carrots	5	NS	6	NS	3	NA	NS	5
Orange Carrots	3	NS	6	*ND*	4	NA	*ND*	4
Asian Cucumbers	3	2	*ND*	NS	2	NA	NS	2
Mini Cucumbers	2	NS	NS	NS	NS	NA	NS	NS
Pickling Cucumbers	2	NS	NS	NS	2	NA	NS	NS
Butterhead Lettuce	2	NS	NS	NS	*ND*	NA	NS	NS
Little Gem Lettuce	2	NS	NS	NS	NS	NA	NS	2
Green One-Cut Lettuce	2	NS	NS	NS	2	NA	NS	NS
Red One-Cut Lettuce	2	2	NS	NS	2	NA	2	2
Blue Green *maxima* Squash	2	2	3	NS	NS	NA	3	5
Red Pink *maxima* Squash	2	NS	3	NS	NS	NA	2	3
Orange-Fleshed Melons	2	4	4	2	*ND*	NA	6	4
Galia Melons	NS	2	NS	NS	NS	NA	2	NS
Red Bell Peppers	5	2	2	NS	2	NA	NS	2
Yellow Orange Bell Peppers	2	2	2	NS	NS	NA	2	2
Red Corno di Toro Peppers	4	NS	NS	NS	NS	NA	NS	NS
Orange Yellow Corno di Toro Peppers	NS	NS	NS	NS	NS	NA	NS	NS
Multi-Colored Potatoes	NS	*ND*	NS	NS	NS	NS	NS	NS
Red Potatoes	2	NS	NS	NS	NS	NS	2	NS
Yellow Potatoes	NS	NS	NS	NS	2	NS	NS	NS
Cherry Tomatoes	NS	NS	NS	NS	NS	NS	2	2
Cocktail Tomatoes	2	NS	NS	2	NS	NS	NS	2
Orange Yellow Tomatoes (Field)	NS	NS	2	NS	NS	NS	NS	2
Pink Tomatoes (Field)	2	NS	2	NS	2	*2*	NS	2
Red Tomatoes (Field)	3	NS	*2*	2	NS	2	2	NS
Pink Tomatoes (High Tunnel)	NS	2	NS	2	2	2	2	2
Red Tomatoes (High Tunnel)	2	2	2	2	NS	*ND*	NS	2
Breeding Tomatoes	*ND*	NS	5	NS	NS	NS	3	2

Table 2.1B: Where the effect of variety was significant (p<0.10) as indicated by the ANOVA, pairwise comparisons were made using emmeans. This table shows the number of significance groupings in the compact letter display that resulted from this follow-up analysis. * In carrots, the term harshness was used instead of bitterness since it better describes the chemical compounds present. NA: Trait not evaluated for that crop. NS: ANOVA results were not significant. *ND*: No differences were detected despite a significant result from the F-test; this occurs because of a lack of statistical power in the pairwise comparisons.

One example of the F-tests looking at the fixed effect of variety on each of the flavor characteristics from mini butternut squash can be seen in Table 2.2. A full set of these detailed

ANOVA tables are in Appendix D. For all except acidity (F=1.4, p=0.22), variety had a significant effect on the trait in question. Looking at taster overall preference, the F-test (F=5.7, p<0.001) suggests statistical differences between varieties in the trial. Table 2.3A shows the follow-up analysis comparing each variety to the others. It indicates the variety 'Butterscotch' was more preferred than all the others except 'Brulée.' Table 2.3B similarly shows the significance grouping for mini butternut squash varieties when looking at perceived sweetness (F=10, p<0.001). In this case, 'Butterscotch' is in a group by itself with an average sweetness rating of 4.3.

Table 2.2: ANOVA Table using Satterthwaite's method: Mini Butternut Squash

Characteristic	SS	MS	F	Pr(>F)
Appearance	19	3.2	5.0	<0.001
Texture	44	7.3	9.3	<0.001
Sweetness	46	7.6	10	<0.001
Acidity	3.6	0.60	1.4	0.22
Bitterness	5.8	1.0	2.2	0.055
Intensity	37	6.1	13	<0.001
Overall preference	29	4.8	5.7	<0.001

Table 2.2: Results from F-tests examining the fixed effect of mini butternut squash variety on each flavor component. P-values less than 0.10 were considered significant.

Table 2.3A: Significance Groupings: Mini Butternut Squash - Overall Preference

Variety	emmean	SE	lowerCI	upperCI	group
Butterscotch	4.1	0.27	3.5	4.6	a
Brulee	3.7	0.27	3.2	4.2	a b
Honeynut	3.1	0.27	2.5	3.6	b c
Hamilton	3.1	0.27	2.5	3.6	b c
Butterbaby1	2.8	0.27	2.3	3.4	b c
Butterbaby2	2.6	0.27	2.1	3.1	c
AutumnFrost	2.3	0.27	1.8	2.8	c

Table 2.3B: Significance Groupings: Mini Butternut Squash - Sweetness					
Variety	emmean	SE	lowerCI	upperCI	group
Butterscotch	4.3	0.27	3.7	4.8	a
Brulee	2.8	0.27	2.2	3.3	b
Butterbaby2	2.8	0.27	2.2	3.3	b
Butterbaby1	2.7	0.27	2.2	3.2	b
Honeynut	2.4	0.27	1.8	2.9	b
Hamilton	2.1	0.27	1.6	2.7	b
AutumnFrost	2.1	0.27	1.6	2.7	b

Table 2.3: Significance groupings of mini butternut squash varieties for taster overall preference (A) and perceived sweetness (B). Varieties that do not share a letter in the "group" column are considered statistically different from each other.

A complete and detailed set of tables showing significance groupings for flavor traits across all crops and market classes is located in Appendix E. Like in the mini butternut case, ANOVA and follow-up pairwise comparisons sometimes revealed exceptional varieties in regard to flavor qualities, but they also helped identify varieties that may be sub-par for certain traits as well. Such a case can be seen with pink slicing tomatoes grown in SKC's high tunnel trial. The results from the ANOVA tests of significance are presented in Table 2.4A. Umami is highly desired by chefs when it comes to tomato flavor, and Table 2.4A shows there are statistical differences between varieties for umami ($F=5.2$, $p=0.0020$). The significance groupings shown in 2.4B reveal 'Chef's Choice Pink' was rated significantly lower (mean=1.7) for perceived umami than all other varieties.

Table 2.4A: ANOVA Table using Satterthwaite's method: Pink Tomatoes (High Tunnel)				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	3.3	0.83	1.3	0.30
Texture	13	3.3	4.2	0.0064
Sweetness	3.8	0.95	0.91	0.47
Acidity	7.9	2.0	2.7	0.045
Bitterness	36	9.1	20	<0.001
Umami	14	3.5	5.2	0.0020
Intensity	12	2.9	4.0	0.0086
Overall preference	12	3.1	3.5	0.017

Table 2.4B: Significance Groupings: Pink Tomatoes (High Tunnel) - Umami					
Variety	emmean	SE	lowerCI	upperCI	group
MarthaWashington2	3.1	0.27	2.6	3.6	a
2401	3.1	0.27	2.6	3.6	a
BWHybrid	3.0	0.27	2.5	3.5	a
MarthaWashington1	2.7	0.27	2.2	3.2	a
ChefsChoicePink	1.7	0.27	1.2	2.2	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Table 2.4: Results from series of F-tests assessing fixed effect of pink tomato variety on each flavor characteristic for SKC's high tunnel trial (A). Significance groupings for pink tomato varieties grown in the high tunnel for umami (B). Varieties that do not share a letter in the "group" column are considered statistically different from one another.

Correlations

Correlation matrices were created to evaluate significant relationships between variables within crops and market classes, but the main interest was examining significant correlations with tasters' overall preference. Table 2.5A summarizes the results for each crop as a whole, while Table 2.5B looks at correlations by market class, and Appendix F contains complete correlation matrices for individual tasting sets, market classes and crop species. The correlation between overall preference and flavor intensity was significant across all crops, while texture and sweetness were significant for all crops except one (sweet peppers and potatoes respectively). In some cases (bolded in Table 2.5), significant correlations between overall preference and a flavor variable were detected despite F-tests not indicating differences between varieties for neither overall preference nor the correlated variable. Table 2.5B is helpful for comparing market classes and/or sets of varieties. For example, red tomatoes grown in SKC's high tunnel trial only show significant correlations with taster preference for texture (r=0.46) and umami (r=0.73). But the results from tastings with the tomato breeding lines indicate significant correlations between taster preference and appearance (r=0.52), texture (r=0.63), sweetness (r=0.73), acidity (r=0.43), umami (r=0.57) and flavor intensity (r=0.81).

Table 2.5A: Significant Correlations with Taster Overall Preference for All Crops in 2019 SKC Organic Variety Trials

	Appearance	Texture	Sweetness	Acidity	Bitterness^	Umami	Intensity
Butternut Squash	0.57***	0.75***	0.77***	NS	-0.52*	NA	0.73***
Carrots	0.30**	0.72***	0.75***	NS	-0.52***	NA	0.56***
Cucumbers	0.54***	0.68***	0.55***	NS	NS	NA	**0.36***
Lettuce	NS	0.64***	0.71***	**-0.29***	-0.75***	NA	0.53***
maxima Squash	0.62**	0.83***	0.92***	NS	NS	NA	0.90***
Melons	NS	0.80***	0.92***	NS	NS	NA	0.94***
Sweet Peppers	NS	NS	0.56***	NS	NS	NA	**0.67*****
Potatoes	NS	**0.73*****	NS	NS	NS	**0.72*****	0.70***
Tomatoes	0.44***	0.68***	0.70***	0.30***	NS	0.45***	0.74***

Table 2.5B: Significant Correlations with Taster Overall Preference across Market Classes in 2019 SKC Organic Variety Trials

	Appearance	Texture	Sweetness	Acidity	Bitterness^	Umami	Intensity
Mini Butternut Squash	0.80**	0.92***	0.75*	NS	NS	NA	0.78**
Large Butternut Squash	NS	NS	0.94***	NS	NS	NA	0.68*
Purple Carrots	NS	0.84***	0.63**	NS	-0.67**	NA	**0.59****
Red Carrots	NS	0.76***	**0.82*****	NS	-0.64***	NA	**0.58****
Orange Carrots	NS	0.68***	0.74***	NS	NS	NA	0.64***
Asian Cucumbers	0.69*	NS	NS	NS	-0.85	NA	NS
Mini Cucumbers	NS	NS	**0.81***	NS	NS	NA	NS
Pickling Cucumbers	NS	0.73***	NS	NS	NS	NA	0.59**
Butterhead Lettuce	NS	NS	**0.85****	NS	NS	NA	**0.76****
Little Gem Lettuce	NS	NS	NS	**-0.97*****	NS	NA	NS
Green One-Cut Lettuce	NS	NS	NS	NS	NS	NA	NS
Red One-Cut Lettuce	NS	NS	NS	NS	NS	NA	NS
Blue Green *maxima* Squash	NS	0.80*	0.93***	NS	NS	NA	0.93***
Red Pink *maxima* Squash	NS	**0.84****	0.93***	NS	NS	NA	0.92***
Orange-Fleshed Melons	NS	0.80***	0.93***	NS	NS	NA	0.94***
Red Bell Peppers	NS	NS	NS	**-0.62****	NS	NA	NS
Yellow Orange Bell Peppers	NS	NS	0.81*	NS	NS	NA	0.96***
Red Corno di Toro Peppers	NS	NS	NS	NS	NS	NA	NS
Orange Yellow Corno di Toro Peppers	NS	NS	NS	NS	**-0.93****	NA	NS
Red Potatoes	NS	NS	NS	NS	NS	NS	0.77*
Yellow Potatoes	NS	NS	NS	NS	-0.81*	NS	**0.91***
Cocktail Tomatoes	NS	NS	NS	NS	NS	NS	**0.91****
Orange Yellow Tomatoes (Field)	NS	**0.89****	NS	NS	NS	NS	0.78*
Red Tomatoes (Field)	NS	0.46*	NS	NS	NS	0.53*	NS
Pink Tomatoes (High Tunnel)	NS	NS	NS	0.86*	NS	NS	NS
Red Tomatoes (High Tunnel)	NS	0.65**	NS	NS	NS	0.73**	NS
Breeding Tomatoes	0.52***	**0.63*****	0.73***	**0.43****	NS	**0.57*****	0.81***

Table 2.5 Summaries of significant correlations with taster overall preference. (A) Shows correlations for crop species. Correlation coefficients are bolded to show cases where the F-test did not indicate differences between varieties for overall preference, the flavor variable

correlated with preference, or both. (B) separates crops into their different market classes. *** p < 0.01, ** p < 0.05, * p< 0.10 Tasting sets did not have enough entries to calculate correlations using variety means for Galia melons, multi-colored potatoes, cherry tomatoes, and pink field-grown tomatoes. ^In carrots, harshness was used instead of bitterness. NA: Trait not evaluated for this crop. NS: Correlation was not significant at the 0.10 level.

k-Means Clustering

To examine the internal reliability of SKC's flavor methods, k-means clustering was applied to each crop species to see whether the internal variety checks clustered together. If the methods are reliable, then the repeated check variety should always appear in the same cluster as its counterpart. Out of a total 37 internal checks, 29 pairs (78%) clustered together. The results are summarized in Table 2.6, which lists the variety used as a check, the total number of clusters (k) for the crop, and whether both entries of the check variety ended up clustered together.

Table 2.6: Internal Reliability as Assessed by k-means Clustering Analysis

Crop	Market Class	Check Variety	Total Clusters (k)	Cluster Together
Butternut Squash	Mini	Butterbaby	3	yes
Butternut Squash	Large	Waltham	3	yes
Carrot	Orange	OSAPopulation	4	yes
Carrot	Orange	Bolero	4	yes
Carrot	Red	RedSamurai	4	yes
Carrot	Red	AtomicRed	4	*no*
Carrot	Purple	P8390	4	yes
Carrot	Purple	PurpleElite	4	yes
Carrot	Purple	PurpleHaze	4	yes
Cucumber	Asian	TastyGreen	4	yes
Cucumber	Asian	Suyo	4	yes
Cucumber	Mini	Manny	4	yes
Cucumber	Mini	Yildo	4	yes
Cucumber	Pickling	Artist	4	yes
Cucumber	Pickling	Bushy	4	yes
Lettuce	Little Gem	Newham	3	*no*
Lettuce	Red One-Cut	EazyleafBurgandy	3	yes
Lettuce	Red One-Cut	SalanovaRedIncised	3	yes
Lettuce	Green One-Cut	SalanovaGreenOakleaf	3	yes
C. maxima Squash	Blue Green	StellaBlue	3	yes
C. maxima Squash	Red Pink	OrangeSummerSP	3	*no*
Melon	Orange-Fleshed	Divergent	3	*no*
Melon	Orange-Fleshed	FirstKiss	3	yes
Melon	Galia	E25G.00345	3	yes
Pepper	Red Bell	Ace	3	yes
Pepper	Red Bell	Beachcraft	3	*no*
Pepper	Orange Yellow Bell	Flavorburst	3	*no*
Pepper	Red Corno	Karma	3	*no*
Pepper	Red Corno	Carmen	3	*no*
Pepper	Red Corno	BridgetoParis	3	yes
Pepper	Orange Yellow Corno	Escamillo	3	yes
Tomato	Cherry	JTO-1099	3	yes
Tomato	Red	2331.1	3	yes
Tomato	Red	MountainPrincess	3	yes
Tomato	Red	Siletz	3	yes
Tomato	Red	PiluKS	3	yes
Tomato	Pink	MarthaWashington	3	yes

Table 2.6: A summary of k-means clustering analysis to assess the internal reliability of SKC's rapid flavor evaluation methods. The algorithm was applied to each crop as a whole and looked across all variables. This table shows the repeated variety checks used throughout the 2019 season as well as the total number of clusters and whether the check variety clustered together.

As an example, the k-means clusters for butternut squash are presented in Figure 2.2. In total, there were two internal checks throughout all the 2019 butternut squash tastings

('Waltham' and 'Butterbaby'). Notably, the internal checks are denoted with a 1 and 2 following the variety name. For example, in Figure 2.2, 'Butterbaby1' and 'Butterbaby2' in cluster #2 represent an internal check as do 'Waltham1' and 'Waltham2.' A complete set of k-means clustering figures can be found in Appendix G along with plots used to determine appropriate number of clusters.

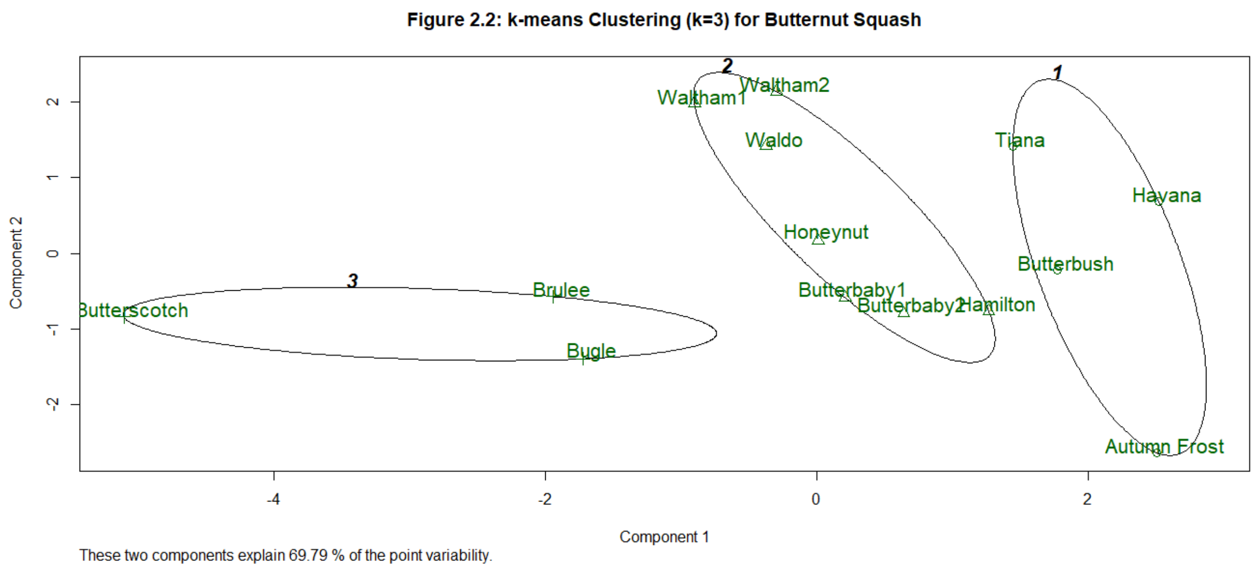

Figure 2.2 k-Means clustering of butternut squash tasted in SKC's 2019 trials.

Figure 2.3 shows the k-means groupings for *C. maxima* squash where the 'Orange Summer' check pairing grown in Spooner did not cluster together. The other check pairs that did not end up clustered together in the final analysis include carrots ('Atomic Red'), lettuce ('Newham'), sweet peppers ('Flavorburst,' 'Beachcraft,' 'Karma,' and 'Carmen'), and melons ('Divergent') grown at the west Madison site. These k-means plots can be found in Appendix G.

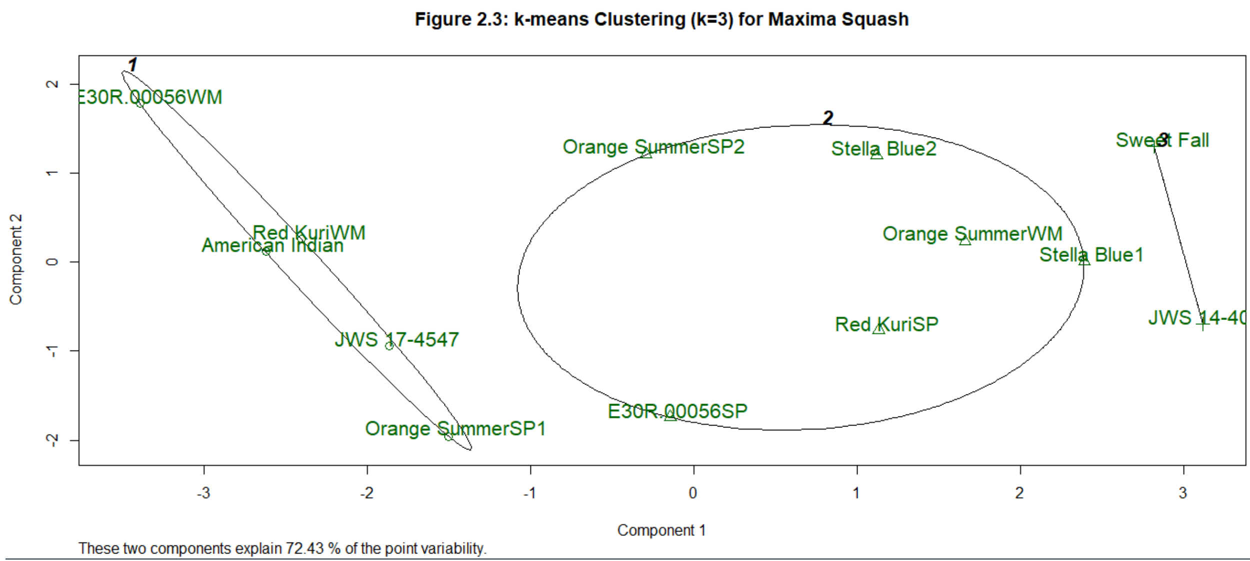

Figure 2.3 k-means clustering for *C. maxima* squash where the internal check variety 'OrangeSummerSP' did not cluster together. Carrots, lettuce, and melons additionally all had one check pair that did not group together, while sweet peppers had four (see Appendix G).

Additionally, as a way to make potential breeding decisions and compare experimental varieties to others, breeding lines for SKC's tomatoes and the Carrot Improvement for Organic Agriculture Project (CIOA) were clustered alongside commercially available cultivars using k-means. Figure 2.4 shows an example of orange carrots.

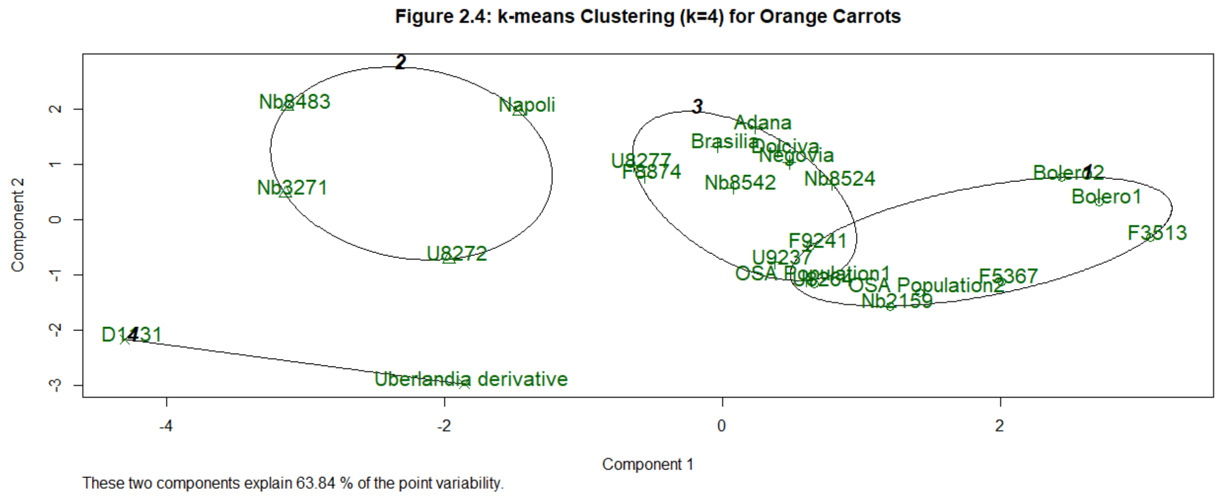

Figure 2.4 k-means clustering for orange carrots comparing breeding lines from the CIOA project with commercially available cultivars.

Discussion

The rapid sensory methods utilized by SKC are more accessible for crop researchers than traditional approaches, and they offer flexibility when it comes to analysis. Depending on the scope or context of the study, different analytic methods can be applied to the same data. For this reason, it is neither informative nor practical to provide an exhaustive discussion of all crop flavor data from SKC’s 2019 trials. (A complete set of visuals and tables for crops and market classes can be found in Appendices D - G). Presented here are only some of the ways to analyze and interpret data from participatory rapid sensory evaluations as well as a few examples that highlight the utility and reliability of these methods. As sensory exploration in the plant science field continues to grow, surely so too will the insights into decision-making based on this type of flavor data.

Identifying Specific Varieties for Flavor-Related Components

In some research contexts, it may be desirable to answer simple questions about a specific group of varieties. One of SKC's goals is to provide relevant information to Upper Midwest organic growers to aid in their variety selection. Importantly, the communication between SKC and their grower-partners is bidirectional. In other words, local growers play a big role in choosing which varieties should be entered in the trials in the first place. With increasing consumer attention toward eating and culinary qualities, growers want to know if any of these specific varieties are more preferred for their flavor than others. This is especially true in the SKC foci of the organic and local food market sectors (Yiridoe et al., 2005; Tropp, 2014).

Mini butternut squash is a relatively new market class; the smaller size has made them quite popular in restaurants as well as for farmers markets and CSAs. Its rise is partly attributed to the success of the variety 'Honeynut,' a mini butternut released specifically for flavor and eating quality as a collaboration between chef Dan Barber at Blue Hill Stone Barns and breeder Michael Mazourek at Cornell (Hultengren et al., 2016). In 2016, one survey showed 90% of squash growers in the Northeast were growing at least one variety of mini butternut, mostly 'Honeynut' (Hultengren et al., 2016). The interest has also spread to the Midwest, where many of SKC's grower-partners cultivate mini butternut types and have a vested interest in finding varieties with superior eating quality for their customers.

The results show that 'Butterscotch' is more preferred than all the other trial varieties except 'Brulee' (Table 2.3A) and was perceived as significantly sweeter than the others too (Table 2.3B). Depending on how 'Butterscotch' performs in the field (i.e. yield, disease resistance, etc.) this type of information can be very useful to a farmer's decision-making when planning their season. In this case, 'Butterscotch' is lower yielding and therefore may be a good recommendation for gardeners or farmers catering to chefs, while 'Brulée' has better field performance and is likely a more appropriate choice for the average farmer. While superior sweetness might not be as impactful as overall preference for farmers making choices about which varieties to grow, it is still useful information for marketing and variety characterization. Direct-consumer sales typically involve face-to-face interactions where sellers (i.e. growers) can emphasize unique characteristics about their produce to buyers (i.e. professional end-users and eaters) (USDA, 2016; Fernquist & Ekelund, 2014). Hypothetically for example, a market farmer may win over a parent by highlighting that 'Butterscotch' tastes sweeter than other varieties, and therefore requires less added sugar to get the kids to eat it.

Similarly, restaurants and chefs are becoming increasingly important parts of the food system. Chefs can offer large and stable contracts or accounts for growing specific crops and varieties, which are often critical to growers' revenue streams (Polling et al., 2017). Likewise, until the COVID-19 pandemic, prevalence of going out to eat at restaurants had been rising since the 1970s, so chefs are increasingly the ones preparing and putting food on people's plates (Guthrie et al., 2013; Tropp, 2014). Even with restaurant restrictions due to COVID-19, chefs continue to be important leaders in food culture on social media and television. With this in mind, it is reasonable to also consider potential interests of chefs when it comes to local food and flavor research. A chef may be interested in contracting with a farmer to grow an early crop of pink tomatoes high in umami for a particular culinary application. The groupings shown in Table 2.4B illustrate a different scenario than with the butternut squash. In this case, it seems as though 'Chef's Choice Pink' would be a variety to avoid, but there are several other potential options. The chef and farmer can then use data on other traits like yield, earliness, or disease resistance to come to a decision that best works for them.

Determinants of Preference

While classical sensory analysis with trained panelists is outside the realm of feasibility for most crop researchers, food scientists have often paired their descriptive panel work with consumer preference tests (Varming et al., 2004; Lawless & Heymann, 2010; Oltman et al., 2014). This is lucky since a trove of information exists on different flavor variables and their relationship to people's preference. The correlations established in the literature can be compared to the ones found with SKC's rapid evaluation methods. With that being said there are a few potential caveats. First, most consumer preference studies have focused on grocery store shoppers rather than local food consumers. It has already been mentioned that local food consumers have higher overall expectations when it comes to flavor and eating quality, so there may be differences in drivers of preference for this subset of local food consumers compared to the broader population (Tropp, 2014; Organic Trade Association, 2019).

Second, the ability to detect significant correlations depends somewhat on the differences among the varieties in question. The variability between cultivars for particular traits (ex: acidity or bitterness) may not be as large as it would be in a more diverse breeding population, or alternatively it may be so large that it obscures other relevant correlations. An example was mentioned in the results from Table 2.5B by comparing the 2019 correlations for SKC's high tunnel red slicing tomato trial versus their breeding program. Neither sweetness, acidity, nor flavor intensity were significantly correlated with overall preference for the varieties in SKC's red slicer trial, which contained five F1 hybrids and two heirloom varieties. However, when looking at a much more diverse group of tomatoes (breeding lines in the F2-F5 generations), appearance, sweetness, acidity, and flavor intensity all had significant relationships with taster preference. In the literature, the relationship between sweetness and overall preference in tomatoes is well established, so its absence in the SKC high tunnel red slicer trial is likely a reflection of the varieties being similar for some traits and not for others (Klee et al., 2018; Oltman et al., 2014).

Overall, the correlations found using SKC's methods align strongly with the existing literature across all crops. This agreement is encouraging for situating these rapid sensory methods in the greater context of sensory and flavor science. Continuing with tomatoes as an example, many variables have found to be significantly correlated with overall preference, the strongest of which is flavor intensity (Klee et al., 2018; Baldwin et al., 1998; Aurand et al., 2012). Sweetness, texture, and appearance have all shown to have significant relationship with eater preference too (Oltman et al., 2014; Baldwin et al., 1998; Aurand et al., 2012). Figure 2.5A shows significant correlations for the combined data of all SKC's 2019 tomato tastings including their breeding material. The strongest relationship appears to be intensity, followed closely by sweetness and texture. The SKC results also show significant correlations with acidity and umami. The relationship between these two variables and tomato preference are not as ubiquitous in the literature, but they do exist, and chefs have articulated that umami is critical to good tomato flavor and very desirable in the kitchen (Oruna-Concha et al., 2007; Marcus, 2005).

The alignment between correlations found with SKC's rapid sensory methods and in the literature does not stop with tomatoes. In their review, Corrigan et al. (2006) found the main drivers of consumer preference in *Curcurbita maxima* squash to be sweetness, flavor intensity, and texture. Table 2.5A shows the correlations between flavor components and preference for all *C. maxima* squash in the SKC crew tastings, which match the literature. This suggests SKC's methods are able to hone in on the same established correlations, and perhaps even find new drivers of preference like appearance (see Table 2.5A)

In carrots, the literature says preference correlates most strongly with perceived sweetness but is also related to texture, flavor intensity, and decreasing harshness (Varming et al., 2004; Simon et al., 1980). Once again, SKC's combined carrot tasting results (Table 2.5A) reflect the established literature quite accurately. Taken together, it appears SKC's methods are robust enough to reach similar conclusions as formal sensory approaches when it comes to correlating flavor variables with preference, and they have additional potential utility, too.

The construction of correlation matrices (seen in Appendix F) can be both insightful and useful. For example, once the main determinants of preference are determined for a crop, a researcher could construct a new survey to evaluate only those variables. When it comes to public events with lots of distractions and people, SKC has learned a shorter and more straightforward survey tends to create a better experience for tasters and provides more complete data for researchers. Correlation matrices for sensory data can also be helpful if there is a desire to do follow-up experiments with other rapid-type methods. For example, they can help create axes for use in projective mapping, an exercise in which assessors place samples in a sensory space based on perceived similarities and differences; this is especially suitable for use with expert end-users like chefs and bakers (Dawson & Healy, 2018; Frost, 2015).

Correlation matrices can also inspire new research questions or areas for further exploration. One curious pattern that arose in SKC's 2019 trials is a significant correlation between sweetness and texture across multiple crops (seen in Appendix F: tomatoes, lettuce, butternut and *C. maxima* squash, melons, cucumbers, and carrots). The explanation behind the relationship between sweetness and texture is intriguing. Perhaps the underlying cell or tissue organization plays a role in releasing sugars once a vegetable or fruit is chewed. Or maybe these traits are correlated because some breeders are actively selecting for flavor and understand the importance of both, so sweeter varieties also tend to have better texture. Further research to understand the relationship between these two traits might enhance breeding efforts aimed at improving sensory qualities.

Likewise, another interesting consideration is whether or not the main drivers of preference change depending on the market class. Lettuce offers a striking example. In 2019, SKC trialed three market classes of lettuce: butterheads, little gems, and one-cut types. The literature around consumer preferences in lettuce is somewhat sparse, but a positive correlation with sweetness and a negative correlation with bitterness have been recognized (Chadwick et al., 2016). The results for lettuce in Table 2.5A show similarly important drivers of preference. Figure 2.5B adds more nuance, however, as correlations with preference change when looking at the different lettuce market types. Preference in little gem types show an extremely close negative relationship with acidity while butterhead lettuce shows a positive correlation with sweetness and flavor intensity. Additionally, no significant correlations were found when looking at red and green one-cut types individually.

Granted, the point made earlier about the nature of differences between varieties in the trial must be considered. It is reasonable to suspect that with a different set of varieties there might be a greater consensus across market classes. However, a similar pattern can be seen in different carrot (i.e. red, purple, and orange) and tomato (red, pink, and orange/yellow) market classes where the main drivers of preference change in rank for different colors (see Table 2.5B and Appendix F). A single gene change underlying the change from red to pink tomatoes has shown to have a significant effect on 122 other fruit metabolites, some of which are involved in flavor (Zhu et al., 2018). When taken alongside the inferences from SKC's variety trials, there may be reason for researchers to look more in-depth at differences in preference and flavor across market classes as well as potential genetic links between sensory qualities and market class to aid future breeding work.

Multi-Trait Comparisons of Varieties

To further situate SKC's sensory evaluation methods among others, the internal reliability was assessed by applying k-means clustering to each crop to assess how check varieties grouped. Overall, k-means analysis indicated the internal reliability of SKC's methods was decent. However, Figure 2.3 shows one of the eight cases in which the internal checks did not cluster together.

In considering why these checks did not group together, sample collection may have played a role. In the case of 'Newham' lettuce, 'Carmen' corno di toro pepper, 'Divergent' melon, and 'Beachcraft' and 'Flavorburst' bell peppers, all of these varieties were used as field checks or fillers meaning they appeared more times in the trial than other varieties. Since sample collection dictates incorporating material from every field plot of the variety, varieties used as fillers and field checks end up with more heterogenous tasting samples. With a more varied sample, there is increased likelihood these checks would not group together especially with each taster only eating one or two pieces of each sample. The 'Orange Summer' squash is less easy to explain, but the Spooner site (zone 4a) is a challenging place to fully ripen squash, and SKC unfortunately lacks access to appropriate squash storage facilities. Both of these may have been relevant factors. For 'Atomic Red' carrots and 'Karma' corno di toro peppers, the explanation behind separately grouped checks is also not clear. One consideration might be both these varieties are open-pollinated, so while relatively uniform in appearance, there may still be some variability in the genes underlying flavor. While they adjust to try and improve their method's internal reliability, in the meantime k-means clustering can serve as a tool to inform SKC of how much weight their flavor evaluation carries on a case-by-case basis. In other words, if k-means clustering reveals an internal check did not group together, then SKC can choose to take those results with a proverbial grain of salt.

K-means clustering can also be useful for comparing breeding lines or varieties soon-to-be-released with cultivars already commercially available. This is especially useful when one cultivar gains in popularity or notoriety such as the 'Honeynut' squash or 'Bolero' carrots, which Varming et al. (2004) found to be "exceptional" in terms of flavor. These varieties can act as a sort of benchmark for good flavor and eating quality. In Figure 2.4, 'Bolero1' and 'Bolero2' appear together along with several breeding lines from the Carrot Improvement for Organic Agriculture (CIOA) project. Notably, flavor is being considered and selected for as part of this project, so it is encouraging these CIOA lines group together alongside 'Bolero' for the flavor data since it has become a standard both for eating qualities and organic growing. Additionally, the other commercially available varieties in the trial ('Adana,' 'Dolciva,' 'Napoli,' and 'Negovia') group separately, showing they are more similar to each other and significantly different than 'Bolero' and the CIOA lines in the other cluster. This is good evidence the breeders are making gains in their selection for better flavor.

It is perhaps obvious, however, that breeding and growing choices cannot be based on flavor and eating quality alone. Realistically, varieties must yield enough such that both farmer livelihoods and food prices for consumers can be optimized. This is especially true in an era marked by expanding populations and increasing climatic chaos. But breeding for flavor (especially traits like increased sugars) often has a negative tradeoff with yield (Klee & Tieman, 2018). Nonetheless the growing interest in better eating qualities of fruit, vegetables, and grains is not likely to wane. Finding ways to overlay flavor data along with other traits (ex: disease resistance, yield, earliness) using k-means clustering or other multivariate techniques would greatly enhance breeding efforts in the future.

Conclusions

It is clear that rapid sensory methods have scientifically valid and practically feasible applications for plant breeders and researchers interested in evaluating flavor. In the case of SKC and its crew survey tool, the network of plant breeders, researchers, field station workers, and students has proven extremely valuable in this type of evaluation. From a scientific perspective, the crew tasters have a unique and important role in the flavor evaluation process. When questions come up or concerning trends are noticed in the data (ex: tasters are giving hedonic ratings on intensity scales), these can be mitigated relatively easily through listserv communication and reminders from the tasting facilitator. Similarly, many crew tasting members participate for multiple years. Through continued participation, their sensory description and detection abilities likely improve. There is also great disappointment when efforts are put into preparing for a tasting and no (or few participants) show up, and the crew network provides some safeguards to having a reasonable number of participants to make sure labor tradeoffs are worth it. This type of organization has also allowed for numerous other plant breeders and graduate students to access SKC's network and incorporate sensory components into their projects.

This analysis has showed how these rapid sensory methods can be used to produce beneficial information about specific varieties for characterization, local marketing, and enlightening grower decisions. Likewise, they can be used to investigate questions about crops as a whole. Potential applications in breeding such as comparing lines to commercially available or standout cultivars have also been discussed alongside possibly relevant questions for further investigation. So, in addition to being more accessible and practical, these rapid sensory methods are flexible in the types of ways crop researchers can use them for their advantage. It is only the beginning of this new context for flavor analysis in agricultural research. As these alternative methods to traditional sensory science become more accepted in plant sciences and beyond, their applications will almost surely expand.

Finally, it must be acknowledged that chasing the results of formal sensory scientists is problematic and cannot be the goal for plant scientists. Some of these reasons, such as the exclusion of everyday eaters, have already been discussed, and the origins of traditional sensory science should not be ignored either. Operating as if a specific group of people (i.e. professionally trained tasters, most of whom were initially white, well-educated men) are better suited to decide what people should eat concentrates power into the hands of a few. This is both scientifically and socially dangerous.

Perhaps Patterson and Aftel (2017) say is best: “what exactly people think defines good food...isn’t easy to tease out, because it’s always been bound up in broader cultural notions about what is familiar and what is exotic, what is healthful or harmful, what goes together and what doesn’t.” As part of a resilient and robust food system, diversity is considered imperative. True, diversity in crops is important, especially when it comes to flavor. Yet, it is must also be realized that the diversity of our crops reflects the diversity of the people involved in their stewarding along the way.

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Chapter Three

Networks: A necessary tool for improving agricultural Extension in an uncertain future, with a focus in organics and examples from the Seed to Kitchen Collaborative

Introduction

Agriculture is fraught with uncertainty and risk, and that has never been truer than now. As the world's population continues to grow, farmers are asked to produce more while extreme temperature and weather events lead to crop losses and serve as a reminder that industrialized agriculture is a paradox: it is seen as essential to feeding a growing population yet at the same time comes with external costs that threaten human existence. Natural disasters and low commodity prices have required billions of dollars in federal bailouts and insurance payments to keep farmers on the land. Additionally, consumers are demanding more ethical and environmentally friendly food production. Meanwhile, the COVID-19 pandemic has created unprecedented circumstances with uncertain futures. Farmers are at the center of this chaos trying to ensure their own family's wellbeing while simultaneously growing the food we put on our tables. Weighing all these demands makes a farmer's job unenviable.

Due to shrinking resources and expanding roles, today the job of Extension agents isn't enviable either. In Wisconsin for example, roughly 100 people work for Cooperative Extension on crops, but there are over 64,000 farms in the state (DATCP, 2020). In their national assessment of Cooperative Extension Services, Warner and Christenson (2019) describe a history of budget tightening by appropriators, which has pressured Extension to prove its worth and severely limited its ability to assist farmers and the public (Chaudhary & Radhakishna, 2018).

With 17,000 employees, Extension's national annual budget stands at $800 million (Warner and Christenson, 2019). This insufficient public funding has caused further diversion of Extension's time and energy, which is increasingly being spent on finding and applying for supplemental resources.

The sheer volume of farms that each county or state agent is responsible for assisting is overwhelming enough, and a bigger challenge is the diversity these farms represent. Wisconsin has more than 1500 organic farms – second in the United States only to California - but only a handful of county and state specialists with a focus in organic production (USDA, 2017), and that is considerably better than other states who have none. Whether a 400-acre conventional dairy or a five-acre integrated biodynamic operation, no two farms are alike. They all essentially require individualized solutions. This is especially true in organic and sustainable agriculture (Park & Lohr, 2007), which needs multifunctional innovation in addition to personalized, place-based solutions. Extension has historically tried to provide one size fits all resolutions which often ignore the realized variation in farming methods, sizes, and styles (Houser & Stuart, 2019).

Navigating the diversity among farms doesn't include only methods and practices. Philosophy, history, and cultural differences have to be acknowledged, too. For example, a beginning farmer, a farmer of color, and a white farmer whose family has owned the land for decades will inherently face different challenges personally and professionally. Any or all of them could call on Extension for assistance, and Extension agents must understand how history, society, and culture affect the past and present agricultural landscape in order to truly be of service. With the challenges facing farmers and Extension agents, it is time to take a step back. We must consider how Extension can become a more meaningful and relevant partner for farmers amid uncertainty and volatility.

Recognizing the existing connections between people introduces powerful new ways for understanding situations, behaviors, and incentives of food system stakeholders including farmers (Goetz et al., 2017; Chaudhary & Radhakishna, 2018). The structure of this network (who is connected to whom) and the nature of these relationships are equally important and informative. Working with networks for agricultural research, education, and outreach addresses Extension shortcomings and embraces peer-to-peer learning that is effective for farmers. Likewise, network mapping can identify leaders and disconnected individuals both of whom can have important roles. Better understanding and utilization of networks is key to improving Extension's outreach now and for the future.

While networks are a tool that can and should be applied to all types of agricultural research and outreach, this chapter focuses on their use in organic systems. The International Federation of Organic Agriculture Movements approved the following definition in 2008: "Organic agriculture is a production system that sustains the health of soils, ecosystems and people. It relies on ecological processes, biodiversity, and cycles adapted to local conditions, rather than the use of inputs with adverse effects. Organic agriculture combines tradition, innovation and science to benefit the shared environment and promote fair relationships and good quality of life for all involved" (Kings & Ilbery, 2012). The organic sector continues to grow in both sales and acreage spurred largely by consumer demand that continues to increase (see Figure 3.1; Organic Trade Association, 2020). The diversity of practices, farming philosophies, and approaches makes organic farming exceptionally difficult for Cooperative Extension to address in its traditional way, which envisions outreach and education as a linear transfer of information (Wood et al., 2014; Park & Lohr, 2007). These are the same qualities that make organic systems particularly well-suited to the application of networks (Chroma, 2008), which is illustrated by their occasional use already. In Wisconsin, joint research-Extension initiatives that have come about in the last few years like the Organic Grain Research and Information Network (OGRAIN) and the Seed to Kitchen Collaborative are examples of successful network-based strategies employed in research, outreach, and education.

The Seed to Kitchen Collaborative (SKC) is based out of the Urban and Regional Food Systems Lab at the University of Wisconsin – Madison. SKC is a participatory research network that links growers, researchers, plant breeders, seed companies, and local end-users like chefs and bakers to identify and develop high-quality vegetable varieties for organic farms in the upper Midwest. The program trials vegetable varieties on university research stations and local farms to provide information that regional organic farmers need to make variety choices. The information is also useful for breeders and seed companies who want to know how new cultivars or breeding lines perform in the region. The participatory approach taken by SKC invites both farmer suggestions and independent breeder/seed companies to submit entries into the trials. Researchers and graduate students collect data for traits like yield and disease resistance, and the group evaluates flavor and eating quality by partnering with local chefs, their field crew, and the general public to do variety tastings. The results are posted to SKC's website and dispersed to each group of stakeholders via email and in-person meetings.

In this chapter, the general implications of more widespread network use in Extension and agricultural research are drawn out as ways to mitigate historic shortcomings and encourage farmer learning. SKC is used as an example of the meaningful work that can be done when networks are used as a tool by reporting on feedback from a recent survey of SKC stakeholder groups (farmer responses = 19, chefs = 6, and breeders/seed companies = 6). Complete survey summaries are available in Appendix H. Finally, network mapping is discussed as a way to identify important individuals and guide Extension programs and goals with a look at potential approaches to mapping SKC as a prospective project. In looking towards the future of farming, change is inevitable, but whether or not Extension will be an active participant in the shaping of this process remains to be seen. Network-based tools and concepts will be vital if Extension is going to step up and be a valuable partner for the future of agriculture and society.

A Brief History of Extension and Organic Agriculture in the United States

The 1914 Smith-Lever Act created the Cooperative Extension Service "to empower farmers, ranchers, and communities of all sizes to meet the challenges they face, adapt to changing technology, improve nutrition and food safety, prepare for and respond to emergencies, and protect our environment" (USDA). Since its beginning, Cooperative Extension has been seen as a messenger and helped spread the latest university-produced research and technology to farmers (Park & Lohr, 2007). While the mission ostensibly was education, effectively Extension enticed growers to adopt the latest tools and innovations provided by industry. Removing the burden for farmers to do on-farm experimentation and refining technologies that improved yields for farm livelihoods and food security was seen as a win-win.

The major industrial growth and technology advancements spurred by the world wars created broad social changes. Admittedly, these changes, both broad and location-specific, cannot fully be described in this chapter, and readers are encouraged to seek out the trove of scholarship on the topic. Here the goal is to provide a historical context for the rise of organic agriculture as a counter-current to mainstream ideas.

The post-war era was marked by increasing segmentation, mechanization, and specialization in just about every industry and sector. Agricultural research became the job of Land Grant universities rather than innovative farmers. And gradually college departments grew and split into smaller more distinct fields of study with less crosstalk. Extension's job was to translate the scientific results from the university to farmers, while the farmer's job became solely to produce, produce, produce. It was this type of reductionism and specialization that led to the formulaic mentality of chemical-based agriculture that persists today (Chroma, 2008). This was the birth of an entirely new type of farming where farmers were expected to eagerly adopt the latest technology (ex: fertilizer, equipment, hybrid variety) in order to make an economic boom (Houser & Stuart, 2019). Otherwise they risked going bust. Before this reductionist approach to agriculture and the rise of the global commodity market, farmers were not necessarily engaging with salespeople who wanted farmers dependent on their products, nor was farming success gauged exclusively by yields and profits (Aeberhard & Rist, 2009). From this point on, there were more and more stakeholders with increasingly specific and vested interests in on-farm practices.

While agriculture and the world changed drastically, organic farming persisted as an alternative despite the characterization by most Land Grant scientists that it was an antiquated, inferior version of agriculture that foolishly rejected chemicals, rather than one based on living systems. At one point, it was described in publications as "Third World agriculture" that would never catch on (Agunga & Igodan, 2007). In the English-speaking world, F. H. King, Sir Albert Howard, Rudolf Steiner, and Lady Eve Balfour are considered some of the pivotal founders of organic agriculture. The influences of Black and other people of color like George Washington Carver, Fannie Lou Hamer, and Booker T. Whatley need also be remembered even in brief historical recounts. Notably, however, the inspirations for this supposedly new school of thought were highly derivative from traditional techniques and ideas about environmental, soil, and pest management in India and China, and these contributors should not be forgotten either. Sir Howard articulated a "living bridge between soil life, crops, livestock, and mankind's health" (Heckman, 2005) that explained the philosophy of organics in a nutshell. In his 1940 manifesto *Look to the Land*, Lord Northbourne was the first to use the word "organic" in print to describe "having a complex, but necessary interrelationship of parts, similar to that in living things" (Paull, 2014).

The period from 1940 to 1979 saw gradual overall growth for organic farming against a backdrop of increasing socio-political polarization. In 1942, J.I. Rodale started publishing his *Organic Farming and Gardening* magazine. By 1960, over 260,000 subscriptions were purchased, and 20 years later, subscriptions reached 1.3 million (Heckman, 2005). Part of this growth was due to the alignment between organic proponents and the environmental movement that started in the early 1960s. The environmental movement was (and still is) highly politicized (McCright & Dunlap, 2011), which in turn brought organic agriculture into the political fire, too. And with politics comes public debate and criticism as even more groups of people became invested in what farmers do and how they do it.

From 1979 to the early 2000s, organic agriculture gained gradual recognition and acceptance mostly due to public interest and demand. In 1979, California became the first state to establish a short-lived law defining organic standards, and in 1981 the American Society of Agronomy held its first organic symposium. While there were certainly times when political agendas did much to bury efforts to advance organic farming, in 1990, passing of the Federal Organic Foods Production Act set the stage to establish national "standards, accountability, and facilitate commerce for organic products" (Heckman, 2005). The law also established the Organic Research and Extension Initiative (OREI), although it was 14 years before they gave out their first grants. And it was over a decade after the law's passing before any agreement was reached on the USDA's National Organic Standards (NOS) in 2002. Still today, the NOS is contentiously debated.

Today there are strict labeling and certification rules and even entire businesses that focus solely on organic products and trade which have become part of everyday life. In 2019, organic made up 5.8% of total agricultural sales (Organic Trade Association, 2020). Both sales and acreage are at all-time highs (see Figure 3.1; Organic Trade Association 2020), and consumer trends focused on environmentally friendly and transparent food production will likely continue to drive demand (Reganold & Wachter, 2016). In the 2018 Farm Bill, OREI was boosted to baseline funding of $50 million to help respond to these demands and support the organic community through research and Extension. Even with additional funding and grant opportunities, Extension and research efforts focused on organics will benefit from the use of networks to maximize their impact.

U.S. Organic Food vs. Total Food Sales, Growth & Penetration, 2010–2019

CATEGORY	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Organic Food	22,961	25,148	27,965	31,378	35,099	39,006	42,507	45,209	47,862	50,065
Growth (%)	8.0%	9.5%	11.2%	12.2%	11.9%	11.1%	9.0%	6.4%	5.9%	4.6%
Total Food	677,354	713,985	740,450	760,486	787,575	807,998	812,907	822,160	840,972	860,583
Growth (%)	1.2%	5.4%	3.7%	2.7%	3.6%	2.6%	0.6%	1.1%	2.3%	2.3%
Organic (as % Total)	**3.4%**	**3.5%**	**3.8%**	**4.1%**	**4.5%**	**4.8%**	**5.2%**	**5.5%**	**5.7%**	**5.8%**

Source: Organic Trade Association's 2020 Organic Industry Survey conducted 2/7/2020–3/27/2020 ($mil., consumer sales).

Figure 3.1 The growth of organic sales in the United States from 2010 to 2019, values are in one hundred thousand USD (Organic Trade Association, 2020). The same trend is visible in organic acreage, which reached 3.1 million acres in 2019 (Organic Trade Association, 2020).

Addressing History and Extension Shortcomings with Networks

The stories of the past shed light on current farmer perceptions of Extension and some of Extension's historic shortcomings. Organic farmers historically have been ignored by the Land Grant university system and their Extension services. In some cases, organic growers were even ridiculed, which for decades forced them to become innovators and experimenters on their own. Importantly, it was through social networks that these farmers shared and legitimized their questions and solutions with other people (Hassanein, 1999; Chroma, 2008; Gailhard et al., 2014). So historically, informal farmer networks have underpinned the spread and adoption of organic innovations, and therefore seem an obvious tool for improving partnerships between organic growers and Extension today.

This farmer-led inquiry was very different than university-led research because it was often reactive to a problem and not designed nor analyzed with statistics the same way as university science. Critics characterized farmers as unqualified and illegitimized their on-farm experimentation (Aeberhard & Rist, 2009). Tensions grew between the two sides as organic farmers felt neglected and unsupported. In the 1980s and 90s, organic proponents publicly accused Land Grant researchers (and in effect their Extension systems) of being "wedded to conventional agriculture" (Agunga & Igodan, 2007).

Luckily, this relationship has improved. In a survey of 99 Ohio organic farmers, 70% expressed a strong interest in Extension information and services (Agunga & Igodan, 2007). Today's organic farmers seem both willing and excited to partner with researchers and Extension to move forward. Unfortunately, the same survey found a similar majority (69%) of organic farmers thought Extension agents did not know enough to help them nor understand the real needs of organic farmers (Agunga & Igodan, 2007). Others have found similar opinions and perceptions both in the United States and across the globe: Extension is ill-equipped to help with adaptable or farm-specific solutions, which is what organic farmers need (Rodriguez et al., 2008; Park & Lohr, 2007; Sarker & Yoshihito, 2009; Wood et al., 2014; Gailhard et al., 2014).

Margaret Chroma (2008) at Cornell encapsulates these thoughts in an interview with a New York organic grower involved in farmer-led research: "In our group, the statement of problems *and* the solutions come from the farmers. Whereas in the Extension model, the problem statement comes from Extension educators and the solutions come from Extension educators" (emphasis added). So, while attitudes seem to have changed between organic farmers and Extension, the perceived disconnect appears unresolved.

Perhaps the flip side of the same coin is how agricultural research has changed since the inception of Extension and the Land Grant universities. Agriculture of any type is inherently complex and dynamic. And even though the foundations of statistics and experimental design are rooted in agricultural research, by its nature, farming does not lend itself well to formal experimentation. Any attempt to make a question more visible or studiable makes it less realistic agriculturally. The history of agricultural research has been to separate and study the sub-components of farming, and the results have often been used to develop and market products for selling to farmers, not to necessarily understand agriculture as a whole (Stone, 2016).

For many proponents of organic and sustainable agriculture – both grower and non-grower – the understanding of agriculture transcends the boundaries of university departments. Farming plays a vital role in the health and strength of rural communities, and certain practices can reflect spiritual beliefs and cultural identities (Boody et al., 2005). In other words, agriculture is "more than a means of livelihood, it is [also] a way of life" (Sutherland, 1987).

The incredible variety of organic farming practices have developed from diverse views of nature and values shaped by places, people, and politics (Kings & Ilbery, 2012). These varying farm philosophies and values ultimately drive different knowledge and innovation needs in the organic and sustainable communities because they have a systems-based understanding of agriculture rather than a narrow scientific understanding of its underlying parts (Chroma, 2008; Wood et al., 2014; Gailhard et al., 2014). Understandably, it has been exceptionally hard for both Extension and researchers to consider these factors in their work. The difficulty comes from both the inherent complexity of transdisciplinary research and also from their own institutional cultures (Park & Lohr, 2007), which ask them to be politically neutral and encourage projects that are more intrinsically “scientific” with tangible deliverables (Warner & Christenson, 2019). Regardless, Extension’s ability to incorporate these issues as part of research and education is fundamental for being a critical resource in today’s agriculture and society.

Organic farmers need multifunctional solutions not solely limited to the bio-physical aspects of farming, but ones that also consider social, cultural, and economic impacts over time and space. Surveys show that while organic farmers appreciate and value the information Extension provides around production and environmental conservation, their biggest needs are around issues like land tenure, time, access to appropriate inputs and equipment, marketing challenges, and navigating bureaucratic red tape (Rodriguez et al., 2008; Lubell & McRoberts, 2018; Piercy et al., 2011; Sarker & Yoshihito, 2009; Agunga & Igodan, 2007). Networks are well-suited to helping Extension in these areas where they have historically fallen short. Embedding Extension work into multidisciplinary networks helps Extension stay relevant and reach an increasingly diverse group of stakeholders while also creating spaces for farmers to build leadership and problem-solving capacity among themselves (Healy & Dawson, 2019; Chroma, 2008; Wood et al., 2014; Gailhard et al., 2014).

SKC does this by partnering with local chefs and end-users who have become more important partners in local food systems over the last few decades (Polling et al., 2017; Lang, 2019). Nearly half of farmer respondents to SKC's stakeholder survey reported that restaurants are a part of their primary market outlets, and in at least one instance, a farmer and chef have independently contracted to grow a specific pepper variety for the chef to feature (Healy & Dawson, 2019). A large contract like this can afford the farmer some financial stability and purchasing power for resources. In another instance, when asked about their favorite experience working with SKC, one farmer said, "the winter squash trial really inspired us in terms of the potential for new varieties and exceptional flavors. This also gave us ideas and clarified some of our own priorities for the traits that suit our operation." In this case, being a part of SKC's network facilitated this farmer finding what works best for them, which could make planning future seasons more efficient.

SKC has a participatory tomato breeding project with a handful of regional farmers that also illustrates how networks can be helpful in organic research, education, and outreach. The initial tomato crosses were done by UW graduate students in a campus greenhouse, and SKC has been selecting promising lines and individuals over the last few years based on their university trials. Participating farmers were also sent early generations of these crosses to make their own selections along with an open invitation for questions or assistance from SKC researchers. There is much already published on the benefits of participatory plant breeding, which focuses mostly on farmers gaining new skills around breeding, selecting, and seed saving as well as the ability to develop locally or farm-specific adapted varieties (Healy & Dawson, 2019).

In their survey response to their favorite SKC experience, one farmer participant said "[SKC] gave me the resources and reason to save my own tomato seed. This was a first for me as a grower of 25 years." This is the type of skill and capacity building that comes along when networks are used as a tool. Before the initial seed was sent to farmers, SKC sought feedback for what types of tomatoes sell best in each of the farmer participant's market, which allowed the project to be tailored to individual farms with minimal effort. In a personal communication, one of these participating farmers also talked about an unforeseen outcome: bringing the breeding lines to their market stand and highlighting the project seemed to attract a new group of buyers. So, in addition to the development of tomato varieties that are well-adapted to organic farms in the upper Midwest, farmers are gaining new skills and confidence, receiving more individualized solutions, and discovering new market niches. These are the types of multifunctional solutions needed by organic farmers, which Extension has largely been unable to deliver.

By doing research and outreach with a network approach, long-term goals and priorities are determined collaboratively while simultaneously encouraging farmer capacity to do self-innovation and discovery (Healy & Dawson, 2019). Networks then allows these ideas to spread, evolve, and become legitimized by other farmers (Gailhard et al., 2014). This approach importantly centralizes farmer expertise rather than implying the dominance of university science and embraces the history of collaboration and resilience in organic farming research. These are both key to Extension and Land Grant universities becoming more meaningful partners for organic growers in the future. Furthermore, working within network structures may provide avenues for farmers to hold Extension and Land Grant universities more accountable in their research and education endeavors. SKC still experiences some drawbacks with their approach since the lab still acts as a hub for planning and communication, and these logistics become more time-consuming as the network grows. Some of the specific challenges identified by the recent survey will be discussed in the section on "Looking Forward: Network Mapping Possibilities."

Networks are Built for Farmer Learning

How farmers learn has been a subject of study for decades. A consensus has emerged that involves both social learning – learning by watching what other farmers do – as well as didactic learning – learning from some type of instructor (Dolinska & d'Aquino, 2016; Stone, 2016). The instructors in didactic learning come in many forms. They may be government or certifier agents, Extension educators, Land Grant researchers, non-profit and NGO representatives, or developers/sellers from an industry. Nonetheless, they are all senders of information that farmers take in and consider. Network-based strategies allow for educators and researchers to leverage these two learning types at the same time.

Linking farmers to diverse stakeholders (i.e. the instructors in didactic learning) is one way to make their learning more efficient. By bringing differing viewpoints together, farmers get a more complete picture presented at once with less opportunity for one person or group interest to be louder than the others. Likewise, some problems may require expertise of people not typically involved in agriculture or organic systems such as lawyers or municipal officials. Facilitating networks also creates opportunities for developing deeper interpersonal relationships, which are more influential than mass communications (Rimal & Lapinski, 2015).

Fostering and strengthening relationships was another founding principle for SKC when they sought to create a network of plant breeders and researchers, seed companies, chefs, and organic growers. SKC recently found out through their survey that their reach extends to other occupations and groups too. Stakeholders were asked with whom they shared their SKC results and experiences with, and most farmers said, “other farmers” (84%), “local chefs” (53%), and “customers” (47%). A few also provided write-in answers saying they shared their experiences with financial backers and donors, class visits from local schools, and Soil Sisters Wisconsin, a women-led program part of the non-profit organization Renewing the Countryside. One seed company added they shared their experiences with distributors, and three chef respondents said they shared with produce sellers, although it’s unclear if these produce sellers were also farmers.

Agricultural educators have historically approached their work assuming farmers simply lack information, and while unjustly so, the trend continues today (Rodriguez et al., 2008). Historically, much university-disseminated information has not been relevant for organic systems, like providing spray recommendations for plant disease rather than cultural control methods.Unfortunately, university information was more likely to point out problems with organic systems rather than propose research-based solutions, which hasn’t encouraged farmers. Luckily, this is changing, and growers are eager for the research starting to come out of realistic organic systems. At the same time university and Extension colleagues view organic systems and growers with increased respect and recognition that they are important parts of the agricultural community (J. C. Dawson, personal communication). In addition to this information, organic farmers need motivation, support and trust (Piercy et al., 2011; Park & Lohr, 2007). Extension must switch to privileging the learning process rather than the specific information, innovation or technology they are trying to spread. So, while linking farmers to other relevant stakeholders is critical, perhaps more important is connecting farmers with each other to create more opportunities for social learning and communities of practice (Dolinska & d'Aquino, 2016; Wood et al., 2014; Gailhard et al., 2014).

Farmer-to-farmer connection is central to participatory research whose whole premise is collaborative and collective inquiry grounded in the real-life experiences of farmers and their locality (Piercy et al., 2011). It is considered essential to advancing and improving organic agriculture for the future (Ponzio et al., 2013; Gailhard et al., 2014) because what results is a body of practical knowledge better suited for those it's intended for (i.e. organic farmers) (Piercy et al., 2011). In studies of grazing networks in New Zealand and Australia, graziers were more likely to adopt a practice if it had been generated through a group process (Beaman et al., 2018; Wood et al., 2014), and in general, organic farmers in the United States enjoy the opportunity to participate in research (Piercy et al., 2011).

Farmers also prefer to and learn best from other farmers (Stone, 2016; Ponzio et al., 2013; Chroma, 2008; Piercy et al., 2011; Gailhard et al., 2014). This is probably because farmers see their peers as experts and also due to higher levels of trust that stem from shared experiences and overlapping values. Most often, farmers seek out other farmers when they are having problems or need advice, and they are typically eager to share their experiences with others (Jansen et al., 2010; Agunga & Igodan, 2007). In the same survey of Ohio organic farmers, 87% sought out other farmers for information while only 16% reported using Extension (Agunga & Igodan, 2007). A similar situation seems to be true for the farmer respondents in SKC's impact survey. When asked which information sources were most important in their decision-making around variety selection, 73% of the respondents said another farmer's recommendation was "very" or "extremely" important. Similarly, 71% of farmer responses said they were "very likely" to share what they learn in SKC with others.

Part of the reason for the effectiveness of participatory research is the increased opportunities for social learning among farmers with hands-on activities and on-farm demonstrations (Piercy et al., 2011; Wood et al., 2014). Importantly, while networks and groups are essential for farmer-to-farmer learning, the learning and collaboration process still has to be actively facilitated (Chroma, 2008; Wood et al., 2014), which should be the role of Extension. The farmer respondents in SKC's survey echoed their appreciation for hands-on experience and empirical observation. When it came to which information was most impactful for their variety selection decisions, 89% said the observed results of their own on-farm trial were "very" or "extremely" influential, and all except one farmer (95%) said that seeing variety performance on their own farm was a "very" or "extremely" important part of their participation in SKC. The farmer survey responses also seem to corroborate the necessity of farmer leaders. Only 11% and 16% of responses said that the January stakeholder meeting in Madison and visits to the university research station, respectively, were "very" or "extremely" important for their decision-making. Notably, both activities are researcher-led, which may underscore why farmers find them less valuable.

Facilitating farmer networks can also address various obstacles to farmer learning. Inconsistencies of a technology or practice over time and space is one barrier to agricultural outreach and education (Dolinska & d'Aquino, 2016), and unrecognizability of products caused by brand names or hybrid seed aliases (like in corn) is exacerbated by marketing (Kloppenburg, 2004). Organic farmers also must pay close attention to active ingredients, product formulations, and regulatory constraints while navigating confusing advertising to avoid jeopardizing their certification. Modern agricultural science and technology are also advancing much faster than farmers and the public can have a conversation or assess the situation (Dolinska & d'Aquino, 2016). If experience, information, and opinion sharing can be facilitated with the use of networks by Extension, then these impediments to farmer learning and knowledge gain can be diminished.

On-farm demonstrations, pasture walks and field days are some familiar and practical examples of bringing farmers together to facilitate these conversations. Farmers must also be central to the leading and planning of these events to make them most effective. One SKC farmer responded to a survey question about their favorite SKC memory by saying, “meeting at events with other farmers and chefs to discuss successes and favorites.” Farmers were also asked if participation in SKC had led to other changes on their farm other than adopting a new variety. One farmer responded they “changed their [hoop house] tomatoes because of the field day visit,” and another reportedly adjusted spacing for lettuce and potatoes for the same reason. In some ways, these unforeseen benefits can be thought of as emergent properties brought about by the use of a network.

These outreach and education activities can also play a role by reinforcing social norms among farmers. In the context of agricultural outreach and education, social norms are often framed as a potential mechanism for instigating widespread adoption of a certain practice, technique, or innovation by addressing social barriers (Matous et al., 2013; Beaman et al., 2018; Griskevicius et al., 2008), but this is not what Extension should be after. The diversity of organic agriculture is inherently one of its strengths. By facilitating networks and creating communities of practice, new discourse and norms are formed that can provide the framework for individual actions which enhance roles in collective knowledge production (Gailhard et al., 2014; Dolinska & d’Aquino, 2016). In other words, the goal is not to normalize and spread a specific agricultural idea but rather the practice of co-generating knowledge and motivating farmers to participate in this process.

Farming behaviors, values, and philosophies also move along cultural and gender lines, and farmers – like people in general – show a preference for learning from others that are most similar to them (Park & Lohr, 2007). Female farmers prefer and are more comfortable learning from other female farmers (Trauger, et al., 2008). The same can be said for queer farmers (Wypler, 2019) and farmers in various ethnolinguistic or religious groups (Matous et al., 2013; Stone, 2016). Obviously, this poses additional challenges for Extension agents, but careful facilitation of on-farm research and outreach activities can allow farmers with common identities to meet and form new bonds. This is another way of building local leadership and capacity as well as trust and strength among farmers while also making room for cultural respect and relevance.

Network Mapping Can Identify Important Individuals

While network frameworks can help deploy research and Extension efforts in organic agriculture, visualizing their structure with mapping techniques also stands to assist Extension in becoming a better partner for organic growers. After being observed in several locations, a core-periphery structure was assumed to be the default way that farmer networks organized themselves (Piercy et al., 2011; Lang, 2019). This type of structure (seen in Figure 3.2) features a central (i.e. core) group of farmers who have more frequent and extensive communication with each other and outside stakeholders, while a peripheral group sits on the edges. The periphery members may still have some connection to core members, although generally they are not as densely connected.

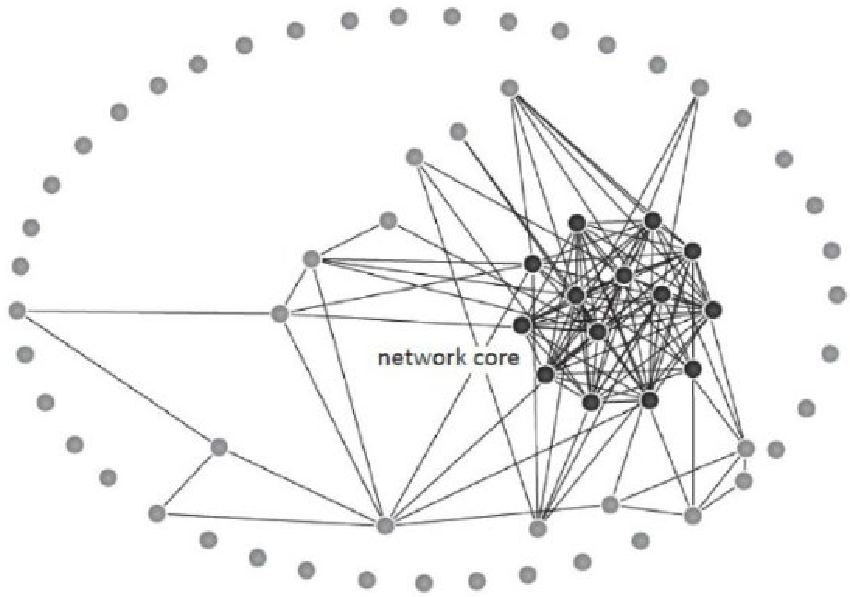

Figure 3.2 An example of a network with a core-periphery structure. Core members are the black-colored dots and are densely connected to one another while the periphery group is gray. (Gluckler & Ries, 2012).

More mapping of farmer knowledge and information networks in the United States and abroad, however, has revealed quite the diversity of network forms aside from the core-periphery. In some cases, no core group nor structural hierarchy can be identified (Goetz et al., 2017; Wood et al., 2014; Chaudhary & Radhakishna, 2018; Gailhard et al., 2014), which extends the idea that each farm is unique to each farmer network as well. Some describe agricultural networks as "distributed systems" (McRoberts & Lubell, 2018) where relevant information is developed and communicated by a wide range of stakeholders organized in complex and dynamic ways.

SKC has not formally mapped their network, which is unfortunate because relatively few agricultural network maps have included non-farmer stakeholder groups. Anecdotally however, there is no obvious core group of farmers, although there does appear to be a central group of chef collaborators. Three out of the six chef survey respondents said they were introduced to SKC by another chef, and researchers have noticed a consistent group that show up for meetings and tasting events more reliably than others. On a day when chefs were invited to tour the university research station trials, this core group of chefs also brought several members of their restaurant staffs, which shows how they can introduce new people into the network.

Whether looking at a network map of chefs, farmers, or another stakeholder group, individuals who are more centrally located or densely connected could be of particular interest for Extension. Figure 3.3 shows an actual network of small-sized farmers served by an Extension program in an unnamed State (Goetz et al., 2017). The yellow dots represent farmers, and the arrows indicate the direction of information flow. Arrows pointing toward a yellow dot, for example, indicate that another grower is coming to that farmer for advice or information. When visualized, the handful of densely connected farmers becomes obvious. These farmers can act as gatekeepers who decide which information to pass on to others (Granovetter, 1983). They can also play an important role as opinion leaders, so named because they are well-respected by their peers and highly visible in their communities (Shaw, 2010). They open doors for identifying innovative responses to problems that are locally meaningful and lead the acceptance of non-farmer agents in the network (Keys et al., 2010; Valente & Pumpuang, 2007). Identifying and engaging with these leaders is imperative for Extension because of their role in information flow; they not only help diffuse behaviors, attitudes, beliefs and motivations (Valente & Pumpuang, 2007; Gailhard et al., 2014), they can also relay relevant issues and problems facing farmers to develop Extension goals and programs. It is likely that early engagement with SKC's chef opinion leaders is one reason for the program's growth and success over the years.

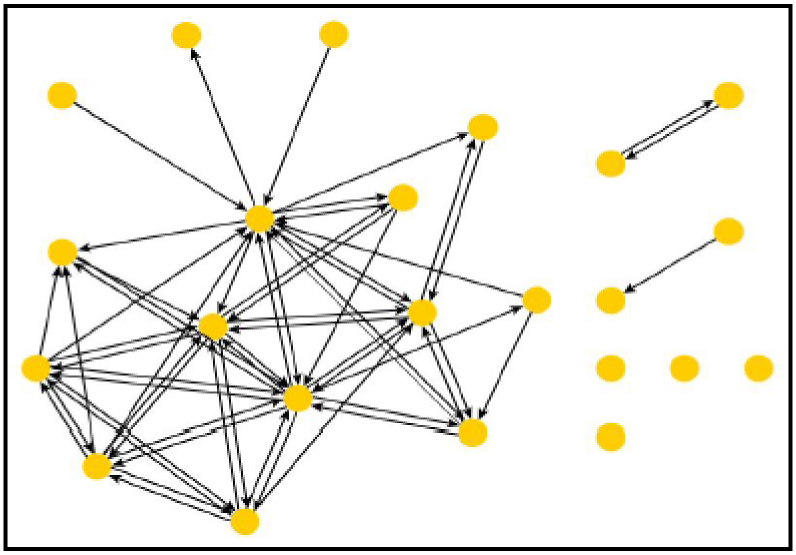

Figure 3.3 A network map of small-sized farmers served by a specific Extension program in an unnamed State from Goetz et al. (2017). Yellow dots represent farmers, and arrows indicate the direction of information/knowledge flow. Notice a central group of densely connected individuals as well as a less connected periphery including several individuals completely unconnected to others.

Figure 3.3 clearly shows not all the farmers are connected; there are two pairs and four individuals who are disconnected from each other and the rest of the farmers in this network. In addition to those highly connected, these unconnected individuals may also be worth more of Extension's attention. Since these farmers are not embedded in the network, they can be less impacted by the influence and judgements of others, which in some cases has made them hubs of innovation and ingenuity (Chroma, 2008; Beaman et al., 2018; Sarker & Yoshihito, 2009). Extension's goal might be to connect these individuals and invite their contributions into the network so other members can learn.

As Extension tries to use networks more, it is necessary to emphasize that networks are both dynamic and contextualized. While relatively few studies have formally mapped networks of diverse stakeholders in agriculture, one Master's thesis at the University of British Columbia did map the north Okanogan regional food system (Lang, 2019), and Chaudhary and Radhakishna (2018) mapped the University of Pennsylvania's Extension system. Most mapping of agricultural networks has included only farmers even though agriculture doesn't exist in a bubble. It sits at the crossroads of many industries and players, so mapping other participants in food system networks needs to happen more because there are surely more insights. Figure 3.4 shows a network of 17 ranchers (blue dots) and five scientists (orange dots) working together on a grazing project in New Zealand (Wood et al., 2014). Notice the scientists are clustered together while the farmers are more distributed. Despite scientists recruiting the rancher participants in this study, no hierarchy is present. Instead, what can be seen is a flat, spanning, and overall densely connected network. While the scientists appear well-connected and embedded in the network, their non-farmer roles likely make their opinions and information less salient for ranchers, which adds complexity to the situation (Wood et al, 2014; Gailhard et al., 2014). Formally mapping organizations like SKC and other diverse stakeholder networks may enlighten ways to go about research and Extension by revealing connections or the lack thereof and the relevance of certain roles and individuals (Gailhard et al. 2014; Chaudhary & Rashakishna, 2018).

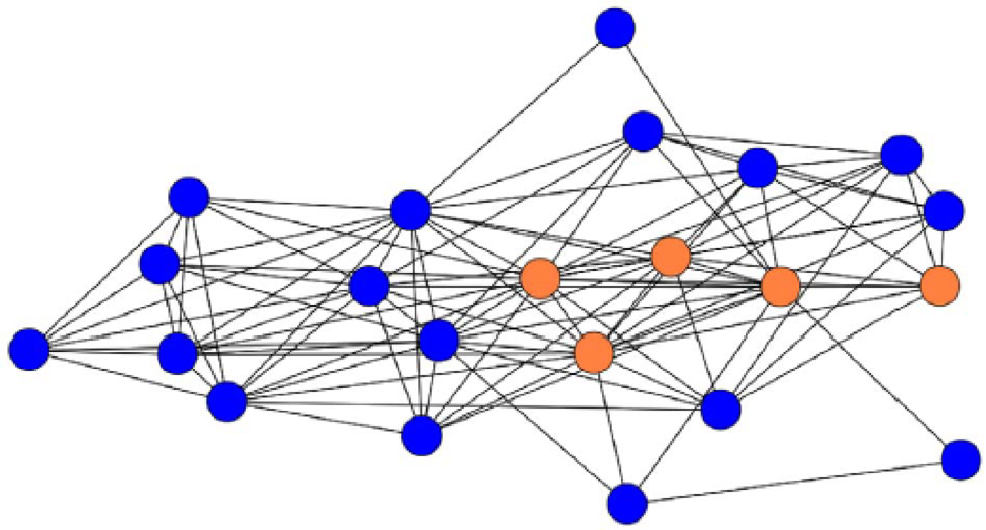

Figure 3.4 A network map of five scientists (orange dots) and 17 ranchers (blue dots) working on a grazing project in New Zealand (Wood et al., 2014). This is the network of contact prior to the start of the project. Despite the scientists recruiting rancher participants, there is no hierarchy in the network structure, which instead shows a densely connected, flat, spanning network of relationships. Network position does not tell the whole story, however, as opinions from researchers do not have equal salience as those from other ranchers.

In addition to network structure changing based on who is being mapped, networks of the same people can shift depending on what type of information is flowing (Chaudhary & Radhakishna, 2018). Figure 3.5 is an adaptation of Figure 3.3 that shows the same network of small-sized farmers when looking only at the flow of marketing information and advice (Goetz et al., 2017). For this small-sized farmer network, the connections between people changed when looking at the sharing of resources versus marketing information or equipment sharing. This could create potential concern for using network tools in Extension.

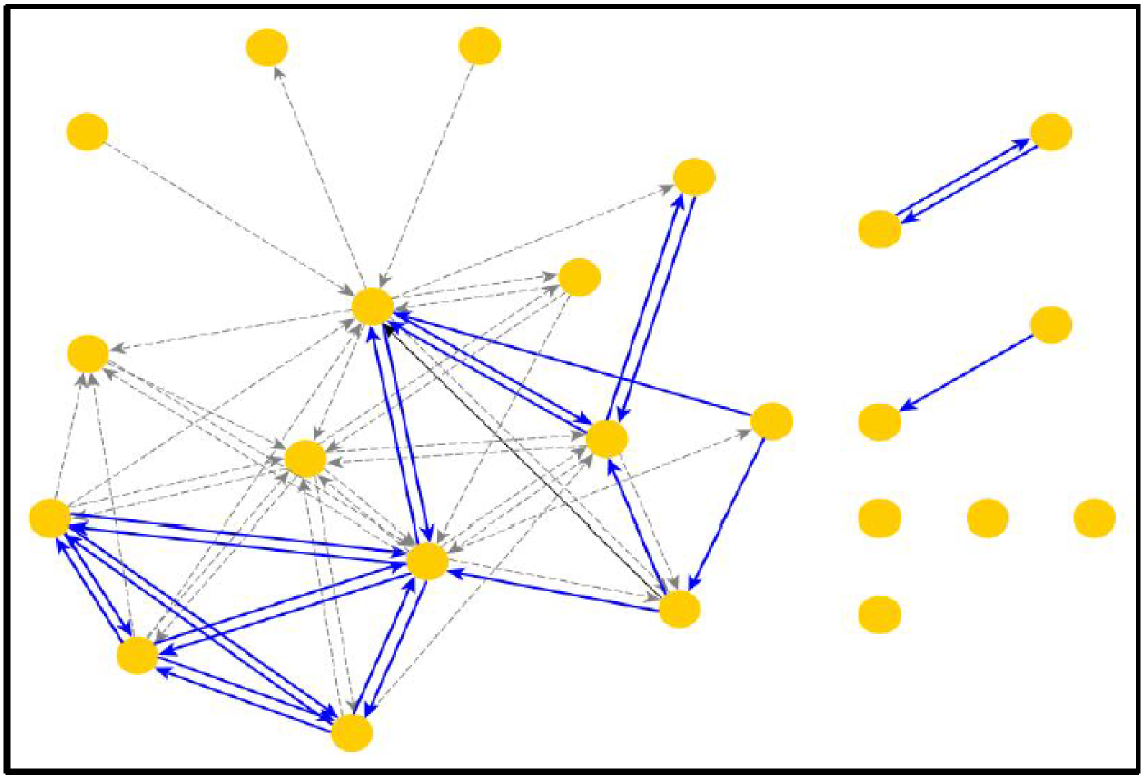

Figure 3.5 Patterns of marketing information exchange in a network of small-sized farmers. This is the same network of small-sized farmers shown in Figure 3.3 from Goetz et al. (2017). The flow of marketing information and advice is shown by the blue arrows. The lighter gray arrows show the overall network from Figure 3.3. In other words, the gray arrows show relationships that are meaningful for one type of information (ex: production advice or equipment sharing) but not for exchanging marketing information.

While the shifting connections may seem like a challenge, they are actually a tool to inform education and outreach efforts. A recent Master's student at Michigan State University used network mapping to propose solutions to challenges faced by the state's beginner farmer training programs. Network maps showed that certain issues like equipment and resource access might be easily improved by simply making new connections between training programs (Comer, 2019). The author also emphasized that creating new ties between groups should come with active facilitation that promotes collective problem-solving and empowers beginning farmers without positioning Extension as “granters of power” (Comer, 2019).

Formal network mapping may also have additional use for Extension in terms of the complementary metrics it can provide (Chaudhary & Radhakishna, 2018). While not the focus here, various statistics can be calculated using network maps that describe qualities like how connected the network and each individual is, or the amount of control the average individual has over information flow (Wood et al., 2014; Goetz et al., 2017; Granovetter, 1983). The quantitative information that comes out of network mapping may have utility for evaluating Extension impacts and social benefits of participatory research (Warner & Christenson, 2019; Chaudhary & Radhakishna, 2018). Both of these have been discussed as barriers to increased funding and adoption of this type of work in agriculture (Park & Lohr, 2007; Healy & Dawson, 2019; Comer, 2019; Warner & Christenson, 2019).

Looking Forward: Network Mapping Possibilities

As SKC researchers have realized the powerful effects of network use in their research and outreach, there has developed a new interest in visualizing their network by creating its map. After attending a conference in upstate New York, SKC came about in 2013 as the brainchild of UW researchers and local chefs in the Madison area (Healy & Dawson, 2019). It became clear that by linking chefs, farmers, plant breeders, and researchers, there was much to gain for everyone involved. It is important to realize, however, that people are already connected to others in less official ways. In some cases, Extension or research endeavors may warrant creating or formalizing a new network like in the case with SKC, while there may also be existing networks with percolating potential that Extension agents and researchers can access. Network mapping may help identify these less formally organized groups so Extension can better engage and plan with them in mind. This section looks at two possible approaches to network mapping for SKC (and others) in the future.

In general, there are two approaches to network mapping: participatory and software-based. The two processes are summarized in Table 3.1 along with some of their advantages and disadvantages. The software-based approach is considered the more formal of the two, although its methods are somewhat prohibitive due to more arduous data collection and the cost and expertise required to use the software (Goetz et al., 2017). Participatory mapping is a relatively new topic in the social sciences and so far, has been applied mostly in global health campaigns (Lang, 2019; Chaudhary & Radhakishna, 2018). While less systematic and more time-consuming than software-based approaches, participatory network mapping surely has more applications for agricultural and food systems work (Lang 2019).

TWO APPROACHES TO NETWORK MAPPING

Step One: Identify Goals and Boundaries

-What is purpose of map/network? (Identify gaps and connections, solve farm-related problem, etc.)

-What are the geographic boundaries? (State, county, watershed, etc.)

-Who are the people being mapped? (Farmers, researchers, chefs, etc.)

-What type(s) of relationships are being mapped? (Equipment sharing, production info., policy work, etc.)

PARTICIPATORY APPROACH	SOFTWARE-BASED APPROACH
Step Two: Gather participants - Introduce activity and identify core and periphery with participants (individually or altogether) **Step Three:** Mapping activities - Participants place stakeholders and map relationships in core and periphery from own perspective (see Lang, 2019) - Can be done once or multiple times and combined **Step Four:** Present and Discuss Results - New ideas and connections - Revisit from time to time and seek feedback	**Step Two:** Generate list of members - Existing groups/networks; Extension and census data; conferences; snowball sampling **Step Three:** Survey/Interview Members - Careful survey construction: "Who do you go to for _____?" See Goetz et al. (2017). **Step Four:** Enter data into software - UCINET; NetDraw; Tulip and many others **Step Five:** Present and Discuss Results - New ideas and connections - Revisit from time to time and seek feedback
Pros: flexible; engaging for participants; easy and accessible; leverages interpersonal relationships; monetarily inexpensive**;** simultaneous learning and empowerment	**Pros:** larger potential reach; more encompassing; easy computer-generated maps, visuals and network metrics; no assumed structure**;** systematic
Cons: cannot identify un/disconnected individuals; time-consuming; assumes core-periphery structure; network metrics not as easily calculated	**Cons:** financial cost and expertise required for software; too "formal" or "academic" to be engaging for stakeholders**;** difficult survey process

Table 3.1 Summaries of two recognized approaches to network mapping. Both essentially start with the same step of identifying goals and boundaries for the network and mapping exercise. From there, participatory (Lang 2019) and software-based (Goetz et al., 2017) approaches diverge slightly before they both end with a sharing and discussion process.

Both approaches to network mapping start similarly. Establishing boundaries, goals and the purpose of the network and its map is a critical first step (Chaudhary & Radhakishna, 2018).

Often these are dictated by an apparent need or observed problem like the case with SKC: local direct-market organic farmers were having trouble finding varieties that grew well on their farms and satisfied the high-quality expectations of their restaurant, CSA, and farmers market customers. Alternatively, the problem could be water pollution caused by agricultural runoff, or rural economic recovery post-COVID-19. There may be other purposes that guide network mapping goals such as examining information sharing patterns amongst Hmong farmers in Wisconsin. In any case, the initial step should involve identifying what types of people and relationships are the focus in the context of the problem (Chaudhary & Radhakishna, 2018).

From there, the two mapping approaches follow slightly different trajectories. In participatory network mapping, the target stakeholders identified in step one are brought together and introduced to the project. One disadvantage to participatory mapping is that it assumes a core-periphery structure (Lang, 2019) even though in reality that's not always true. Nonetheless, participants collaboratively assign what individuals or roles are core members and which are periphery. From there, participants create their own maps, usually color-coded, that show the people and relationships relevant to the problem from their perspective. These can be compiled and layered together over time and with different groups to produce a more complete picture (Lang, 2019). The process can also be a learning exercise and a way to empower participants in and of itself.

Software-based mapping however follows slightly different procedures. After the purpose and goals are established in step one, they should be used to generate a list of network members (Goetz et al., 2017). In the case of farmers, agricultural census and Extension records can be helpful (Chaudhary & Radhakishna, 2018). Looking for and working with other groups nearby can also be a viable option. In setting up SKC, Associate Professor Julie Dawson tapped heavily into listservs and contacts at FairShare CSA Coalition (Madison, WI) to find interested farmer participants. In recent years, SKC has also engaged with chefs in Wisconsin's Culinary Ladies Collective to continue expanding its reach throughout the state.

Once a list of members is generated, survey(s) and/or interviews are conducted to uncover relevant relationships that weave people into a network. While seemingly straightforward, creating a survey to assess social network relationships is deceptively hard and care should be taken to construct the survey tool appropriately. For more discussion and advice on survey creation see Goetz et al. (2017). Once the survey and interview process are complete, data is entered and analyzed with one of many potential software programs to create statistics and visuals.

Both participatory and software-based mapping approaches also end with the same process of sharing and discussing the results (Goetz et al., 2017; Lang, 2019). Just by itself this can be an informative process where people get new ideas about potential collaborations, learn who to contact with questions, and talk about the next steps toward solving the problem. Some post-mapping discussion and reflection questions adapted from Lang (2019) are shown in Table 3.2. Importantly, while the two mapping techniques differ, they should not be considered mutually exclusive nor in opposition to each another. Surely the two approaches can complement one another in new applications for organic farming and agriculture broadly.

Post-Mapping Discussion/Reflection Questions
- Does network include all individuals, groups, and organizations needed for success?
- Are the right connections in place? If so, are they strong or weak?
- Who is not connected that should be? Why might that be?
- Are any key connections missing? How can they be connected?
- Where are the gaps? What impact is that having?
- Who is actively engaged? Which members are making a difference?
-Who is playing a leadership role? Who is not but should be?
-Who are the experts in process? In planning? In practice?
- Who are the mentors that others seek out for advice?
- Who are the innovators? Are ideas shared and acted upon?
- Are there collaborative alliances? Should there be?

Table 3.2 Suggestions for discussion/reflection questions following mapping of a network. These can help guide the collective next steps in addressing the established problem and act in individual learning. Adapted from Lang (2019).

The end-process of sharing and discussing results is critical to the sustained impact of networks in Extension and research as is the continued re-assessment of impacts and relationships (Goetz et al., 2017; Shaw, 2010). SKC has used surveys every few years to evaluate its performance and seek ways to improve. The most recent survey had some insightful feedback from farmers on perceived gaps within SKC's network. One respondent said they would like to see "resources/networking for people not farming in Madison area," another echoed similar challenges of attending any off-farm events in Madison, and a third farmer requested more "on-farm visits from researchers." Perhaps as SKC has grown, the increasing number of farmers outside Madison's geographic area are feeling left out. This makes sense since time and labor commitments for communication and logistics increase as the network grows especially when the lab at UW-Madison still serves as a centralized hub. Mapping the SKC network could help pinpoint ideal locations to focus on for new field days or outreach events. With the uncertainty of a new post-COVID-19 normal, SKC and other participatory networks will also have to be creative in coming up with solutions to farmer's feedback especially in their efforts to continue evaluating flavor and sensory qualities in vegetable varieties. If SKC researchers can do more farm visits, then perhaps filming farmers and/or their on-farm trials might be a possibility. Footage from different areas could be combined, edited, and distributed to show growers participating and highlight results. This would address farmer requests for more visits, portray farmers as leaders in their communities, and engage with farmers outside the Madison area who may feel forgotten. To evaluate flavor without public or crew tastings that violate COVID-19 restrictions, there may be potential for farms to do more on-farm sensory evaluations with their crew or maybe even CSA members. In any case, sharing and discussing results as well as seeking stakeholder feedback on their network participation has always been and will continue to be an integral part of SKC. The same should be true for Extension agents and researchers looking to incorporate network-based tools and perspectives into their work.

Conclusion

Today's agricultural landscape is unlike any before, and new normals are on the horizon. Farmers and ranchers (especially organic) need relevant and meaningful partners to ensure their success in the future, so Land Grant universities and Extension must step up to the plate. The history of ignoring farmers as experts needs to change as does the view that farmers are passive recipients of knowledge. Extension must correct its own shortcomings by addressing farmer needs outside technology and the bio-physical aspects of farming. The time has come for Land Grant universities and their Extension systems to focus on the learning process and facilitate capacity building and leadership among farmers and farming communities. While more Extension workers are awakening to the power and possibilities afforded by network-based strategies and tools, their application in agricultural research, education, and outreach has been slow (Chaudhary & Radhakishna, 2018)

In truth no paper nor class will ever be able to provide a blueprint for this work, but network tools and concepts can provide important foundations and launching points for ideas. For some, this may require a reimagining of Extension and its role. To navigate the variety of worldviews, practices and farming philosophies, Extension agents cannot think of themselves as simply conduits of information; they must be willing to learn from the farmers and communities they serve and act as enablers of network relationships. Their actions must become meaningful and purposeful in the quest to help farmers address the complex and multifarious problems they deal with daily. Extension agents and researchers familiarizing themselves with network-based strategies and concepts is the beginning to this process of change.

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Appendix A – Crew Survey Example

The following is a series of screenshots from SKC's crew tasting survey built under Qualtrics software, version 2019.6 (SAP, Provo, UT). First, tasters are asked for their name and whether or not they attended the pre-season training activity in June 2019.


WISCONSIN
UNIVERSITY OF WISCONSIN–MADISON

Name:

Pete Sample

Answer yes to the following question if you participated in the Dawson Lab's taste training activity in June 2019.

Training

- Yes
- No

→

Next, tasters are asked to give a hedonic score from 1 – 5 for each variety's appearance. They are instructed to consider both the whole, uncut sample, which is similar to what might be encountered at a market, and the cut sample. Notice that variety names are replaced by random 3-letter codes, and any well-known acronyms such as 'CIA' or 'FBI' are avoided.

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For appearance, rate how appealing each variety looks on a scale from 1-5:

What is the likelihood you would purchase this variety at a market?
1= poor 2= fair 3= moderate 4= good 5= excellent

Appearance

	Low Market Appeal				High Market Appeal
	1	2	3	4	5
XKA Appearance	○	●	○	○	○
DHF Appearance	○	○	○	●	○
RXI Appearance	○	○	○	●	○
GHK Appearance	○	○	●	○	○
IKR Appearance	○	●	○	○	○
JVX Appearance	○	○	●	○	○
FXV Appearance	○	○	○	○	●

← →

Tasters are then asked to taste each variety one by one. The picture below shows an example for one variety, and varieties are presented in a random order. Once the taster completes this page and presses the 'Next' button, the next variety appears. Texture is rated hedonically from 1 – 5, while the other traits are intensity scales. This example includes umami as a trait, but this is only used in SKC evaluations of tomatoes and potatoes. Previously, spiciness (in hot peppers) and earthiness (in beets) have also been included for evaluation. Additionally, an open-ended evaluation is included so tasters can record any perceived unique attributes or descriptors.

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Use a 1 - 5 score for each category below:
Texture:
1= poor 2= fair 3= moderate 4= good 5= excellent

Sweetness, acidity, bitterness, umami, and intensity:
1= low 2= moderately low 3= moderate 4= moderately high 5= high

Taste

	Low		Moderate		High
	1	2	3	4	5
IKR Texture	○	○	○	●	○
IKR Sweetness	○	○	○	●	○
IKR Acidity	○	○	●	○	○
IKR Bitterness	●	○	○	○	○
IKR Umami	○	●	○	○	○
IKR Intensity	○	○	●	○	○

Describe IKR unique characteristics

fruity, lemon

→

Finally, tasters are asked to taste each variety again and give a hedonic score from 1 – 5 for their overall liking (ie: preference) for each variety.

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Taste each variety again.

Without considering appearance, give your overall liking for each variety.

Overall

XKA Overall	3
DHF Overall	5
RXI Overall	2
GHK Overall	4
IKR Overall	3
JVX Overall	2
FXV Overall	4

← →

Appendix B – Pre-season Crew Training Activity

Training Activity

Directions Identify each set as bitter, umami, salt, sour or sweet. Label the solution levels within each set as level **I, II**, or **III**, (**I** being the weakest and **III** being the strongest). Cups and sets should be labeled; if not, please inform the facilitator.

Tastes	Sour Sweet Salt Bitter Umami	**Concentration levels**	I = Weakest II = Medium III = Strongest

Name ___________________ **Circle one:** **Water** **Tomato**

SET 1		**SET 2**		**SET 3**		**SET 4**		**SET 5**	
Taste		**Taste**		**Taste**		**Taste**		**Taste**	
Cup	**Conc. Level**	**Cup**	**Conc. Level**	**Cup**	**Conc. Level**	**Cup**	**Conc. Level**	**Cup**	**Conc. Level**
A		A		A		A		A	
B		B		B		B		B	
C		C		C		C		C	

Appendix C – Summary of crops, market classes, tasting sets and internal checks

Project	Crop	Market	SubMarket	#Tastings	#internalChecks
CIOA	Carrot	Orange		3	1
		Non-Orange	Purple	1	1
			Red	2	0
			White Yellow	1	0
SKC	Carrot	Orange		1	1
		Non-Orange	Red	1	2
			Purple	1	2
	Cucumber	Asian		1	2
		Pickling	Raw	2	2
		Mini		1	2
	Lettuce	Butterhead		1	0
		LittleGem		1	1
		OneCut	Green	2	1
			Red	4	2
	Melon	Orange-Flesh		2	2
		Galia		1	1
	Pepper	Bell	Orange Yellow	1	1
			Red	2	2
		Corno di Toro	Orange Yellow	1	1
			Red	2	3
	Potato	Red		1	0
		Yellow		1	0
		Multi-Color		1	0
	Tomato	Breeding		4	0
		Cherry		1	1
		Cocktail		1	0
		Slicer	Orange Yellow	1	0
			Red	5	4
			Pink	2	1
	WinterSquash	Butternut	Large	1	1
			Small	1	1
		Maxima	BlueGreen	1	1
			PinkRed	1	1

This table shows a breakdown of each crop and its market classes. The '#Tastings' column refers to how many tasting sets were created from all the trial entries, while the '#internalChecks' column tells how many internal checks were evaluated between all tasting sets.

Appendix D - ANOVA tables using Satterthwaite's Method to assess Fixed Effect of Variety on Flavor Variables

CIOA Orange Carrots				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	65	3.8	6.0	<0.001
Texture	11	0.64	0.76	0.73
Sweetness	59	3.5	4.5	<0.001
Acidity	9.6	0.57	1.5	0.13
Harshness	63	3.7	3.9	<0.001
Intensity	19	1.1	1.5	0.13
Overall preference	60	3.5	3.6	<0.001

CIOA Purple Carrots				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	19	3.7	4.2	0.0024
Texture	18	3.6	6.4	<0.001
Sweetness	30	5.9	7.9	<0.001
Acidity	1.0	0.20	0.62	0.69
Harshness	5.7	1.1	0.87	0.51
Intensity	4.2	0.85	1.1	0.38
Overall preference	24	4.7	3.3	0.011

CIOA Red Carrots				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	49	5.5	6.5	<0.001
Texture	12	1.3	1.8	0.089
Sweetness	61	6.8	9.7	<0.001
Acidity	3.3	0.36	0.76	0.65
Harshness	74	8.3	7.8	<0.001
Intensity	21	2.4	1.8	0.086
Overall preference	74	8.2	8.1	<0.001

CIOA White+Yellow Carrots				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	12	2.9	2.1	0.13
Texture	9.5	2.4	2.9	0.058
Sweetness	15	3.7	4.2	0.024
Acidity	0.70	0.18	1.0	0.45
Harshness	13	3.1	1.7	0.23
Intensity	4.5	1.1	1.5	0.25
Overall preference	11	2.8	2.4	0.10

CIOA Non-Orange Carrots				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	83	4.1	4.4	<0.001
Texture	41	2.1	3.1	<0.001
Sweetness	107	5.3	6.9	<0.001
Acidity	7.7	0.38	0.94	0.54
Harshness	95	4.8	3.8	<0.001
Intensity	33	1.7	1.6	0.059
Overall preference	109	5.5	4.6	<0.001

SKC Orange Carrots				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	7.9	1.6	1.7	0.15
Texture	3.1	0.60	1.3	0.28
Sweetness	21	4.2	4.2	0.0031
Acidity	1.5	0.30	0.70	0.65
Harshness	4.0	0.80	0.90	0.48
Intensity	7.5	1.5	2.0	0.090
Overall preference	42	8.3	8.0	<0.001

SKC Red Carrots				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	11	2.3	2.7	0.045
Texture	3.8	0.8	1.2	0.34
Sweetness	8.8	1.8	2.1	0.11
Acidity	0.80	0.16	0.91	0.50
Harshness	12	2.4	3.6	0.017
Intensity	5.1	1.0	1.0	0.44
Overall preference	12	2.3	2.0	0.11

SKC Purple Carrots				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	4.8	0.97	0.92	0.49
Texture	6.3	1.3	2.1	0.12
Sweetness	10	2.1	5.4	0.0050
Acidity	0.71	0.14	0.61	0.69
Harshness	7.4	1.5	1.0	0.42
Intensity	6.8	1.4	2.7	0.052
Overall preference	24	4.9	5.8	0.0022

SKC Non-Orange Carrots				
Characteristic	SS	MS	F	Pr(>F)
Appearance	20	1.8	1.9	0.063
Texture	11	1.0	1.6	0.14
Sweetness	19	1.8	2.8	0.0095
Acidity	1.6	0.14	0.76	0.68
Harshness	26	2.4	2.3	0.027
Intensity	15	1.3	1.7	0.11
Overall preference	36	3.3	3.2	0.0033

All Orange Carrots				
Characteristic	SS	MS	F	Pr(>F)
Appearance	81	3.5	5.0	<0.001
Texture	14	0.62	0.86	0.65
Sweetness	82	3.6	4.2	<0.001
Acidity	16	0.70	1.6	0.057
Harshness	81	3.5	3.7	<0.001
Intensity	32	1.4	1.8	0.022
Overall preference	107	4.6	4.6	<0.001

All Red Carrots				
Characteristic	SS	MS	F	Pr(>F)
Appearance	61	4.1	4.8	<0.001
Texture	16	1.0	1.4	0.15
Sweetness	76	5.1	6.8	<0.001
Acidity	4.1	0.27	0.66	0.81
Harshness	88	5.9	6.0	<0.001
Intensity	27	1.8	1.4	0.16
Overall preference	86	5.7	5.4	<0.001

All Purple Carrots				
Characteristic	SS	MS	F	Pr(>F)
Appearance	23	2.1	2.3	0.020
Texture	24	2.2	3.9	<0.001
Sweetness	42	3.8	5.5	<0.001
Acidity	1.9	0.18	0.58	0.84
Harshness	14	1.3	0.95	0.50
Intensity	12	1.1	1.4	0.18
Overall preference	48	4.4	3.3	0.0012

All Non-Orange Carrots				
Characteristic	SS	MS	F	Pr(>F)
Appearance	102	3.2	3.4	<0.001
Texture	52	1.6	2.4	<0.001
Sweetness	133	4.1	5.7	<0.001
Acidity	9.3	0.29	0.79	0.78
Harshness	122	3.8	3.2	<0.001
Intensity	48	1.5	1.5	0.052
Overall preference	146	4.6	3.9	<0.001

All Carrots				
Characteristic	SS	MS	F	Pr(>F)
Appearance	183	3.3	3.9	<0.001
Texture	66	1.20	1.7	0.0038
Sweetness	216	3.9	5.0	<0.001
Acidity	25	0.45	1.2	0.24
Harshness	203	3.6	3.4	<0.001
Intensity	81	1.5	1.6	0.0071
Overall preference	251	4.5	4.0	<0.001

Asian Cucumbers				
Characteristic	SS	MS	F	Pr(>F)
Appearance	17	2.9	4.5	<0.001
Texture	12	1.9	2.7	0.023
Sweetness	10	1.7	1.9	0.099
Acidity	1.2	0.19	0.36	0.90
Bitterness	18	3.0	3.7	0.0040
Intensity	3.2	0.54	0.66	0.69
Overall preference	15	2.5	2.2	0.054

Raw Pickling Cucumbers				
Characteristic	SS	MS	F	Pr(>F)
Appearance	17	1.5	1.8	0.061
Texture	9.3	0.84	0.97	0.48
Sweetness	14	1.3	1.4	0.18
Acidity	9.6	0.87	1.0	0.44
Bitterness	29	2.6	2.2	0.020
Intensity	9.3	0.85	1.1	0.39
Overall preference	11	1.0	0.94	0.50

Mini Cucumbers				
Characteristic	SS	MS	F	Pr(>F)
Appearance	4.8	1.0	2.2	0.061
Texture	6.4	1.2	1.6	0.16
Sweetness	5.3	1.1	1.3	0.29
Acidity	2.0	0.39	0.53	0.76
Bitterness	5.6	1.1	1.1	0.35
Intensity	1.1	0.21	0.27	0.92
Overall preference	4.8	1.0	1.1	0.39

All Cucumbers				
Characteristic	SS	MS	F	Pr(>F)
Appearance	44	1.8	2.7	<.001
Texture	32	1.3	1.6	0.036
Sweetness	41	1.7	1.9	0.0096
Acidity	17	0.73	0.96	0.52
Bitterness	50	2.1	2.1	0.0029
Intensity	18	0.74	0.94	0.54
Overall preference	34	1.4	1.4	0.12

Butterhead Lettuce				
Characteristic	SS	MS	F	Pr(>F)
Appearance	17	2.9	3.3	0.012
Texture	9.5	1.6	1.6	0.18
Sweetness	6.1	1.0	1.3	0.28
Acidity	1.8	0.29	0.46	0.83
Bitterness	6.1	1.0	2.0	0.10
Intensity	5.1	0.84	1.3	0.30
Overall preference	4.7	0.78	0.70	0.65

Little Gem Lettuce				
Characteristic	SS	MS	F	Pr(>F)
Appearance	9.2	1.5	2.1	0.065
Texture	4.9	0.81	1.1	0.38
Sweetness	1.8	0.30	0.25	0.96
Acidity	5.4	0.89	1.2	0.32
Bitterness	12	2.0	1.7	0.14
Intensity	2.9	0.48	0.51	0.80
Overall preference	20	3.4	2.9	0.016

Green One-Cut Lettuce				
Characteristic	SS	MS	F	Pr(>F)
Appearance	18	2.2	2.8	0.0070
Texture	11	1.4	1.5	0.16
Sweetness	12	1.4	1.3	0.23
Acidity	1.9	0.24	0.51	0.85
Bitterness	21	2.6	2.6	0.010
Intensity	11	1.4	1.5	0.16
Overall preference	11	1.3	1.0	0.42

Red One-Cut Lettuce				
Characteristic	SS	MS	F	Pr(>F)
Appearance	30	2.3	3.2	<0.001
Texture	18	1.4	2.1	0.015
Sweetness	6.2	0.48	0.57	0.88
Acidity	6.8	0.52	1.1	0.32
Bitterness	31	2.4	2.2	0.012
Intensity	16	1.2	2.2	0.011
Overall preference	26	2.0	2.3	0.0080

All One-Cut Lettuce				
Characteristic	SS	MS	F	Pr(>F)
Appearance	49	2.2	2.8	<0.001
Texture	36	1.7	2.0	0.0070
Sweetness	29	1.3	1.4	0.094
Acidity	8.8	0.40	0.87	0.63
Bitterness	96	4.3	4.0	<0.001
Intensity	29	1.3	1.8	0.013
Overall preference	57	2.6	2.5	<0.001

All Lettuce				
Characteristic	SS	MS	F	Pr(>F)
Appearance	75	2.1	2.7	<0.001
Texture	68	1.9	2.2	<0.001
Sweetness	67	1.9	1.9	0.0014
Acidity	17	0.46	0.88	0.67
Bitterness	138	3.8	3.7	<0.001
Intensity	46	1.3	1.7	0.011
Overall preference	98	2.7	2.5	<0.001

Orange-Fleshed Melons				
Characteristic	SS	MS	F	Pr(>F)
Appearance	21	1.6	2.2	0.012
Texture	69	5.3	5.7	<0.001
Sweetness	70	5.4	7.0	<0.001
Acidity	8.1	0.62	1.8	0.056
Bitterness	7.9	0.61	2.1	0.021
Intensity	72	5.6	9.9	<0.001
Overall preference	90	6.9	6.8	<0.001

Galia Melons				
Characteristic	SS	MS	F	Pr(>F)
Appearance	0.067	0.033	0.31	0.74
Texture	16	7.9	11	<0.001
Sweetness	0.067	0.033	0.053	0.95
Acidity	0.067	0.0	0.060	0.94
Bitterness	0.20	0.10	0.23	0.80
Intensity	2.5	1.2	3.0	0.078
Overall preference	2.4	1.2	1.6	0.23

All Melons				
Characteristic	SS	MS	F	Pr(>F)
Appearance	21	1.3	2.0	0.017
Texture	92	5.7	6.4	<0.001
Sweetness	73	4.6	6.0	<0.001
Acidity	8.2	0.51	1.3	0.20
Bitterness	8.4	0.52	1.7	0.062
Intensity	77	4.8	8.5	<0.001
Overall preference	97	6.1	5.8	<0.001

Orange+Yellow Bell Peppers				
Characteristic	SS	MS	F	Pr(>F)
Appearance	15	3.8	4.9	0.0025
Texture	14	3.4	6.4	<0.001
Sweetness	11	2.8	3.3	0.018
Acidity	1.3	0.32	0.47	0.76
Bitterness	0.25	0.064	0.16	0.96
Intensity	7.6	1.9	3.8	0.011
Overall preference	38	9.4	9.2	<0.001

Red Bell Peppers				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	32	2.9	6.2	<0.001
Texture	10	0.94	2.2	0.018
Sweetness	21	1.9	2.2	0.018
Acidity	9.8	0.89	1.3	0.23
Bitterness	13	1.2	2.6	0.0061
Intensity	4.4	0.40	0.52	0.88
Overall preference	20	1.8	2.5	0.0072

Orange+Yellow Corno di Toro Peppers				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	1.5	0.39	0.82	0.52
Texture	5.0	1.2	1.5	0.22
Sweetness	2.5	0.61	0.85	0.51
Acidity	1.5	0.39	0.55	0.70
Bitterness	0.74	0.19	0.61	0.66
Intensity	0.17	0.042	0.044	1.0
Overall preference	4.1	1.0	1.7	0.19

Red Corno di Toro Peppers				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	28	2.5	5.1	<0.001
Texture	9.3	0.85	0.52	0.24
Sweetness	5.1	0.46	0.52	0.89
Acidity	11	1.0	1.4	0.20
Bitterness	7.3	0.66	1.2	0.29
Intensity	8.0	0.73	1.4	0.21
Overall preference	3.8	0.35	0.32	0.98

All Sweet Peppers				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	78	2.4	4.6	<.001
Texture	42	1.3	2.3	<.001
Sweetness	59	1.8	2.0	0.0012
Acidity	24	0.73	1.1	0.36
Bitterness	23	0.71	1.5	0.039
Intensity	25	0.75	1.1	0.40
Overall preference	72	2.2	2.5	<0.001

Red Potatoes				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	8.7	1.7	3.0	0.046
Texture	5.2	1.0	1.0	0.45
Sweetness	2.9	0.58	0.70	0.63
Acidity	2.5	0.50	0.82	0.56
Bitterness	6.0	1.2	1.3	0.33
Umami	2.2	0.44	0.77	0.59
Intensity	8.5	1.7	3.6	0.025
Overall preference	3.2	0.64	0.53	0.75

Yellow Potatoes				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	1.6	0.40	0.43	0.78
Texture	4.4	1.1	0.72	0.59
Sweetness	3.4	0.86	0.92	0.48
Acidity	1.0	0.26	0.72	0.59
Bitterness	7.6	1.9	3.3	0.037
Umami	1.4	0.34	0.87	0.50
Intensity	3.2	0.80	1.3	0.32
Overall preference	0.96	0.24	0.16	0.96

Multi-Colored Potatoes				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	3.7	1.2	1.2	0.37
Texture	6.0	2.0	2.8	0.10
Sweetness	1.2	0.40	0.70	0.57
Acidity	2.8	0.92	1.4	0.30
Bitterness	3.5	1.2	2.1	0.17
Umami	4.7	1.6	2.3	0.14
Intensity	2.0	0.67	1.2	0.36
Overall preference	6.0	2.0	2.0	0.18

All Potatoes				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	19	1.4	1.4	0.21
Texture	21	1.5	1.1	0.40
Sweetness	8.5	0.61	0.64	0.82
Acidity	8.1	0.58	1.1	0.41
Bitterness	21	1.5	2.2	0.023
Umami	11	0.79	1.4	0.18
Intensity	17	1.2	2.1	0.032
Overall preference	13	0.89	0.73	0.74

Breeding Tomatoes (High Tunnel)				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	26	1.3	1.5	0.078
Texture	26	1.3	1.3	0.19
Sweetness	59	3.0	5.3	<0.001
Acidity	19	0.94	1.1	0.40
Bitterness	6.3	0.32	0.58	0.92
Umami	16	0.79	0.92	0.57
Intensity	33	1.6	2.2	0.0038
Overall preference	49	2.4	2.2	0.0035

Cherry Tomatoes (Field)				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	0.38	0.19	1.4	0.28
Texture	1.5	0.76	1.6	0.25
Sweetness	2.0	1.0	1.3	0.31
Acidity	0.095	0.048	0.067	0.94
Bitterness	0.29	0.14	0.56	0.58
Umami	1.2	0.62	1.8	0.21
Intensity	1.5	0.76	5.1	0.026
Overall preference	2.6	1.3	3.8	0.054

Cocktail Tomatoes (Field)				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	11	2.3	4.5	0.0024
Texture	2.8	0.56	0.83	0.54
Sweetness	3.8	0.76	1.1	0.36
Acidity	19	3.8	4.3	0.0033
Bitterness	1.2	0.24	0.85	0.52
Umami	0.80	0.17	0.26	0.93
Intensity	4.7	0.93	1.2	0.34
Overall preference	10	2.1	1.9	0.10

Orange+Yellow Tomatoes (Field)				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	5.0	1.0	1.2	0.31
Texture	3.9	0.78	1.2	0.33
Sweetness	7.9	1.6	3.3	0.017
Acidity	4.6	0.91	1.3	0.30
Bitterness	1.6	0.32	0.6	0.71
Umami	2.9	0.57	0.93	0.48
Intensity	2.9	0.57	1.0	0.43
Overall preference	11	2.1	2.3	0.066

Red Tomatoes (Field)				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	31	2.4	4.1	<0.001
Texture	11	0.83	1.4	0.17
Sweetness	10	0.80	2.2	0.017
Acidity	25	1.9	2.3	0.010
Bitterness	4.7	0.36	1.6	0.11
Umami	15	1.2	1.8	0.051
Intensity	12	0.89	1.7	0.079
Overall preference	13	1.0	1.1	0.36

Red Tomatoes (High Tunnel)				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	10	2.1	2.9	0.015
Texture	10	2.1	2.4	0.042
Sweetness	6.6	1.3	1.9	0.091
Acidity	8.3	1.7	2.7	0.021
Bitterness	0.90	0.18	0.62	0.69
Umami	8.1	1.6	2.4	0.038
Intensity	4.9	1.0	1.5	0.18
Overall preference	10	2.0	2.4	0.039

Pink Tomatoes (Field)				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	8.6	2.9	4.0	0.022
Texture	1.8	0.61	0.74	0.54
Sweetness	2.6	0.88	2.7	0.074
Acidity	2.3	0.75	1.4	0.27
Bitterness	4.6	1.5	6.6	0.0025
Umami	4.1	1.4	3.7	0.029
Intensity	1.4	0.46	1.0	0.41
Overall preference	8.6	2.9	2.7	0.063

Pink Tomatoes (High Tunnel)				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	3.3	0.83	1.3	0.30
Texture	13	3.3	4.2	0.0064
Sweetness	3.8	0.95	0.91	0.47
Acidity	7.9	2.0	2.7	0.045
Bitterness	36	9.1	20	<0.001
Umami	14	3.5	5.2	0.0020
Intensity	12	2.9	4.0	0.0086
Overall preference	12	3.1	3.5	0.017

All Tomatoes				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	152	1.7	2.5	<.001
Texture	197	2.2	2.8	<.001
Sweetness	224	2.5	4.1	<.001
Acidity	133	1.5	2.1	<.001
Bitterness	76	0.85	2.2	<.001
Umami	92	1.0	1.5	0.0040
Intensity	152	1.7	2.7	<.001
Overall preference	295	3.3	3.4	<.001

Large Butternut Squash				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	27	4.5	5.8	<0.001
Texture	27	4.5	5.6	<0.001
Sweetness	15	2.4	3.7	0.0025
Acidity	2.8	0.46	1.1	0.34
Bitterness	4.4	0.73	1.9	0.086
Intensity	14	2.3	4.0	0.0013
Overall preference	29	4.8	5.1	<0.001

Mini Butternut Squash				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	19	3.2	5.0	<0.001
Texture	44	7.3	9.3	<0.001
Sweetness	46	7.6	10	<0.001
Acidity	3.6	0.60	1.4	0.22
Bitterness	5.8	1.0	2.2	0.055
Intensity	37	6.1	13	<0.001
Overall preference	29	4.8	5.7	<0.001

All Butternut Squash				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	49	3.7	5.3	<0.001
Texture	71	5.5	7.0	<0.001
Sweetness	61	4.7	6.7	<0.001
Acidity	6.5	0.50	1.2	0.27
Bitterness	10	0.80	2.0	0.027
Intensity	51	3.9	7.2	<0.001
Overall preference	61	4.7	5.0	<0.001

Blue/Green ***maxima*** Squash				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	19	3.8	3.2	0.023
Texture	30	6.0	14	<0.001
Sweetness	32	6.4	11	<0.001
Acidity	0.27	0.053	0.10	0.99
Bitterness	1.6	0.32	0.73	0.61
Intensity	15	3.1	6.5	<0.001
Overall preference	42	8.4	22	<0.001

Pink/Red ***maxima*** Squash				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	16	2.7	5.5	0.023
Texture	10	1.7	1.6	0.18
Sweetness	24	4.0	7.3	<0.001
Acidity	0.80	0.13	0.26	0.95
Bitterness	3.9	0.66	0.83	0.56
Intensity	25	4.2	6.3	<0.001
Overall preference	22	3.7	4.0	0.0010

All ***maxima*** Squash				
Characteristic	**SS**	**MS**	**F**	**Pr(>F)**
Appearance	35	3.0	3.6	<0.001
Texture	47	3.9	5.0	<0.001
Sweetness	59	5.0	8.7	<0.001
Acidity	2.4	0.20	0.37	0.97
Bitterness	6.8	0.57	0.96	0.50
Intensity	47	3.9	6.6	<0.001
Overall preference	72	6.0	7.8	<0.001

Appendix E - Significance Groupings after Pairwise Comparisons where Fixed Effect of Variety was Significant

Orange Carrots - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
OSAPopulation1	4.3	0.30	3.7	4.9	a
Nb8524	4.3	0.30	3.7	4.9	a
Brasilia	4.1	0.37	3.4	4.9	a b
Negovia	4.0	0.30	3.4	4.6	a b
Adana	4.0	0.30	3.4	4.6	a b
Napoli	3.9	0.29	3.3	4.5	a b
U8277	3.8	0.37	3.1	4.5	a b
Dolciva	3.8	0.30	3.2	4.4	a b
Bolero2	3.5	0.30	2.9	4.1	a b
Nb8483	3.6	0.40	2.8	4.4	a b c
U9237	3.5	0.37	2.7	4.2	a b c
Nb3271	3.4	0.40	2.6	4.2	a b c
F8874	3.4	0.40	2.6	4.2	a b c
F5367	3.3	0.30	2.7	3.9	a b c
Nb8542	3.1	0.37	2.4	3.9	a b c
OSAPopulation2	2.9	0.30	2.3	3.5	b c
Bolero1	2.8	0.32	2.2	3.5	b c
F3513	2.8	0.30	2.2	3.4	b c
Nb2159	2.7	0.30	2.1	3.2	b c
U8264	2.6	0.37	1.9	3.4	b c
U8272	2.4	0.40	1.6	3.2	b c
F9241	2.4	0.40	1.6	3.2	b c
UberlandiaDerivative	2.1	0.30	1.5	2.7	c
D1131	1.8	0.40	1.0	2.6	c

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange Carrots - Sweetness					
Variety	emmean	SE	lowerCI	upperCI	group
F3513	4.2	0.33	3.6	4.9	a
F5367	3.8	0.33	3.1	4.4	a b
Bolero2	3.6	0.32	3.0	4.2	a b c
Bolero1	3.5	0.32	2.9	4.1	a b c
F9241	3.6	0.45	2.7	4.5	a b c d
Nb2159	3.2	0.33	2.6	3.9	a b c d e
Nb8524	3.1	0.33	2.5	3.8	a b c d e f
Nb8542	3.1	0.41	2.3	3.9	a b c d e f
OSAPopulation1	3.0	0.33	2.3	3.7	a b c d e f
F8874	2.8	0.45	1.9	3.7	a b c d e f
OSAPopulation2	2.8	0.33	2.1	3.4	a b c d e f
U9237	2.7	0.41	1.9	3.5	a b c d e f
Brasilia	2.4	0.41	1.6	3.2	a b c d e f
U8277	2.4	0.41	1.6	3.2	a b c d e f
U8264	2.4	0.41	1.6	3.2	a b c d e f
Dolciva	2.7	0.32	2.1	3.3	b c d e f
Negovia	2.6	0.32	2.0	3.2	b c d e f
Adana	2.5	0.32	1.9	3.1	b c d e f
U8272	2.0	0.45	1.1	2.9	b c d e f
Nb8483	1.8	0.45	0.9	2.7	c d e f
Uberlandia derivative	2.0	0.33	1.3	2.7	d e f
Napoli	1.9	0.32	1.3	2.5	d e f
Nb3271	1.4	0.45	0.5	2.3	e f
D1131	1.2	0.45	0.3	2.1	f

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange Carrots - Harshness					
Variety	emmean	SE	lowerCI	upperCI	group
Uberlandia derivative	4.2	0.33	3.6	4.9	a
D1131	4.1	0.45	3.2	4.9	a b
OSAPopulation1	3.6	0.33	2.9	4.2	a b c
Nb3271	3.1	0.45	2.2	3.9	a b c d
OSAPopulation2	2.9	0.33	2.2	3.6	a b c d
U9237	2.9	0.41	2.0	3.7	a b c d
Nb2159	2.7	0.33	2.0	3.3	a b c d
U8272	2.5	0.45	1.6	3.3	a b c d
Nb8524	2.5	0.33	1.8	3.1	b c d
Negovia	2.4	0.32	1.8	3.0	b c d
U8277	2.4	0.41	1.5	3.2	b c d
Nb8542	2.4	0.41	1.5	3.2	b c d
F5367	2.4	0.33	1.7	3.0	b c d
Napoli	2.3	0.32	1.7	2.9	b c d
F9241	2.3	0.45	1.4	3.1	b c d
Bolero2	2.2	0.32	1.6	2.8	b c d
U8264	2.2	0.41	1.4	3.0	b c d
Brasilia	2.2	0.41	1.4	3.0	b c d
Dolciva	2.1	0.32	1.5	2.7	c d
Nb8483	1.9	0.45	1.0	2.7	c d
F8874	1.9	0.45	1.0	2.7	c d
Bolero1	2.0	0.32	1.4	2.6	d
Adana	1.6	0.32	1.0	2.2	d
F3513	1.6	0.33	0.9	2.2	d

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange Carrots - Overall Preference					
Variety	emmean	SE	lowerCI	upperCI	group
Bolero1	4.5	0.32	3.9	5.0	a
Bolero2	3.6	0.32	3.0	4.2	a b
Nb2159	3.6	0.34	2.9	4.2	a b
F3513	3.6	0.34	2.9	4.2	a b
U8264	3.4	0.46	2.5	4.3	a b c
Nb8542	3.2	0.46	2.3	4.1	a b c d
U9237	3.2	0.46	2.3	4.1	a b c d
Brasilia	3.2	0.46	2.3	4.1	a b c d
OSAPopulation2	3.0	0.34	2.3	3.7	a b c d
F5367	3.0	0.34	2.3	3.7	a b c d
F9241	3.0	0.51	2.0	4.0	a b c d
Negovia	3.0	0.32	2.4	3.6	a b c d
F8874	2.5	0.51	1.5	3.5	a b c d
Adana	2.8	0.32	2.2	3.4	b c d
OSAPopulation1	2.8	0.34	2.1	3.5	b c d
Dolciva	2.7	0.32	2.1	3.3	b c d
Nb8524	2.1	0.34	1.4	2.8	b c d
Uberlandia derivative	2.0	0.34	1.3	2.7	b c d
U8277	2.0	0.46	1.1	2.9	b c d
Nb3271	2.0	0.51	1.0	3.0	b c d
Napoli	1.8	0.32	1.2	2.4	c d
Nb8483	1.3	0.51	0.2	2.3	c d
D1131	1.3	0.51	0.2	2.3	c d
U8272	1.0	0.51	0.0	2.0	d

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Purple Carrots - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
P8390_2	4.1	0.29	3.5	4.6	a
P8390_1	4.0	0.29	3.4	4.6	a b
PurpleHaze1	4.3	0.54	3.2	5.0	a b c
PurpleHaze2	4.0	0.54	2.9	5.0	a b c
PurpleElite1	3.8	0.54	2.7	4.8	a b c
PR7300	3.6	0.29	3.0	4.1	a b c
P9806	3.6	0.29	3.0	4.1	a b c
PurpleElite2	3.3	0.54	2.2	4.3	a b c
P0114	3.3	0.54	2.2	4.3	a b c
P6423	3.0	0.54	1.9	4.1	a b c
PR5100	2.9	0.29	2.4	3.5	b c
P9804	2.9	0.29	2.3	3.4	c

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Purple Carrots - Texture					
Variety	emmean	SE	lowerCI	upperCI	group
P0114	4.3	0.5	3.2	5.0	a b c
PR7300	4.1	0.3	3.6	4.7	a d
P9806	3.9	0.3	3.3	4.4	a b d e
P8390_1	3.9	0.3	3.3	4.4	a b d e
P8390_2	3.8	0.3	3.2	4.4	a b d e
PurpleElite2	3.5	0.5	2.4	4.6	a b c d e f
PurpleElite1	3.5	0.5	2.4	4.6	a b c d e f
PurpleHaze2	3.5	0.5	2.4	4.6	a b c d e f
PurpleHaze1	3.3	0.5	2.2	4.3	a b c d e f
P9804	3.2	0.3	2.7	3.8	b c e f
PR5100	2.8	0.3	2.2	3.4	c f
P6423	2.5	0.5	1.4	3.6	d e f

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Purple Carrots - Sweetness					
Variety	emmean	SE	lowerCI	upperCI	group
P0114	4.3	0.47	3.3	5.0	a
PR7300	3.4	0.25	2.9	3.9	a b
PurpleElite2	3.0	0.47	2.1	3.9	a b c d
PurpleElite1	2.8	0.47	1.8	3.7	a b c d
PurpleHaze2	2.5	0.47	1.6	3.4	a b c d
PurpleHaze1	2.5	0.47	1.6	3.4	a b c d
P9806	2.5	0.25	2.0	3.0	b c
P6423	2.3	0.47	1.3	3.2	b c d
P8390_1	2.4	0.25	1.9	2.9	c
P8390_2	2.4	0.25	1.9	2.9	c
P9804	2.1	0.25	1.6	2.6	c d
PR5100	1.4	0.25	0.9	1.9	d

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Purple Carrots - Overall Preference					
Variety	emmean	SE	lowerCI	upperCI	group
P0114	4.3	0.6	3.1	5.0	a
P8390_2	3.4	0.3	2.7	4.0	a
P8390_1	3.1	0.3	2.5	3.7	a
PurpleElite1	3.3	0.6	2.1	4.4	a b
P9806	2.9	0.3	2.2	3.5	a b
PurpleHaze2	2.8	0.6	1.6	3.9	a b
PurpleHaze1	2.8	0.6	1.6	3.9	a b
PR7300	2.7	0.3	2.1	3.3	a b
P9804	2.4	0.3	1.7	3.0	a b
PurpleElite2	2.0	0.6	0.8	3.2	a b
PR5100	1.7	0.3	1.1	2.3	b
P6423	1.0	0.6	1.0	2.2	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Carrots - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
R6220	4.1	0.26	3.6	4.6	a
R7286	4.1	0.44	3.3	5.0	a b
R5646	3.6	0.26	3.1	4.1	a b c
R6304	3.8	0.44	2.9	4.6	a b c d
R7284	3.3	0.26	2.8	3.8	a b c d
RedSamurai1	3.6	0.44	2.7	4.5	a b c d e
RedSamurai2	3.4	0.44	2.5	4.3	a b c d e
R6636	3.4	0.44	2.5	4.3	a b c d e
R5647	3.4	0.44	2.5	4.3	a b c d e
R4294	3.1	0.26	2.6	3.6	a b c d e
AtomicRed2	2.8	0.44	1.9	3.7	a b c d e
R6637	2.8	0.44	1.9	3.6	a b c d e
R7361	2.4	0.44	1.5	3.2	b c d e
R7294	2.2	0.44	1.3	3.0	c d e
AtomicRed1	1.8	0.44	0.9	2.7	d e
R8201	2.1	0.26	1.6	2.6	e

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Carrots - Sweetness					
Variety	emmean	SE	lowerCI	upperCI	group
R6637	4.0	0.40	3.3	4.8	a
R6304	3.8	0.40	3.1	4.6	a
R6220	3.3	0.2	2.8	3.7	a b
RedSamurai1	3.6	0.4	2.8	4.4	a b c
R5647	3.4	0.4	2.6	4.2	a b c d
R8201	3.0	0.2	2.5	3.5	a b c d
RedSamurai2	3.2	0.4	2.4	4.0	a b c d e
AtomicRed1	3.2	0.4	2.4	4.0	a b c d e
R7286	2.6	0.40	1.9	3.4	a b c d e f
AtomicRed2	2.6	0.4	1.8	3.4	a b c d e f
R6636	2.0	0.4	1.2	2.8	b c d e f
R5646	2.1	0.2	1.7	2.6	c d e f
R7361	1.6	0.40	0.9	2.4	d e f
R7294	1.6	0.40	0.9	2.4	d e f
R7284	1.7	0.2	1.2	2.2	e f
R4294	1.7	0.2	1.2	2.1	f

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Carrots - Harshness

Variety	emmean	SE	lowerCI	upperCI	group
R7361	4.3	0.48	3.4	5.0	a
R4294	3.7	0.28	3.1	4.2	a
R6636	3.8	0.49	2.8	4.8	a b
AtomicRed2	3.8	0.49	2.8	4.8	a b
R7284	3.3	0.28	2.8	3.9	a b
AtomicRed1	3.2	0.49	2.2	4.2	a b c
R8201	2.7	0.28	2.1	3.2	a b c
RedSamurai2	2.4	0.49	1.4	3.4	a b c
RedSamurai1	2.4	0.49	1.4	3.4	a b c
R5647	2.4	0.49	1.4	3.4	a b c
R5646	2.3	0.28	1.8	2.9	b c
R7286	1.7	0.48	0.8	2.7	b c
R6220	1.8	0.28	1.2	2.4	c
R7294	1.5	0.48	0.6	2.5	c
R6637	1.3	0.48	0.4	2.3	c
R6304	1.3	0.48	0.4	2.3	c

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Carrots - Overall Preference

Variety	emmean	SE	lowerCI	upperCI	group
R6637	4.5	0.5	3.5	5.0	a
R6220	3.8	0.3	3.2	4.4	a b
R6304	4.1	0.5	3.1	5.0	a b c
R5646	3.1	0.3	2.5	3.6	a b c d
RedSamurai2	3.4	0.5	2.4	4.4	a b c d e
R5647	3.2	0.5	2.2	4.2	a b c d e
RedSamurai1	3.0	0.5	2.0	4.0	a b c d e
R8201	2.9	0.3	2.4	3.5	a b c d e
AtomicRed1	2.2	0.5	1.2	3.2	b c d e
R7286	2.1	0.5	1.1	3.1	b c d e
AtomicRed2	2.0	0.5	1.0	3.0	b c d e
R7284	2.4	0.3	1.8	3.0	c d e
R6636	1.8	0.5	0.8	2.8	d e
R7294	1.7	0.5	0.7	2.7	d e
R7361	1.5	0.5	0.5	2.5	d e
R4294	1.8	0.3	1.2	2.4	e

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Asian Cucumbers - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
Nokya	4.3	0.30	3.7	4.9	a
TastyJade	4.2	0.30	3.6	4.8	a b
TastyGreen1	3.8	0.30	3.2	4.4	a b c
TastyGreen2	3.6	0.30	3.0	4.2	a b c
Suyo1	3.3	0.30	2.7	3.9	b c
Suyo2	3.1	0.30	2.5	3.7	c
YamatoSanjaku	3.0	0.30	2.4	3.6	c

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Asian Cucumbers - Texture					
Variety	emmean	SE	lowerCI	upperCI	group
TastyJade	4.1	0.31	3.5	4.7	a
Nokya	3.6	0.31	3.0	4.3	a b
TastyGreen2	3.4	0.31	2.7	4.0	a b
TastyGreen1	3.4	0.31	2.7	4.0	a b
Suyo2	3.3	0.31	2.7	3.9	a b
Suyo1	3.2	0.31	2.6	3.8	a b
YamatoSanjaku	2.7	0.31	2.1	3.4	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Asian Cucumbers - Bitterness					
Variety	emmean	SE	lowerCI	upperCI	group
YamatoSanjaku	2.9	0.29	2.3	3.5	a
TastyJade	1.7	0.29	1.2	2.3	b
TastyGreen2	1.6	0.29	1.1	2.2	b
TastyGreen1	1.6	0.29	1.0	2.1	b
Suyo1	1.6	0.29	1.0	2.1	b
Nokya	1.5	0.29	0.9	2.0	b
Suyo2	1.5	0.29	0.9	2.0	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Asian Cucumbers - Overall Preference					
Variety	emmean	SE	lowerCI	upperCI	group
Nokya	3.4	0.34	2.7	4.0	a
TastyGreen2	3.2	0.34	2.5	3.9	a
TastyGreen1	3.0	0.34	2.3	3.7	a b
Suyo2	2.9	0.34	2.2	3.6	a b
TastyJade	2.8	0.34	2.2	3.5	a b
Suyo1	2.6	0.34	1.9	3.2	a b
YamatoSanjaku	1.9	0.34	1.2	2.6	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Raw Pickling Cucumbers - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
Excelsior	4.3	0.39	3.5	5.1	a
Amour	4.2	0.39	3.4	4.9	a b
Bushy	4.1	0.37	3.3	4.8	a b
Bushy1	4.0	0.45	3.1	4.9	a b
Artist2	3.8	0.39	3.0	4.6	a b
Bushy2	3.7	0.47	2.8	4.7	a b
Artist1	3.7	0.39	2.9	4.4	a b
GY14DM2	3.7	0.32	3.0	4.3	a b
GY14DM1	3.6	0.31	2.9	4.2	a b
GY14DM3	3.4	0.31	2.7	4.0	a b
GherKing	3.3	0.39	2.5	4.1	a b
GY14	3.0	0.31	2.4	3.6	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Raw Pickling Cucumbers - Bitterness					
Variety	emmean	SE	lowerCI	upperCI	group
GY14	2.6	0.3	2.0	3.3	a
GY14DM1	2.4	0.3	1.8	3.0	a b
Bushy	2.1	0.4	1.4	2.9	a b
GY14DM3	1.8	0.3	1.2	2.5	a b
GY14DM2	1.8	0.3	1.2	2.5	a b
Bushy1	1.8	0.5	0.8	2.7	a b
Bushy2	1.7	0.5	0.7	2.8	a b
Artist1	1.6	0.4	0.8	2.4	a b
Excelsior	1.4	0.4	0.6	2.2	a b
Artist2	1.4	0.4	0.6	2.2	a b
GherKing	1.0	0.4	0.2	1.8	b
Amour	1.0	0.4	0.2	1.8	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Mini Cucumbers - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
Manny2	4.3	0.25	3.8	4.8	a
Yildo1	4.1	0.25	3.6	4.6	a b
Manny1	3.9	0.25	3.3	4.4	a b
WI7204	3.8	0.25	3.3	4.3	a b
Yildo2	3.6	0.25	3.1	4.2	a b
WI7204DM2	3.6	0.25	3.1	4.1	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Butterhead Lettuce - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
Alkindus	4.3	0.38	3.6	5.0	a
Cindy	4.2	0.36	3.4	4.9	a
Australe	3.8	0.38	3.1	4.6	a b
Lovelock	3.7	0.38	2.9	4.5	a b
CrispAsIce	3.6	0.42	2.7	4.5	a b
Joker	3.0	0.38	2.2	3.8	a b
ManoaLeopard	2.3	0.38	1.6	3.1	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Little Gem Lettuce - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
PomegranateCrunch	4.2	0.26	3.7	4.7	a
Pandero	3.9	0.26	3.4	4.4	a b
IreneGreenGem	3.8	0.26	3.3	4.3	a b
RubyZoisite	3.5	0.26	2.9	4.0	a b
LittleGemPearl	3.5	0.26	2.9	4.0	a b
Newham1	3.4	0.26	2.8	3.9	a b
Newham2	3.1	0.26	2.6	3.6	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Little Gem Lettuce - Overall Preference					
Variety	emmean	SE	lowerCI	upperCI	group
IreneGreenGem	3.9	0.33	3.3	4.6	a
RubyZoisite	3.6	0.33	2.9	4.2	a b
Pandero	3.2	0.33	2.5	3.8	a b
PomegranateCrunch	2.6	0.33	2.0	3.3	a b
Newham2	2.6	0.33	2.0	3.3	a b
LittleGemPearl	2.6	0.33	1.9	3.2	b
Newham1	2.6	0.33	1.9	3.2	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Green One-Cut Lettuce - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
SalanovaGreenButter	4.3	0.26	3.8	4.8	a
EazyleafHampton	3.7	0.25	3.2	4.2	a b
SalanovaGreenOakleaf1	3.6	0.30	3.0	4.2	a b
SalanovaGreenSweetCrisp	3.6	0.25	3.1	4.1	a b
EazyleafEzrilla	3.3	0.25	2.8	3.8	b
SalanovaGreenOakleaf2	3.2	0.31	2.6	3.9	b
SalanovaGreenIncised	3.2	0.25	2.7	3.7	b
EazyleafEztron	3.2	0.25	2.7	3.7	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Green One-Cut Lettuce - Bitterness					
Variety	emmean	SE	lowerCI	upperCI	group
SalanovaGreenIncised	3.1	0.27	2.6	3.6	a
SalanovaGreenOakleaf2	2.6	0.33	1.9	3.2	a b
EazyleafHampton	2.5	0.27	2.0	3.1	a b
SalanovaGreenSweetCrisp	2.5	0.27	1.9	3.0	a b
EazyleafEztron	2.4	0.27	1.9	3.0	a b
EazyleafEzrilla	2.4	0.27	1.8	2.9	a b
SalanovaGreenOakleaf1	2.2	0.33	1.6	2.9	a b
SalanovaGreenButter	2.1	0.27	1.5	2.6	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red One-Cut Lettuce - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
SalanovaRedButter	4.4	0.23	4.0	4.9	a
SalanovaRedIncised1	4.2	0.35	3.5	4.9	a b
EazyleafBurgandy1	4.0	0.28	3.5	4.6	a b
EazyleafStanford	3.7	0.28	3.2	4.3	a b
SalanovaRedOakleaf	3.7	0.23	3.2	4.1	a b
EazyleafEzbruke	3.7	0.23	3.2	4.1	a b
EazyleafBurgandy2	3.7	0.30	3.1	4.3	a b
EazyleafBrentwood	3.6	0.23	3.1	4.0	a b
SalanovaRedIncised2	3.5	0.35	2.8	4.2	a b
EazyleafBoynton	3.4	0.23	2.9	3.8	b
SalanovaRedSweetCrisp	3.1	0.23	2.7	3.6	b
EazyleafBuckley	2.9	0.35	2.2	3.6	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red One-Cut Lettuce - Texture					
Variety	emmean	SE	lowerCI	upperCI	group
SalanovaRedButter	3.6	0.21	3.2	4.0	a
EazyleafEzbruke	3.5	0.21	3.1	4.0	a
EazyleafBoynton	3.4	0.21	3.0	3.8	a
SalanovaRedSweetCrisp	3.3	0.21	2.9	3.8	a b
EazyleafBuckley	3.3	0.33	2.6	3.9	a b
SalanovaRedIncised1	3.2	0.33	2.6	3.9	a b
SalanovaRedIncised2	3.2	0.33	2.6	3.9	a b
EazyleafBurgandy1	3.1	0.27	2.6	3.7	a b
EazyleafBrentwood	2.9	0.21	2.5	3.4	a b
SalanovaRedOakleaf	2.9	0.21	2.5	3.3	a b
EazyleafStanford	2.8	0.27	2.3	3.3	a b
EazyleafBurgandy2	2.4	0.27	1.9	2.9	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red One-Cut Lettuce - Bitterness					
Variety	emmean	SE	lowerCI	upperCI	group
EazyleafEzbruke	3.7	0.28	3.2	4.3	a
EazyleafBurgandy2	3.6	0.35	2.9	4.3	a b
EazyleafStanford	3.6	0.35	2.9	4.3	a b
EazyleafBoynton	3.5	0.28	2.9	4.0	a b
EazyleafBuckley	3.4	0.43	2.6	4.3	a b
EazyleafBurgandy1	3.2	0.35	2.5	3.8	a b
SalanovaRedIncised1	3.1	0.43	2.2	3.9	a b
EazyleafBrentwood	3.0	0.28	2.5	3.6	a b
SalanovaRedIncised2	2.9	0.43	2.1	3.8	a b
SalanovaRedOakleaf	2.7	0.28	2.2	3.3	a b
SalanovaRedSweetCrisp	2.7	0.28	2.1	3.2	a b
SalanovaRedButter	2.4	0.28	1.9	3.0	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red One-Cut Lettuce - Intensity					
Variety	emmean	SE	lowerCI	upperCI	group
SalanovaRedOakleaf	3.2	0.23	2.7	3.6	a
SalanovaRedIncised2	3.3	0.33	2.7	3.9	a b
EazyleafBurgandy1	3.1	0.27	2.6	3.7	a b
SalanovaRedSweetCrisp	2.9	0.23	2.4	3.3	a b
EazyleafBrentwood	2.9	0.23	2.4	3.3	a b
SalanovaRedIncised1	2.6	0.33	1.9	3.2	a b
EazyleafBoynton	2.6	0.23	2.1	3.0	a b
EazyleafStanford	2.6	0.27	2.0	3.1	a b
EazyleafEzbruke	2.5	0.23	2.0	2.9	a b
EazyleafBuckley	2.4	0.33	1.8	3.1	a b
SalanovaRedButter	2.4	0.23	2.0	2.9	b
EazyleafBurgandy2	2.2	0.27	1.7	2.7	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red One-Cut Lettuce - Overall Preference					
Variety	emmean	SE	lowerCI	upperCI	group
SalanovaRedButter	3.2	0.25	2.7	3.7	a
SalanovaRedSweetCrisp	2.9	0.25	2.4	3.4	a b
EazyleafBuckley	2.7	0.38	1.9	3.4	a b
SalanovaRedOakleaf	2.5	0.25	2.0	3.0	a b
EazyleafBurgandy1	2.5	0.31	1.8	3.1	a b
EazyleafEzbruke	2.4	0.25	1.9	2.9	a b
EazyleafBurgandy2	2.4	0.31	1.8	3.0	a b
SalanovaRedIncised1	2.2	0.38	1.4	2.9	a b
EazyleafStanford	2.1	0.31	1.5	2.7	a b
SalanovaRedIncised2	2.0	0.38	1.3	2.8	a b
EazyleafBrentwood	2.2	0.25	1.7	2.7	b
EazyleafBoynton	2.1	0.25	1.6	2.6	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange-Fleshed Melons - Appearance

Variety	emmean	SE	lowerCI	upperCI	group
OrangeSherbet	4.3	0.32	3.6	4.9	a
AnnasCharentais	4.0	0.32	3.3	4.6	a
TrueLove	3.8	0.32	3.1	4.4	a b
Triton	3.7	0.32	3.1	4.3	a b
Tirreno	3.7	0.32	3.1	4.3	a b
Divergent2	3.7	0.32	3.1	4.3	a b
Dago	3.7	0.32	3.0	4.3	a b
Iperione	3.6	0.32	3.0	4.2	a b
Divergent1	3.6	0.32	3.0	4.2	a b
Savor	3.3	0.32	2.7	3.9	a b
FirstKiss2	3.3	0.32	2.6	3.9	a b
Spear	3.2	0.32	2.6	3.8	a b
FirstKiss1	3.1	0.32	2.4	3.7	a b
DakotaSisters	2.7	0.32	2.0	3.3	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange-Fleshed Melons - Texture

Variety	emmean	SE	lowerCI	upperCI	group
TrueLove	4.3	0.33	3.6	4.9	a
Dago	4.1	0.33	3.4	4.7	a
DakotaSisters	4.1	0.33	3.4	4.7	a
FirstKiss2	3.9	0.33	3.2	4.5	a b
FirstKiss1	3.7	0.33	3.0	4.3	a b c
Triton	3.2	0.33	2.5	3.8	a b c d
AnnasCharentais	3.1	0.33	2.4	3.7	a b c d
Divergent2	3.0	0.33	2.3	3.6	a b c d
Spear	2.7	0.33	2.0	3.3	b c d
Divergent1	2.7	0.33	2.0	3.3	b c d
Iperione	2.5	0.33	1.8	3.1	c d
Savor	2.4	0.33	1.7	3.0	c d
OrangeSherbet	2.4	0.33	1.7	3.0	c d
Tirreno	2.1	0.33	1.4	2.7	d

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange-Fleshed Melons - Sweetness

Variety	emmean	SE	lowerCI	upperCI	group
TrueLove	4.5	0.32	3.9	5.0	a
Divergent2	3.8	0.32	3.2	4.5	a b
DakotaSisters	3.4	0.32	2.8	4.1	a b c
FirstKiss2	3.2	0.32	2.6	3.9	b c
Divergent1	3.2	0.32	2.6	3.9	b c
FirstKiss1	3.1	0.32	2.5	3.8	b c
Dago	2.7	0.32	2.1	3.4	b c d
Spear	2.7	0.32	2.1	3.4	b c d
OrangeSherbet	2.6	0.32	2.0	3.3	b c d
Iperione	2.6	0.32	2.0	3.3	b c d
Triton	2.4	0.32	1.8	3.1	c d
Savor	2.4	0.32	1.8	3.1	c d
AnnasCharentais	2.2	0.32	1.6	2.9	c d
Tirreno	1.5	0.32	0.9	2.2	d

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange-Fleshed Melons - Acidity

Variety	emmean	SE	lowerCI	upperCI	group
DakotaSisters	2.2	0.26	1.7	2.8	a
Savor	2.0	0.26	1.5	2.6	a b
TrueLove	1.8	0.26	1.3	2.4	a b
Divergent1	1.8	0.26	1.3	2.4	a b
FirstKiss1	1.7	0.26	1.2	2.3	a b
Tirreno	1.7	0.26	1.2	2.3	a b
AnnasCharentais	1.6	0.26	1.1	2.2	a b
FirstKiss2	1.5	0.26	1.0	2.1	a b
Triton	1.5	0.26	1.0	2.1	a b
Iperione	1.5	0.26	1.0	2.1	a b
Divergent2	1.5	0.26	1.0	2.1	a b
Dago	1.4	0.26	0.9	2.0	a b
Spear	1.4	0.26	0.9	2.0	a b
OrangeSherbet	1.3	0.26	0.8	1.9	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange-Fleshed Melons - Intensity

Variety	emmean	SE	lowerCI	upperCI	group
TrueLove	4.3	0.25	3.8	4.8	a
DakotaSisters	3.7	0.25	3.2	4.2	a b
FirstKiss2	3.4	0.25	2.9	3.9	a b c
Divergent2	3.4	0.25	2.9	3.9	a b c
FirstKiss1	3.3	0.25	2.8	3.8	a b c d
Spear	3.0	0.25	2.5	3.5	b c d e
Triton	2.9	0.25	2.4	3.4	b c d e
Dago	2.8	0.25	2.3	3.3	b c d e
Divergent1	2.7	0.25	2.2	3.2	b c d e
AnnasCharentais	2.4	0.25	1.9	2.9	c d e f
Savor	2.4	0.25	1.9	2.9	c d e f
Iperione	2.3	0.25	1.8	2.8	d e f
OrangeSherbet	2.0	0.25	1.5	2.5	e f
Tirreno	1.4	0.25	0.9	1.9	f

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange-Fleshed Melons - Overall Preference

Variety	emmean	SE	lowerCI	upperCI	group
TrueLove	4.8	0.35	4.1	5.0	a
DakotaSisters	4.0	0.35	3.3	4.7	a b
Divergent2	3.4	0.35	2.7	4.1	a b c
FirstKiss1	3.4	0.35	2.7	4.1	a b c
FirstKiss2	3.4	0.35	2.7	4.1	a b c
Dago	2.8	0.35	2.1	3.5	b c d
Divergent1	2.7	0.35	2.0	3.4	b c d
Triton	2.6	0.35	1.9	3.3	b c d
Iperione	2.6	0.35	1.9	3.3	b c d
Spear	2.5	0.35	1.8	3.2	c d
Savor	2.3	0.35	1.6	3.0	c d
OrangeSherbet	2.3	0.35	1.6	3.0	c d
AnnasCharentais	2.0	0.35	1.3	2.7	c d
Tirreno	1.6	0.35	0.9	2.3	d

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Galia Melons - Texture					
Variety	emmean	SE	lowerCI	upperCI	group
E25G.00488	3.6	0.27	3.1	4.2	a
E25G.00345	2.3	0.27	1.8	2.9	b
E25G.00345_2	1.9	0.27	1.4	2.5	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Galia Melons - Intensity					
Variety	emmean	SE	lowerCI	upperCI	group
E25G.00488	3.0	0.29	2.4	3.6	a
E25G.00345_2	2.6	0.29	2.0	3.2	a b
E25G.00345	2.3	0.29	1.7	2.9	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange+Yellow Bell Peppers - Texture					
Variety	emmean	SE	lowerCI	upperCI	group
E20B.30199	4.1	0.24	3.6	4.6	a
OrangeMarmalade	3.8	0.24	3.3	4.3	a
Flavorburst2	3.6	0.24	3.2	4.1	a
Flavorburst1	3.4	0.24	2.9	3.9	a b
Whitney	2.6	0.24	2.2	3.1	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange+Yellow Bell Peppers - Sweetness					
Variety	emmean	SE	lowerCI	upperCI	group
Flavorburst1	3.6	0.28	3.1	4.2	a
E20B.30199	3.3	0.28	2.7	3.8	a b
OrangeMarmalade	3.2	0.28	2.6	3.8	a b
Flavorburst2	2.9	0.28	2.3	3.5	a b
Whitney	2.3	0.28	1.7	2.8	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange+Yellow Bell Peppers - Intensity					
Variety	emmean	SE	lowerCI	upperCI	group
Flavorburst1	3.1	0.24	2.6	3.6	a
OrangeMarmalade	3.0	0.24	2.5	3.5	a
Flavorburst2	3.0	0.24	2.5	3.5	a
E20B.30199	2.6	0.24	2.2	3.1	a b
Whitney	2.1	0.24	1.6	2.6	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange+Yellow Bell Peppers - Overall Preference					
Variety	emmean	SE	lowerCI	upperCI	group
Flavorburst2	3.6	0.31	3.0	4.3	a
Flavorburst1	3.5	0.31	2.8	4.1	a
OrangeMarmalade	3.4	0.31	2.7	4.0	a
E20B.30199	3.1	0.31	2.5	3.7	a
Whitney	1.4	0.31	1.0	2.0	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange+Yellow Bell Peppers - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
Flavorburst2	4.5	0.28	3.9	5.0	a
OrangeMarmalade	4.1	0.28	3.5	4.7	a
Whitney	3.6	0.28	3.1	4.2	a b
Flavorburst1	3.6	0.28	3.0	4.1	a b
E20B.30199	2.9	0.28	2.4	3.5	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Bell Peppers - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
KingoftheNorth	4.4	0.22	3.9	4.8	a
Procraft	4.3	0.21	3.9	4.8	a b
Ace1	4.2	0.22	3.7	4.6	a b c
E20B.30236	4.1	0.21	3.7	4.5	a b c
Beachcraft2	3.9	0.21	3.5	4.3	a b c d
EarlyRedSweet	3.6	0.22	3.2	4.1	a b c d e
Peacework	3.5	0.22	3.0	3.9	b c d e
Ace2	3.5	0.22	3.0	3.9	b c d e
Aristotle	3.4	0.21	3.0	3.8	c d e
WisconsinLakes	3.2	0.22	2.7	3.6	d e
Beachcraft1	3.1	0.21	2.7	3.5	d e
E20B.30136	2.9	0.21	2.5	3.3	e

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Bell Peppers - Texture					
Variety	emmean	SE	lowerCI	upperCI	group
E20B.30236	4.4	0.21	3.9	4.8	a
Beachcraft2	4.0	0.21	3.6	4.4	a b
Aristotle	4.0	0.21	3.6	4.4	a b
WisconsinLakes	3.9	0.22	3.5	4.3	a b
Beachcraft1	3.9	0.21	3.4	4.3	a b
KingoftheNorth	3.8	0.22	3.4	4.2	a b
E20B.30136	3.8	0.21	3.4	4.2	a b
Peacework	3.7	0.22	3.3	4.1	a b
Procraft	3.6	0.21	3.2	4.0	a b
Ace1	3.5	0.22	3.1	4.0	a b
EarlyRedSweet	3.3	0.22	2.9	3.8	b
Ace2	3.3	0.22	2.9	3.8	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Bell Peppers - Sweetness					
Variety	emmean	SE	lowerCI	upperCI	group
WisconsinLakes	3.5	0.29	2.9	4.0	a
KingoftheNorth	3.5	0.29	2.9	4.0	a
Peacework	3.0	0.29	2.5	3.6	a b
E20B.30136	2.9	0.27	2.4	3.5	a b
Ace2	2.8	0.29	2.3	3.4	a b
Procraft	2.8	0.27	2.3	3.4	a b
E20B.30236	2.8	0.27	2.3	3.4	a b
Beachcraft1	2.8	0.27	2.2	3.3	a b
Aristotle	2.7	0.27	2.1	3.2	a b
Beachcraft2	2.4	0.27	1.9	3.0	a b
Ace1	2.4	0.29	1.8	3.0	a b
EarlyRedSweet	2.0	0.29	1.5	2.6	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Bell Peppers - Bitterness					
Variety	emmean	SE	lowerCI	upperCI	group
Beachcraft2	2.5	0.29	1.9	3.1	a
Ace2	2.5	0.30	1.9	3.1	a
Ace1	2.3	0.30	1.7	2.9	a b
EarlyRedSweet	2.3	0.30	1.7	2.9	a b
Peacework	2.0	0.30	1.4	2.6	a b
Procraft	2.0	0.29	1.4	2.6	a b
KingoftheNorth	1.8	0.30	1.2	2.4	a b
E20B.30236	1.8	0.29	1.2	2.4	a b
E20B.30136	1.7	0.29	1.1	2.3	a b
Beachcraft1	1.7	0.29	1.1	2.2	a b
Aristotle	1.7	0.29	1.1	2.2	a b
WisconsinLakes	1.6	0.30	1.0	2.2	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Bell Peppers - Overall Preference					
Variety	emmean	SE	lowerCI	upperCI	group
Procraft	3.6	0.28	3.0	4.1	a
Aristotle	3.4	0.28	2.8	3.9	a b
KingoftheNorth	3.3	0.29	2.7	3.9	a b
Beachcraft1	3.2	0.28	2.7	3.8	a b
Beachcraft2	3.1	0.28	2.6	3.7	a b
WisconsinLakes	2.8	0.29	2.3	3.4	a b
E20B.30236	2.7	0.28	2.2	3.3	a b
E20B.30136	2.6	0.28	2.1	3.2	a b
Ace2	2.6	0.29	2.0	3.1	a b
Ace1	2.6	0.29	2.0	3.1	a b
EarlyRedSweet	2.5	0.29	1.9	3.0	a b
Peacework	2.4	0.29	1.8	3.0	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Corno di Toro Peppers - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
Carmen2	4.5	0.27	4.0	5.0	a
Karma1	4.4	0.29	3.8	5.0	a b
Carmen1	4.3	0.27	3.7	4.8	a b
Karma2	4.2	0.29	3.7	4.8	a b
EarlyPerfectItalian	4.2	0.29	3.7	4.8	a b
GypsyQueens	4.1	0.29	3.5	4.7	a b c
STSDLS213	4.0	0.27	3.5	4.6	a b c
BridgetoParis2	4.0	0.27	3.5	4.6	a b c
StockyRedRoaster	4.0	0.29	3.4	4.5	a b c
ItalianSweetFryer	3.3	0.27	2.7	3.8	b c d
BridgetoParis1	3.0	0.27	2.5	3.6	c d
JohnsSweetFry	2.7	0.29	2.1	3.2	d

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Potatoes - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
RedPrairie	4.3	0.62	2.8	5.0	a
RedEndeavor	4.0	0.62	2.5	5.0	a b
WLxRDT404	3.8	0.62	2.3	5.0	a b
PxC	3.3	0.62	1.8	4.7	a b
AlaskaSweetheart	3.0	0.62	1.5	4.5	a b
Cinnabar	2.5	0.62	1.0	4.0	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Potatoes - Umami					
Variety	emmean	SE	lowerCI	upperCI	group
Cinnabar	4.3	0.44	3.3	5.0	a
WLxRDT404	3.8	0.44	2.8	4.7	a b
RedPrairie	3.3	0.44	2.3	4.2	a b
RedEndeavor	3.0	0.44	2.0	4.0	a b
AlaskaSweetheart	2.8	0.44	1.8	3.7	b
PxC	2.5	0.44	1.5	3.5	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Yellow Potatoes - Bitterness					
Variety	emmean	SE	lowerCI	upperCI	group
Allehanna	2.8	0.38	2.0	3.6	a
DaisyGold	1.8	0.38	1.0	2.6	a b
GoldCoin	1.8	0.38	1.0	2.6	a b
Carola	1.4	0.38	1.0	2.2	b
W13103-16Y	1.2	0.38	1.0	2.0	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Breeding Tomatoes (High Tunnel) - Sweetness					
Variety	emmean	SE	lowerCI	upperCI	group
SGLL.SM.2.17.4	4.2	0.24	3.8	4.7	a
SGLL.LG.1.17.1	3.7	0.25	3.2	4.2	a b
GGO4.F4.3	3.5	0.24	3.1	4.0	a b c
JBDE.F3.3	3.3	0.34	2.7	4.0	a b c d
45L23.S2.16.1	3.0	0.34	2.3	3.6	a b c d e
SGTA.F4.4	2.9	0.34	2.3	3.6	a b c d e
SGPF.F3.4	2.9	0.34	2.3	3.6	a b c d e
A6JB.F3.5	2.8	0.34	2.2	3.5	a b c d e
A6JB.F3.4	2.8	0.34	2.2	3.5	a b c d e
GGO4.F4.2	3.0	0.25	2.5	3.5	b c d
JBGG.F3.4	3.0	0.25	2.5	3.5	b c d
CSDE.F4.3	3.0	0.20	2.6	3.3	b c d
623	2.9	0.24	2.4	3.4	b c d
SGPF.F3.1	2.8	0.34	2.1	3.5	b c d e
15H07.10.4.4	2.8	0.24	2.3	3.2	b c d e
GGO4.F4.1	2.4	0.34	1.8	3.1	b c d e
45L23R.17.1	2.4	0.34	1.8	3.1	b c d e
JBGG.F3.2	2.3	0.34	1.7	3.0	c d e
SGPF.F3.2	2.5	0.24	2.1	3.0	d e
08H02.EB911	2.1	0.34	1.4	2.8	d e
JBGG.F3.5	1.7	0.25	1.2	2.2	e

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Breeding Tomatoes (High Tunnel) - Intensity					
Variety	emmean	SE	lowerCI	upperCI	group
SGLL.SM.2.17.4	3.7	0.25	3.2	4.2	a
GGO4.F4.3	3.4	0.25	2.9	3.9	a b
SGLL.LG.1.17.1	3.3	0.26	2.7	3.8	a b
45L23.S2.16.1	3.4	0.37	2.7	4.1	a b c
SGPF.F3.2	3.1	0.25	2.5	3.6	a b c
623	3.1	0.25	2.5	3.6	a b c
CSDE.F4.3	3.0	0.21	2.6	3.4	a b c
15H07.10.4.4	3.0	0.25	2.5	3.5	a b c
JBGG.F3.4	2.9	0.26	2.4	3.5	a b c
SGTA.F4.4	2.8	0.37	2.1	3.5	a b c
45L23R.17.1	2.8	0.37	2.1	3.5	a b c
JBDE.F3.3	2.8	0.37	2.1	3.5	a b c
GGO4.F4.2	2.7	0.26	2.2	3.2	a b c
SGPF.F3.4	2.6	0.37	1.9	3.4	a b c
A6JB.F3.5	2.5	0.37	1.7	3.2	a b c
08H02.EB911	2.4	0.37	1.7	3.1	a b c
SGPF.F3.1	2.3	0.37	1.6	3.0	a b c
GGO4.F4.1	2.3	0.37	1.6	3.0	a b c
JBGG.F3.2	2.3	0.37	1.6	3.0	a b c
A6JB.F3.4	2.1	0.37	1.4	2.9	b c
JBGG.F3.5	1.9	0.26	1.4	2.5	c

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Breeding Tomatoes (High Tunnel) - Overall Preference					
Variety	emmean	SE	lowerCI	upperCI	group
GGO4.F4.3	4.1	0.30	3.5	4.7	a
SGLL.LG.1.17.1	4.0	0.31	3.4	4.6	a
45L23.S2.16.1	4.2	0.44	3.3	5.0	a b
SGLL.SM.2.17.4	3.8	0.30	3.2	4.4	a b
CSDE.F4.3	3.4	0.25	2.9	3.9	a b
GGO4.F4.1	3.4	0.44	2.5	4.2	a b
15H07.10.4.4	3.2	0.30	2.6	3.8	a b
45L23R.17.1	3.2	0.44	2.3	4.1	a b
GGO4.F4.2	3.1	0.31	2.5	3.7	a b
JBGG.F3.4	3.1	0.31	2.5	3.7	a b
SGTA.F4.4	3.0	0.44	2.2	3.9	a b
JBGG.F3.2	3.0	0.44	2.2	3.9	a b
623	3.0	0.30	2.4	3.6	a b
SGPF.F3.4	2.9	0.44	2.0	3.7	a b
SGPF.F3.1	2.9	0.44	2.0	3.7	a b
JBDE.F3.3	2.9	0.44	2.0	3.7	a b
A6JB.F3.5	2.9	0.44	2.0	3.7	a b
SGPF.F3.2	2.8	0.30	2.3	3.4	a b
08H02.EB911	2.5	0.44	1.6	3.4	a b
JBGG.F3.5	2.4	0.31	1.8	3.0	b
A6JB.F3.4	2.2	0.44	1.3	3.1	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Cherry Tomatoes (Field) - Intensity

Variety	emmean	SE	lowerCI	upperCI	group
Sungold	3.7	0.24	3.2	4.2	a
JTO1099_2	3.1	0.24	2.6	3.7	b
JTO1099_1	3.1	0.24	2.6	3.7	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Cherry Tomatoes (Field) - Overall Preference

Variety	emmean	SE	lowerCI	upperCI	group
Sungold	4.7	0.25	4.2	5.0	a
JTO1099_1	4.3	0.25	3.8	4.8	a b
JTO1099_2	3.9	0.25	3.3	4.4	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Cocktail Tomatoes (Field) - Acidity

Variety	emmean	SE	lowerCI	upperCI	group
Latah	3.6	0.34	2.9	4.2	a
45L23	3.3	0.34	2.7	4.0	a
RedRacer	3.3	0.34	2.7	4.0	a
RCHybrid	2.8	0.34	2.1	3.5	a b
MountainMagic	2.7	0.34	2.0	3.4	a b
SGLL4	1.8	0.34	1.1	2.5	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Cocktail Tomatoes (Field) - Appearance

Variety	emmean	SE	lowerCI	upperCI	group
45L23	4.7	0.30	4.1	5.0	a
Latah	4.3	0.30	3.7	4.9	a b
RCHybrid	4.0	0.30	3.4	4.6	a b
MountainMagic	3.7	0.30	3.1	4.3	b
RedRacer	3.4	0.30	2.8	4.1	b
SGLL4	3.4	0.30	2.8	4.1	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Cocktail Tomatoes (Field) - Overall Preference

Variety	emmean	SE	lowerCI	upperCI	group
RCHybrid	3.9	0.35	3.2	4.6	a
MountainMagic	3.0	0.35	2.3	3.7	a b
Latah	3.0	0.35	2.3	3.7	a b
RedRacer	2.9	0.35	2.2	3.6	a b
45L23	2.8	0.35	2.1	3.5	a b
SGLL4	2.4	0.35	1.8	3.1	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange+Yellow Tomatoes (Field) - Sweetness

Variety	emmean	SE	lowerCI	upperCI	group
DeWeeseStreaked	3.3	0.35	2.6	4.0	a
623	2.9	0.35	2.1	3.6	a b
OmasOrange	2.4	0.35	1.7	3.2	a b
665	2.4	0.35	1.7	3.2	a b
Azoychka	2.1	0.35	1.4	2.9	b
SunriseSauce	2.0	0.35	1.3	2.7	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Orange+Yellow Tomatoes (Field) - Overall Preference

Variety	emmean	SE	lowerCI	upperCI	group
DeWeeseStreaked	2.9	0.41	2.0	3.7	a
665	2.6	0.41	1.7	3.4	a b
OmasOrange	2.1	0.41	1.3	3.0	a b
Azoychka	2.1	0.41	1.3	3.0	a b
623	1.9	0.41	1.0	2.7	a b
SunriseSauce	1.3	0.41	1.0	2.1	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Tomatoes (Field) - Appearance

Variety	emmean	SE	lowerCI	upperCI	group
Aurora	4.1	0.37	3.4	4.9	a
2331.1_2	3.9	0.36	3.1	4.6	a b
15H07.10.4.4	3.9	0.36	3.1	4.6	a b
WHybrid	3.8	0.36	3.0	4.5	a b
VitalisLBresistant	3.5	0.36	2.8	4.2	a b c
Scotia	3.3	0.37	2.5	4.0	a b c
MountainPrincess1	3.3	0.37	2.5	4.0	a b c
Galahad	3.0	0.36	2.3	3.7	a b c
MountainPrincess2	3.0	0.37	2.2	3.8	a b c
2331.1_1	2.9	0.36	2.1	3.6	a b c
OSA404	2.7	0.37	1.9	3.5	b c
08H02.EB911	2.7	0.37	1.9	3.5	b c
Brandywise	2.5	0.36	1.8	3.2	c
Starfire	2.3	0.37	1.5	3.0	c

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Tomatoes (Field) - Sweetness					
Variety	emmean	SE	lowerCI	upperCI	group
Brandywise	2.4	0.25	1.9	2.9	a
OSA404	2.3	0.27	1.8	2.8	a b
WHybrid	1.9	0.25	1.4	2.4	a b
08H02.EB911	1.9	0.27	1.3	2.4	a b
Galahad	1.8	0.25	1.2	2.3	a b
MountainPrincess2	1.7	0.27	1.2	2.3	a b
MountainPrincess1	1.7	0.27	1.2	2.3	a b
Aurora	1.7	0.27	1.2	2.3	a b
15H07.10.4.4	1.6	0.25	1.1	2.1	a b
Starfire	1.6	0.27	1.0	2.1	a b
VitalisLBresistant	1.4	0.25	1.0	1.9	b
2331.1_2	1.4	0.25	1.0	1.9	b
2331.1_1	1.4	0.25	1.0	1.9	b
Scotia	1.3	0.27	1.0	1.8	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Tomatoes (Field) - Acidity					
Variety	emmean	SE	lowerCI	upperCI	group
Aurora	3.4	0.45	2.5	4.3	a
MountainPrincess2	3.1	0.45	2.2	4.0	a b
Starfire	3.1	0.45	2.2	4.0	a b
15H07.10.4.4	3.0	0.43	2.1	3.9	a b
MountainPrincess1	3.0	0.45	2.1	3.9	a b
2331.1_1	2.5	0.43	1.6	3.4	a b
08H02.EB911	2.4	0.45	1.5	3.3	a b
Scotia	2.3	0.45	1.4	3.2	a b
WHybrid	2.3	0.43	1.4	3.1	a b
Brandywise	2.3	0.43	1.4	3.1	a b
OSA404	2.1	0.45	1.2	3.0	a b
VitalisLBresistant	2.1	0.43	1.2	3.0	a b
2331.1_2	2.0	0.43	1.1	2.9	a b
Galahad	1.8	0.43	1.0	2.6	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Tomatoes (Field) - Umami					
Variety	emmean	SE	lowerCI	upperCI	group
WHybrid	2.9	0.34	2.2	3.6	a
VitalisLBresistant	2.8	0.34	2.1	3.4	a b
Brandywise	2.5	0.34	1.8	3.2	a b
15H07.10.4.4	2.4	0.34	1.7	3.1	a b
Galahad	2.3	0.34	1.6	2.9	a b
08H02.EB911	2.2	0.36	1.5	3.0	a b
Starfire	2.2	0.36	1.5	3.0	a b
Scotia	2.2	0.36	1.5	3.0	a b
MountainPrincess2	2.2	0.36	1.5	3.0	a b
MountainPrincess1	2.2	0.36	1.5	3.0	a b
OSA404	2.1	0.36	1.4	2.8	a b
Aurora	2.0	0.36	1.2	2.7	a b
2331.1_1	1.5	0.34	1.0	2.2	b
2331.1_2	1.5	0.34	1.0	2.2	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Tomatoes (Field) - Intensity					
Variety	emmean	SE	lowerCI	upperCI	group
15H07.10.4.4	2.6	0.31	2.0	3.3	a
VitalisLBresistant	2.5	0.31	1.9	3.1	a b
Starfire	2.4	0.33	1.7	3.1	a b
08H02.EB911	2.3	0.33	1.6	2.9	a b
MountainPrincess2	2.3	0.33	1.6	2.9	a b
MountainPrincess1	2.3	0.33	1.6	2.9	a b
Aurora	2.3	0.33	1.6	2.9	a b
WHybrid	2.1	0.31	1.5	2.8	a b
Galahad	2.1	0.31	1.5	2.8	a b
Brandywise	2.1	0.31	1.5	2.8	a b
OSA404	2.1	0.33	1.4	2.8	a b
Scotia	2.1	0.33	1.4	2.8	a b
2331.1_1	1.5	0.31	1.0	2.1	a b
2331.1_2	1.4	0.31	1.0	2.0	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Tomatoes (High Tunnel) - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
2330.1	4.2	0.21	3.7	4.6	a
EWS-TOM-206	4.1	0.23	3.6	4.5	a
MountainMerit	3.7	0.23	3.2	4.1	a b
Siletz	3.6	0.17	3.3	3.9	a b
JTO1007	3.6	0.18	3.2	3.9	a b
PiluKS	3.4	0.17	3.1	3.8	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Tomatoes (High Tunnel) - Texture					
Variety	emmean	SE	lowerCI	upperCI	group
JTO1007	3.2	0.18	2.9	3.6	a
PiluKS	3.0	0.16	2.7	3.3	a b
EWS-TOM-206	2.9	0.24	2.4	3.4	a b
Siletz	2.9	0.16	2.5	3.2	a b
MountainMerit	2.5	0.24	2.1	3.0	a b
2330.1	2.4	0.22	2.0	2.9	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Tomatoes (High Tunnel) - Sweetness					
Variety	emmean	SE	lowerCI	upperCI	group
MountainMerit	3.0	0.23	2.6	3.5	a
PiluKS	2.8	0.17	2.5	3.1	a b
EWS-TOM-206	2.8	0.23	2.3	3.2	a b
Siletz	2.6	0.16	2.3	2.9	a b
JTO1007	2.5	0.18	2.1	2.8	a b
2330.1	2.3	0.21	1.9	2.7	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Tomatoes (High Tunnel) - Acidity					
Variety	emmean	SE	lowerCI	upperCI	group
2330.1	3.0	0.20	2.6	3.4	a
PiluKS	2.8	0.16	2.5	3.1	a
Siletz	2.8	0.15	2.5	3.1	a
JTO1007	2.8	0.17	2.5	3.1	a
EWS-TOM-206	2.6	0.22	2.2	3.0	a b
MountainMerit	2.1	0.22	1.7	2.5	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Red Tomatoes (High Tunnel) - Overall Preference					
Variety	emmean	SE	lowerCI	upperCI	group
Siletz	3.0	0.16	2.7	3.3	a
JTO1007	2.9	0.18	2.5	3.3	a b
PiluKS	2.8	0.16	2.5	3.1	a b
EWS-TOM-206	2.8	0.24	2.3	3.2	a b
MountainMerit	2.3	0.24	1.8	2.8	a b
2330.1	2.3	0.22	1.9	2.7	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Pink Tomatoes (Field) - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
A6	4.4	0.32	3.7	5.0	a
A6TW-13	3.5	0.32	2.8	4.2	a b
CouncilBluffsHeirloom	3.3	0.32	2.6	3.9	b
15H08.4.3.4.1	3.0	0.32	2.3	3.7	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Pink Tomatoes (Field) - Sweetness					
Variety	emmean	SE	lowerCI	upperCI	group
A6TW-13	2.6	0.25	2.1	3.2	a
A6	2.5	0.25	2.0	3.0	a b
CouncilBluffsHeirloom	2.3	0.25	1.7	2.8	a b
15H08.4.3.4.1	1.9	0.25	1.4	2.4	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Pink Tomatoes (Field) - Bitterness					
Variety	emmean	SE	lowerCI	upperCI	group
A6	2.4	0.34	1.6	3.1	a
15H08.4.3.4.1	2.3	0.34	1.5	3.0	a
A6TW-13	1.6	0.34	1.0	2.4	b
CouncilBluffsHeirloom	1.5	0.34	1.0	2.2	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Pink Tomatoes (Field) - Umami					
Variety	emmean	SE	lowerCI	upperCI	group
A6TW-13	3.4	0.38	2.5	4.2	a
A6	2.9	0.38	2.0	3.7	a b
CouncilBluffsHeirloom	2.5	0.38	1.7	3.3	b
15H08.4.3.4.1	2.5	0.38	1.7	3.3	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Pink Tomatoes (Field) - Overall Preference					
Variety	emmean	SE	lowerCI	upperCI	group
A6TW-13	3.3	0.36	2.5	4.0	a
A6	2.8	0.36	2.0	3.5	a b
CouncilBluffsHeirloom	2.3	0.36	1.5	3.0	a b
15H08.4.3.4.1	1.9	0.36	1.1	2.6	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Pink Tomatoes (High Tunnel) - Texture					
Variety	emmean	SE	lowerCI	upperCI	group
ChefsChoicePink	4.6	0.30	4.0	5.2	a
2401	3.8	0.30	3.2	4.4	a b
BWHybrid	3.5	0.30	2.9	4.1	b
MarthaWashington2	3.4	0.30	2.8	4.0	b
MarthaWashington1	3.1	0.30	2.5	3.7	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Pink Tomatoes (High Tunnel) - Acidity					
Variety	emmean	SE	lowerCI	upperCI	group
2401	3.2	0.31	2.6	3.8	a
BWHybrid	3.0	0.31	2.4	3.6	a b
MarthaWashington2	2.9	0.31	2.3	3.5	a b
MarthaWashington1	2.3	0.31	1.7	2.9	a b
ChefsChoicePink	2.2	0.31	1.6	2.8	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Pink Tomatoes (High Tunnel) - Bitterness					
Variety	emmean	SE	lowerCI	upperCI	group
ChefsChoicePink	3.8	0.28	3.2	4.4	a
MarthaWashington1	1.8	0.28	1.2	2.4	b
MarthaWashington2	1.7	0.28	1.1	2.3	b
BWHybrid	1.6	0.28	1.0	2.2	b
2401	1.6	0.28	1.0	2.2	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Pink Tomatoes (High Tunnel) - Umami					
Variety	emmean	SE	lowerCI	upperCI	group
MarthaWashington2	3.1	0.27	2.6	3.6	a
2401	3.1	0.27	2.6	3.6	a
BWHybrid	3.0	0.27	2.5	3.5	a
MarthaWashington1	2.7	0.27	2.2	3.2	a
ChefsChoicePink	1.7	0.27	1.2	2.2	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Pink Tomatoes (High Tunnel) - Intensity					
Variety	emmean	SE	lowerCI	upperCI	group
BWHybrid	3.9	0.27	3.4	4.5	a
2401	3.5	0.27	3.0	4.1	a b
MarthaWashington2	3.5	0.27	3.0	4.1	a b
ChefsChoicePink	2.8	0.27	2.3	3.4	b
MarthaWashington1	2.6	0.27	2.1	3.2	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Pink Tomatoes (High Tunnel) - Overall Preference					
Variety	emmean	SE	lowerCI	upperCI	group
2401	4.1	0.30	3.5	4.7	a
BWHybrid	3.6	0.30	3.0	4.2	a b
MarthaWashington2	3.1	0.30	2.5	3.7	a b
ChefsChoicePink	3.0	0.30	2.4	3.6	b
MarthaWashington1	2.7	0.30	2.1	3.3	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Large Butternut Squash - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
Waltham1	4.3	0.26	3.8	4.8	a
Waldo	4.0	0.26	3.5	4.5	a b
Waltham2	3.9	0.26	3.4	4.5	a b
Havana	3.7	0.26	3.2	4.2	a b
Bugle	3.4	0.26	2.9	4.0	b c
Tiana	3.4	0.26	2.9	3.9	b c
Butterbush	2.7	0.26	2.2	3.2	c

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Large Butternut Squash - Texture					
Variety	emmean	SE	lowerCI	upperCI	group
Waltham2	3.9	0.24	3.4	4.3	a
Bugle	3.8	0.24	3.3	4.3	a
Waldo	3.6	0.24	3.1	4.0	a
Tiana	3.4	0.24	2.9	3.8	a
Waltham1	3.1	0.24	2.7	3.6	a b
Butterbush	3.1	0.24	2.7	3.6	a b
Havana	2.3	0.24	1.8	2.8	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Large Butternut Squash - Sweetness					
Variety	emmean	SE	lowerCI	upperCI	group
Bugle	3.3	0.25	2.8	3.7	a
Waltham1	2.8	0.25	2.3	3.3	a b
Waldo	2.8	0.25	2.3	3.3	a b
Waltham2	2.7	0.25	2.2	3.2	a b
Butterbush	2.6	0.25	2.1	3.1	a b
Havana	2.3	0.25	1.8	2.7	b
Tiana	2.1	0.25	1.6	2.6	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Large Butternut Squash - Bitterness					
Variety	emmean	SE	lowerCI	upperCI	group
Butterbush	2.3	0.25	1.8	2.8	a
Waldo	2.0	0.25	1.5	2.5	a b
Havana	2.0	0.25	1.5	2.5	a b
Waltham2	1.9	0.25	1.4	2.4	a b
Tiana	1.8	0.25	1.3	2.3	a b
Waltham1	1.7	0.25	1.2	2.2	a b
Bugle	1.6	0.25	1.1	2.1	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Large Butternut Squash - Intensity					
Variety	emmean	SE	lowerCI	upperCI	group
Bugle	3.0	0.24	2.5	3.5	a
Waldo	2.9	0.25	2.5	3.4	a
Waltham1	2.9	0.24	2.4	3.4	a
Butterbush	2.8	0.24	2.3	3.3	a
Waltham2	2.4	0.24	2.0	2.9	a b
Tiana	2.3	0.24	1.8	2.8	a b
Havana	2.0	0.24	1.5	2.5	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Large Butternut Squash - Overall Preference					
Variety	emmean	SE	lowerCI	upperCI	group
Bugle	3.7	0.29	3.1	4.3	a
Waldo	2.9	0.29	2.4	3.5	a b
Waltham2	2.9	0.29	2.3	3.5	a b
Waltham1	2.9	0.29	2.3	3.5	a b
Butterbush	2.3	0.29	1.7	2.9	b
Havana	2.2	0.29	1.6	2.8	b
Tiana	2.1	0.29	1.6	2.7	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Mini Butternut Squash - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
Brulee	4.3	0.26	3.8	4.9	a
Honeynut	4.2	0.26	3.7	4.7	a
Hamilton	4.1	0.26	3.6	4.7	a
Butterscotch	4.1	0.26	3.6	4.7	a
Butterbaby2	3.6	0.26	3.1	4.2	a b
Butterbaby1	3.6	0.26	3.1	4.2	a b
AutumnFrost	3.0	0.26	2.5	3.5	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Mini Butternut Squash - Texture					
Variety	emmean	SE	lowerCI	upperCI	group
Brulee	4.3	0.28	3.7	4.8	a
Butterscotch	4.2	0.28	3.6	4.7	a
Honeynut	3.6	0.28	3.0	4.1	a b
Butterbaby1	3.1	0.28	2.5	3.6	b c
Butterbaby2	2.9	0.29	2.4	3.5	b c
Hamilton	2.8	0.28	2.3	3.4	b c
AutumnFrost	2.3	0.28	1.8	2.9	c

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Mini Butternut Squash - Sweetness					
Variety	emmean	SE	lowerCI	upperCI	group
Butterscotch	4.3	0.27	3.7	4.8	a
Brulee	2.8	0.27	2.2	3.3	b
Butterbaby2	2.8	0.27	2.2	3.3	b
Butterbaby1	2.7	0.27	2.2	3.2	b
Honeynut	2.4	0.27	1.8	2.9	b
Hamilton	2.1	0.27	1.6	2.7	b
AutumnFrost	2.1	0.27	1.6	2.7	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Mini Butternut Squash - Intensity					
Variety	emmean	SE	lowerCI	upperCI	group
Butterscotch	4.1	0.21	3.7	4.5	a
Brulee	3.0	0.21	2.6	3.5	b
Butterbaby2	2.9	0.22	2.4	3.3	b c
Honeynut	2.8	0.21	2.4	3.2	b c
Butterbaby1	2.8	0.21	2.4	3.2	b c
AutumnFrost	2.2	0.21	1.7	2.6	c d
Hamilton	2.1	0.21	1.7	2.5	d

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Mini Butternut Squash - Overall Preference					
Variety	emmean	SE	lowerCI	upperCI	group
Butterscotch	4.1	0.27	3.5	4.6	a
Brulee	3.7	0.27	3.2	4.2	a b
Honeynut	3.1	0.27	2.5	3.6	b c
Hamilton	3.1	0.27	2.5	3.6	b c
Butterbaby1	2.8	0.27	2.3	3.4	b c
Butterbaby2	2.6	0.27	2.1	3.1	c
AutumnFrost	2.3	0.27	1.8	2.8	c

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Blue/Green maxima Squash - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
JWS14-4069	4.6	0.49	3.6	5.0	a
StellaBlue1	4.4	0.49	3.4	5.0	a b
StellaBlue2	4.0	0.49	3.0	5.0	a b
SweetFall	3.0	0.49	2.0	4.0	a b
JWS17-4547	2.8	0.49	1.8	3.8	a b
AmericanIndian	2.6	0.49	1.6	3.6	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Blue/Green maxima Squash - Texture					
Variety	emmean	SE	lowerCI	upperCI	group
StellaBlue1	4.6	0.36	3.8	5.0	a
SweetFall	4.2	0.36	3.4	5.0	a
JWS14-4069	4.0	0.36	3.2	4.8	a
StellaBlue2	3.8	0.36	3.0	4.6	a
JWS17-4547	2.2	0.36	1.4	3.0	b
AmericanIndian	2.0	0.36	1.2	2.8	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Blue/Green maxima Squash - Sweetness					
Variety	emmean	SE	lowerCI	upperCI	group
SweetFall	4.4	0.35	3.7	5.0	a
JWS14-4069	4.2	0.35	3.5	4.9	a b
StellaBlue1	3.0	0.35	2.3	3.7	b c
StellaBlue2	2.6	0.35	1.9	3.3	c
AmericanIndian	1.8	0.35	1.1	2.5	c
JWS17-4547	1.8	0.35	1.1	2.5	c

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Blue/Green maxima Squash - Intensity					
Variety	emmean	SE	lowerCI	upperCI	group
JWS14-4069	4.4	0.35	3.7	5.0	a
SweetFall	4.0	0.35	3.3	4.7	a b
StellaBlue1	3.2	0.35	2.5	3.9	a b c
StellaBlue2	3.0	0.35	2.3	3.7	b c
AmericanIndian	2.6	0.35	1.9	3.3	c
JWS17-4547	2.4	0.35	1.7	3.1	c

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Blue/Green maxima Squash - Overall Preference					
Variety	emmean	SE	lowerCI	upperCI	group
JWS14-4069	5.0	0.28	4.4	5.0	a
SweetFall	4.2	0.28	3.6	4.8	a b
StellaBlue1	3.6	0.28	3.0	4.2	b c
StellaBlue2	2.8	0.28	2.2	3.4	c d
JWS17-4547	2.4	0.28	1.8	3.0	d e
AmericanIndian	1.4	0.28	0.8	2.0	e

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Pink/Red maxima Squash - Appearance					
Variety	emmean	SE	lowerCI	upperCI	group
RedKuriSP	4.2	0.46	3.2	5.0	a
OrangeSummerWM	4.0	0.46	3.0	5.0	a
E30R.00056SP	4.0	0.46	3.0	5.0	a
OrangeSummerSP2	3.8	0.46	2.8	4.8	a
RedKuriWM	3.6	0.46	2.6	4.6	a
OrangeSummerSP1	3.6	0.46	2.6	4.6	a
E30R.00056WM	2.0	0.46	1.0	3.0	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Pink/Red maxima Squash - Sweetness					
Variety	emmean	SE	lowerCI	upperCI	group
OrangeSummerWM	3.8	0.38	3.0	4.6	a
E30R.00056SP	3.2	0.38	2.4	4.0	a b
RedKuriSP	3.2	0.38	2.4	4.0	a b
OrangeSummerSP2	2.4	0.38	1.6	3.2	b c
OrangeSummerSP1	2.4	0.38	1.6	3.2	b c
RedKuriWM	1.8	0.38	1.0	2.6	c
E30R.00056WM	1.2	0.38	0.4	2.0	c

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Pink/Red maxima Squash - Intensity					
Variety	emmean	SE	lowerCI	upperCI	group
RedKuriSP	3.4	0.41	2.6	4.2	a
E30R.00056SP	3.4	0.41	2.6	4.2	a
OrangeSummerWM	3.2	0.41	2.4	4.0	a
OrangeSummerSP2	3.2	0.41	2.4	4.0	a
OrangeSummerSP1	2.2	0.41	1.4	3.0	a b
RedKuriWM	1.4	0.41	0.6	2.2	b
E30R.00056WM	1.4	0.41	0.6	2.2	b

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Pink/Red maxima Squash - Overall Preference					
Variety	emmean	SE	lowerCI	upperCI	group
OrangeSummerWM	3.6	0.48	2.6	4.6	a
RedKuriSP	3.2	0.48	2.2	4.2	a b
E30R.00056SP	3.0	0.48	2.0	4.0	a b
OrangeSummerSP2	2.6	0.48	1.6	3.6	a b c
OrangeSummerSP1	2.4	0.48	1.4	3.4	a b c
E30R.00056WM	1.6	0.48	0.6	2.6	b c
RedKuriWM	1.2	0.48	0.2	2.2	c

- *Upper and lower limits for 95% confidence interval*
- *Significance level for differences (alpha) = 0.10*

Appendix F - Correlation Matrices of Relationships between Sensory Variables

2019 CIOA Flavor Correlations: Orange Carrots

	Appearance	Texture	Sweetness	Acidity	Harshness	Intensity
Appearance						
Texture	0.33					
Sweetness	0.16	0.77***				
Acidity	-0.05	0.34	0.28			
Harshness	-0.30	-0.49**	-0.46*	0.22		
Intensity	-0.06	0.54**	0.75***	0.56**	0.03	
Overall Preference	0.13	0.61***	0.71***	0.26	-0.29	0.71***

*** *$p < 0.01$* ***$p < 0.05$* **$p < 0.10$*

2019 CIOA Flavor Correlations: Purple Carrots

	Appearance	Texture	Sweetness	Acidity	Harshness	Intensity
Appearance						
Texture	0.77*					
Sweetness	0.52	0.92***				
Acidity	-0.68	-0.73	-0.56			
Harshness	-0.40	-0.86**	-0.98***	0.42		
Intensity	0.47	0.67	0.78*	-0.62	-0.68	
Overall Preference	0.91**	0.82**	0.60	-0.91**	-0.45	0.61

*** *$p < 0.01$* ***$p < 0.05$* **$p < 0.10$*

2019 CIOA Flavor Correlations: Red Carrots

	Appearance	Texture	Sweetness	Acidity	Harshness	Intensity
Appearance						
Texture	0.49					
Sweetness	0.26	0.77***				
Acidity	0.48	0.33	-0.24			
Harshness	-0.29	-0.39	-0.69**	0.43		
Intensity	-0.03	0.64**	0.50	0.39	0.19	
Overall Preference	0.35	0.87***	0.88***	-0.01	-0.59*	0.51

*** *$p < 0.01$* ***$p < 0.05$* **$p < 0.10$*

2019 CIOA Flavor Correlations: White Yellow Carrots

	Appearance	Texture	Sweetness	Acidity	Harshness	Intensity
Appearance						
Texture	0.92**					
Sweetness	0.65	0.44				
Acidity	0.63	0.39	0.61			
Harshness	-0.81*	-0.67	-0.90**	-0.42		
Intensity	0.52	0.69	0.15	0.42	-0.13	
Overall Preference	0.97***	0.84*	0.83*	0.68	-0.90**	0.46

*** *$p < 0.01$* ***$p < 0.05$* **$p < 0.10$*

2019 CIOA Flavor Correlations: Non-Orange Carrots						
	Appearance	Texture	Sweetness	Acidity	Harshness	Intensity
Appearance						
Texture	0.66***					
Sweetness	0.37	0.63***				
Acidity	0.26	0.26	-0.04			
Harshness	-0.40*	-0.49**	-0.73***	0.08		
Intensity	0.13	0.63***	0.40*	0.49**	-0.01	
Overall Preference	0.55**	0.77***	0.82***	0.03	-0.63***	0.45**

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: Orange Carrots						
	Appearance	Texture	Sweetness	Acidity	Harshness	Intensity
Appearance						
Texture	-0.86**					
Sweetness	-0.74*	0.92***				
Acidity	-0.57	0.40	0.57			
Harshness	0.08	0.00	-0.09	-0.69		
Intensity	-0.38	0.68	0.85**	0.27	0.24	
Overall Preference	-0.84**	0.84**	0.92***	0.74*	-0.18	0.72

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 Flavor Correlations: All Orange Carrots						
	Appearance	Texture	Sweetness	Acidity	Harshness	Intensity
Appearance						
Texture	0.30					
Sweetness	0.08	0.76***				
Acidity	-0.10	0.29	0.29			
Harshness	-0.35*	-0.51**	-0.43**	0.19		
Intensity	-0.13	0.46**	0.74***	0.54***	0.08	
Overall Preference	0.07	0.68***	0.74***	0.28	-0.32	0.64***

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: Red Carrots						
	Appearance	Texture	Sweetness	Acidity	Harshness	Intensity
Appearance						
Texture	-0.45					
Sweetness	0.02	0.66				
Acidity	0.40	0.00	0.38			
Harshness	-0.39	-0.51	-0.88**	-0.26		
Intensity	0.09	0.70	0.96***	0.20	-0.95***	
Overall Preference	0.47	0.48	0.79*	0.33	-0.97***	0.89**

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 Flavor Correlations: All Red Carrots						
	Appearance	Texture	Sweetness	Acidity	Harshness	Intensity
Appearance						
Texture	0.22					
Sweetness	0.19	0.75***				
Acidity	0.45*	0.25	-0.09			
Harshness	-0.30	-0.34	-0.58**	0.30		
Intensity	0.00	0.66***	0.60**	0.35	-0.03	
Overall Preference	0.38	0.76***	0.82***	0.05	-0.64***	0.58**

*** *p < 0.01* **p < 0.05* *p < 0.10*

2019 SKC Flavor Correlations: Purple Carrots						
	Appearance	Texture	Sweetness	Acidity	Harshness	Intensity
Appearance						
Texture	0.12					
Sweetness	-0.32	0.86**				
Acidity	-0.50	0.08	0.23			
Harshness	-0.13	-0.80*	-0.67	0.16		
Intensity	-0.49	0.70	0.89**	0.42	-0.70	
Overall Preference	0.32	0.91**	0.76*	0.10	-0.78*	0.65

*** *p < 0.01* **p < 0.05* *p < 0.10*

2019 Flavor Correlations: All Purple Carrots						
	Appearance	Texture	Sweetness	Acidity	Harshness	Intensity
Appearance						
Texture	0.41					
Sweetness	0.12	0.74***				
Acidity	-0.41	0.02	-0.32			
Harshness	-0.22	-0.67**	-0.76***	0.39		
Intensity	-0.20	0.66**	0.55*	0.42	-0.48	
Overall Preference	0.50	0.84***	0.63**	-0.09	-0.67**	0.59**

*** *p < 0.01* **p < 0.05* *p < 0.10*

2019 Flavor Correlations: All Non-Orange Carrots						
	Appearance	Texture	Sweetness	Acidity	Harshness	Intensity
Appearance						
Texture	0.42**					
Sweetness	0.23	0.66***				
Acidity	0.06	0.21	0.00			
Harshness	-0.41**	-0.46***	-0.64***	0.19		
Intensity	-0.03	0.65***	0.51***	0.49***	-0.12	
Overall Preference	0.48***	0.77***	0.75***	0.05	-0.65***	0.52***

*** *p < 0.01* **p < 0.05* *p < 0.10*

2019 Flavor Correlations: All Carrots						
	Appearance	Texture	Sweetness	Acidity	Harshness	Intensity
Appearance						
Texture	0.37***					
Sweetness	0.17	0.68***				
Acidity	-0.02	0.22	0.14			
Harshness	-0.39***	-0.47***	-0.56***	0.17		
Intensity	-0.07	0.56***	0.60***	0.53***	-0.05	
Overall Preference	0.30**	0.72***	0.75***	0.16	-0.52***	0.56***

**** $p < 0.01$ **$p < 0.05$ *$p < 0.10$*

2019 SKC Flavor Correlations: Asian Cucumbers						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.85**					
Sweetness	0.79**	0.61				
Acidity	0.01	-0.42	0.08			
Bitterness	-0.46	-0.59	-0.40	0.21		
Intensity	0.35	0.07	0.45	0.31	0.22	
Overall Preference	0.69*	0.64	0.61	0.17	-0.85**	-0.09

**** $p < 0.01$ **$p < 0.05$ *$p < 0.10$*

2019 SKC Flavor Correlations: Pickling Cucumbers						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.53*					
Sweetness	0.42	0.60**				
Acidity	-0.40	-0.45	-0.67**			
Bitterness	-0.38	0.27	-0.08	0.20		
Intensity	0.58**	0.61**	0.27	-0.14	0.20	
Overall Preference	0.40	0.73***	0.45	-0.25	0.15	0.59**

**** $p < 0.01$ **$p < 0.05$ *$p < 0.10$*

2019 SKC Flavor Correlations: Mini Cucumbers						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	-0.04					
Sweetness	0.02	0.85**				
Acidity	0.62	-0.01	0.44			
Bitterness	0.50	-0.59	-0.80*	-0.16		
Intensity	0.78*	-0.21	-0.40	-0.78*	-0.09	
Overall Preference	0.12	0.64	0.81*	0.47	-0.49	-0.42

**** $p < 0.01$ **$p < 0.05$ *$p < 0.10$*

2019 SKC Flavor Correlations: All Cucumbers						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.60***					
Sweetness	0.52***	0.64***				
Acidity	-0.04	-0.22	-0.21			
Bitterness	-0.31	-0.11	-0.2	0.16		
Intensity	0.44**	0.42**	0.37*	0.10	0.18	
Overall Preference	0.54***	0.68***	0.55***	0.10	-0.26	0.36*

**** p < 0.01 **p < 0.05 *p < 0.10*

2019 SKC Flavor Correlations: Butterhead Lettuce						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.06					
Sweetness	0.02	0.59				
Acidity	0.05	-0.47	0.11			
Bitterness	0.23	-0.03	-0.37	0.30		
Intensity	-0.21	0.55	0.92***	0.19	-0.34	
Overall Preference	0.01	0.34	0.85**	-0.09	-0.63	0.76**

**** p < 0.01 **p < 0.05 *p < 0.10*

2019 SKC Flavor Correlations: Little Gem Lettuce						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.89***					
Sweetness	0.12	-0.09				
Acidity	-0.40	-0.51	-0.16			
Bitterness	-0.36	-0.56	-0.38	0.57		
Intensity	0.26	-0.03	0.69*	-0.13	-0.21	
Overall Preference	0.26	0.46	0.05	-0.97***	-0.52	0.00

**** p < 0.01 **p < 0.05 *p < 0.10*

2019 SKC Flavor Correlations: Green One-Cut Lettuce						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.20					
Sweetness	0.31	0.31				
Acidity	0.19	-0.20	-0.21			
Bitterness	-0.16	-0.27	-0.47*	0.56**		
Intensity	-0.01	0.08	0.63**	0.05	-0.46*	
Overall Preference	0.14	0.32	0.18	-0.39	-0.45	-0.18

**** p < 0.01 **p < 0.05 *p < 0.10*

2019 SKC Flavor Correlations: Red One-Cut Lettuce						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.20					
Sweetness	0.31	0.31				
Acidity	0.19	-0.20	-0.21			
Bitterness	-0.16	-0.27	-0.47*	0.56**		
Intensity	-0.01	0.08	0.63**	0.05	-0.46*	
Overall Preference	0.14	0.32	0.18	-0.39	-0.45	-0.18

*** *p* < 0.01 ***p* < 0.05 **p* < 0.10

2019 SKC Flavor Correlations: All One-Cut Lettuce						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.18					
Sweetness	-0.06	0.34				
Acidity	0.09	-0.10	-0.08			
Bitterness	-0.01	-0.36*	-0.42**	0.42**		
Intensity	-0.06	0.25	0.66***	0.15	-0.13	
Overall Preference	0.09	0.52**	0.45**	-0.29	-0.65***	0.09

*** *p* < 0.01 ***p* < 0.05 **p* < 0.10

2019 SKC Flavor Correlations: All Lettuce						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.11					
Sweetness	-0.08	0.68***				
Acidity	0.00	-0.09	0.03			
Bitterness	0.05	-0.54***	-0.66***	0.31*		
Intensity	-0.11	0.58***	0.86***	0.10	-0.51***	
Overall Preference	0.02	0.64***	0.71***	-0.29*	-0.75***	0.53***

*** *p* < 0.01 ***p* < 0.05 **p* < 0.10

2019 SKC Flavor Correlations: Orange-Fleshed Melons						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	-0.33					
Sweetness	-0.19	0.65**				
Acidity	-0.59**	0.20	0.21			
Bitterness	0.05	0.28	-0.05	-0.01		
Intensity	-0.42	0.82***	0.90***	0.27	0.06	
Overall Preference	-0.36	0.80***	0.93***	0.34	-0.02	0.94***

*** *p* < 0.01 ***p* < 0.05 **p* < 0.10

Correlations could not be calculated for the Galia Melons market class because it contained too few varieties (only three tasting samples).

2019 SKC Flavor Correlations: All Melons						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	-0.30					
Sweetness	-0.18	0.60**				
Acidity	-0.58**	0.13	0.14			
Bitterness	0.05	0.32	-0.03	-0.02		
Intensity	-0.41	0.79***	0.88***	0.23	0.08	
Overall Preference	-0.34	0.80***	0.92***	0.27	0.02	0.94***

**** p < 0.01 **p < 0.05 *p < 0.10*

2019 SKC Flavor Correlations: Orange Yellow Bell Peppers						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	-0.13					
Sweetness	-0.23	0.66				
Acidity	0.48	-0.61	-0.31			
Bitterness	0.23	-0.23	-0.73	-0.32		
Intensity	0.37	0.62	0.81*	-0.03	-0.55	
Overall Preference	0.27	0.78	0.81*	-0.12	-0.55	0.96***

**** p < 0.01 **p < 0.05 *p < 0.10*

2019 SKC Flavor Correlations: Red Bell Peppers						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.03					
Sweetness	-0.08	0.32				
Acidity	0.29	-0.29	-0.33			
Bitterness	0.36	-0.59**	-0.52*	0.38		
Intensity	0.23	0.16	0.31	-0.13	-0.15	
Overall Preference	0.27	0.34	0.21	-0.62**	-0.44	0.43

**** p < 0.01 **p < 0.05 *p < 0.10*

2019 SKC Flavor Correlations: All Bell Peppers						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	-0.06					
Sweetness	-0.11	0.34				
Acidity	0.32	-0.32	-0.29			
Bitterness	0.30	-0.34	-0.48*	0.34		
Intensity	0.29	0.41*	0.52**	-0.08	-0.15	
Overall Preference	0.26	0.56**	0.48*	-0.38	-0.32	0.77***

**** p < 0.01 **p < 0.05 *p < 0.10*

2019 SKC Flavor Correlations: Orange Yellow Corno di Toro Peppers						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.04					
Sweetness	-0.63	-0.52				
Acidity	0.20	0.94**	-0.76			
Bitterness	0.35	-0.4	-0.44	-0.08		
Intensity	-0.44	0.68	-0.40	0.72	-0.08	
Overall Preference	-0.58	0.53	0.38	0.24	-0.93**	0.41

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: Red Corno di Toro Peppers						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.37					
Sweetness	-0.11	-0.20				
Acidity	-0.33	-0.22	-0.02			
Bitterness	-0.14	-0.01	-0.59**	0.32		
Intensity	-0.23	-0.07	0.44	0.26	0.11	
Overall Preference	0.25	0.00	-0.09	-0.26	0.29	0.07

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: All Corno di Toro Peppers						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.28					
Sweetness	-0.16	-0.32				
Acidity	-0.29	0.06	-0.20			
Bitterness	-0.14	-0.04	-0.54**	0.29		
Intensity	-0.22	0.00	0.33	0.26	0.05	
Overall Preference	0.09	0.21	0.13	-0.12	-0.03	0.11

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: All Sweet Peppers						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.03					
Sweetness	0.04	-0.05				
Acidity	0.05	-0.17	-0.06			
Bitterness	0.03	-0.14	-0.50***	0.25		
Intensity	0.21	-0.05	0.65***	0.25	-0.17	
Overall Preference	0.28	0.25	0.56***	-0.10	-0.27	0.67***

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: Red Potatoes							
	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	-0.90**						
Sweetness	0.97***	-0.87**					
Acidity	0.48	-0.55	0.37				
Bitterness	-0.17	-0.04	-0.18	0.45			
Umami	-0.45	0.45	-0.45	-0.85**	-0.55		
Intensity	-0.26	0.26	-0.40	-0.33	-0.14	0.69	
Overall Preference	-0.20	0.48	-0.29	-0.44	-0.34	0.58	0.77*

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

2019 SKC Flavor Correlations: Yellow Potatoes							
	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	-0.15						
Sweetness	-0.51	0.87*					
Acidity	-0.62	-0.47	-0.08				
Bitterness	0.06	-0.97***	-0.86*	0.57			
Umami	0.00	0.65	0.50	-0.77	-0.75		
Intensity	0.44	0.75	0.48	-0.88*	-0.85*	0.77	
Overall Preference	0.48	0.78	0.48	-0.72	-0.81*	0.49	0.91**

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Correlations could not be calculated for the Multi-Colored Potatoes market class because it contained too few varieties (only four tasting samples).

2019 SKC Flavor Correlations: All Potatoes							
	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	-0.33						
Sweetness	0.29	-0.12					
Acidity	-0.11	-0.01	0.41				
Bitterness	-0.12	-0.12	-0.15	0.61**			
Umami	-0.37	0.70***	-0.15	-0.02	-0.17		
Intensity	-0.10	0.41	-0.06	0.03	-0.09	0.58**	
Overall Preference	0.05	0.73***	-0.14	0.01	-0.13	0.72***	0.70***

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

2019 SKC Flavor Correlations: Breeding Tomatoes (Set 1)							
	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.13						
Sweetness	0.43	0.68*					
Acidity	0.66	-0.12	-0.22				
Bitterness	-0.11	-0.35	-0.41	-0.14			
Umami	-0.04	-0.52	-0.79**	0.66	0.18		
Intensity	0.73*	0.50	0.51	0.41	0.14	-0.23	
Overall Preference	0.68*	0.13	0.45	0.11	0.35	-0.27	0.54

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: Breeding Tomatoes (Set 2)							
	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.56						
Sweetness	0.59	0.46					
Acidity	0.56	0.30	0.80**				
Bitterness	-0.64	0.00	-0.13	-0.54			
Umami	0.58	0.75*	0.46	0.00	0.24		
Intensity	0.92***	0.47	0.78**	0.76**	-0.57	0.45	
Overall Preference	0.90***	0.41	0.26	0.24	-0.57	0.54	0.76**

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: Breeding Tomatoes (Set 3)							
	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.86**						
Sweetness	0.88**	0.71					
Acidity	-0.36	-0.46	-0.45				
Bitterness	-0.71	-0.47	-0.80*	-0.11			
Umami	0.32	0.38	0.50	0.22	-0.58		
Intensity	0.90**	0.64	0.96***	-0.48	-0.74*	0.31	
Overall Preference	0.81**	0.56	0.80*	0.03	-0.76*	0.64	0.80*

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: Breeding Tomatoes (Field Day)							
	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	-0.23						
Sweetness	-0.30	0.81*					
Acidity	-0.17	0.80*	0.52				
Bitterness	0.71	-0.40	-0.59	-0.47			
Umami	-0.63	0.52	0.63	0.50	-0.95***		
Intensity	-0.08	0.90**	0.94***	0.64	-0.47	0.58	
Overall Preference	-0.24	0.87**	0.87**	0.67	-0.65	0.79*	0.94***

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: All Breeding Tomatoes							
	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.33						
Sweetness	0.43**	0.68***					
Acidity	0.26	0.30	0.36*				
Bitterness	0.16	-0.02	-0.13	-0.18			
Umami	0.18	0.42**	0.40**	0.38*	0.06		
Intensity	0.52***	0.65***	0.82***	0.47**	0.20	0.59***	
Overall Preference	0.52***	0.63***	0.73***	0.43**	-0.03	0.57***	0.81***

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

Correlations could not be calculated for the Cherry Tomatoes market class because it contained too few varieties (only three tasting samples).

2019 SKC Flavor Correlations: Cocktail Tomatoes							
	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	-0.03						
Sweetness	-0.53	0.17					
Acidity	0.59	-0.52	-0.31				
Bitterness	0.40	0.02	-0.31	0.77*			
Umami	-0.11	0.07	0.31	0.43	0.72		
Intensity	0.43	0.18	0.29	0.61	0.70	0.73*	
Overall Preference	0.18	0.53	0.48	0.24	0.53	0.72	0.91**

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: Orange Yellow Tomatoes							
	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.70						
Sweetness	0.24	0.39					
Acidity	-0.24	0.41	-0.26				
Bitterness	-0.88**	-0.53	-0.41	0.53			
Umami	0.11	0.21	0.51	0.00	-0.07		
Intensity	0.04	0.51	0.75*	0.36	0.07	0.50	
Overall Preference	0.41	0.89**	0.66	0.41	-0.35	0.23	0.78*

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: Red Tomatoes (Field)

	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.14						
Sweetness	-0.38	0.32					
Acidity	0.12	0.46	-0.09				
Bitterness	-0.06	0.29	0.02	0.20			
Umami	-0.03	0.46*	0.32	-0.04	0.54**		
Intensity	-0.03	0.62**	0.19	0.43	0.72***	0.74***	
Overall Preference	0.20	0.46*	0.45	0.00	0.24	0.53*	0.44

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: Red Tomatoes (High Tunnel Set 1)

	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.17						
Sweetness	-0.03	0.13					
Acidity	0.65	-0.07	-0.43				
Bitterness	0.27	-0.20	-0.95**	0.69			
Umami	-0.54	0.48	0.52	-0.35	-0.60		
Intensity	0.24	0.24	-0.15	0.77	0.34	0.32	
Overall Preference	-0.50	0.54	0.52	-0.86*	-0.75	0.65	-0.44

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: Red Tomatoes (High Tunnel Set 2)

	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.17						
Sweetness	-0.03	0.13					
Acidity	0.65	-0.07	-0.43				
Bitterness	0.27	-0.20	-0.95**	0.69			
Umami	-0.54	0.48	0.52	-0.35	-0.60		
Intensity	0.24	0.24	-0.15	0.77	0.34	0.32	
Overall Preference	-0.50	0.54	0.52	-0.86*	-0.75	0.65	-0.44

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: Red Tomatoes (High Tunnel Set 3)

	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.23						
Sweetness	0.87**	0.46					
Acidity	-0.61	0.16	-0.35				
Bitterness	-0.67	0.22	-0.47	0.20			
Umami	-0.49	0.23	-0.11	0.52	0.58		
Intensity	-0.74*	0.04	-0.62	0.34	0.85**	0.72*	
Overall Preference	0.35	0.66	0.64	0.36	-0.12	0.10	-0.34

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: All Red Tomatoes (High Tunnel)

	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	-0.45						
Sweetness	-0.45	0.35					
Acidity	0.04	0.15	-0.50				
Bitterness	-0.14	0.46	-0.04	0.33			
Umami	-0.49	0.47	0.13	0.45	0.07		
Intensity	-0.44	0.59*	0.00	0.52*	0.71**	0.49	
Overall Preference	-0.25	0.65**	0.24	0.13	-0.01	0.73**	0.08

*** *p < 0.01* ****p < 0.05** **p < 0.10*

2019 SKC Flavor Correlations: All Red Tomatoes

	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.32						
Sweetness	0.17	0.79***					
Acidity	0.20	0.40**	0.12				
Bitterness	0.21	0.66***	0.54***	0.32			
Umami	0.12	0.65***	0.56***	0.17	0.62***		
Intensity	0.25	0.85***	0.71***	0.46**	0.84***	0.77***	
Overall Preference	0.31	0.73***	0.67***	0.17	0.48**	0.71***	0.63***

$***\ p < 0.01$ $**p < 0.05$ $*p < 0.10$

Correlations could not be calculated for the Pink (Field) Tomatoes market class because it contained too few varieties (only four tasting samples).

2019 SKC Flavor Correlations: Pink Tomatoes (High Tunnel)

	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.40						
Sweetness	0.06	0.92**					
Acidity	-0.42	-0.27	0.00				
Bitterness	0.54	0.86*	0.66	-0.71			
Umami	-0.44	-0.76	-0.56	0.82*	-0.98***		
Intensity	-0.52	-0.16	0.18	0.89**	-0.54	0.66	
Overall Preference	-0.42	0.13	0.40	0.86*	-0.38	0.48	0.73

$***\ p < 0.01$ $**p < 0.05$ $*p < 0.10$

2019 SKC Flavor Correlations: All Pink Tomatoes							
	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.52						
Sweetness	0.53	0.82***					
Acidity	-0.20	-0.44	-0.44				
Bitterness	0.39	0.68**	0.33	-0.39			
Umami	-0.04	-0.50	-0.11	0.56	-0.82***		
Intensity	0.15	0.21	0.63*	0.20	-0.32	0.51	
Overall Preference	0.35	0.46	0.80***	0.02	-0.19	0.45	0.83***

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: All Tomatoes (Field)							
	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.43***						
Sweetness	0.35***	0.65***					
Acidity	0.37***	0.32***	0.03				
Bitterness	0.13	0.23**	0.04	0.18*			
Umami	0.18*	0.41***	0.44***	0.24**	0.06		
Intensity	0.40***	0.70***	0.71***	0.37***	0.10	0.65***	
Overall Preference	0.44***	0.68***	0.70***	0.30***	-0.03	0.45***	0.74***

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: All Tomatoes (High Tunnel)							
	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.17						
Sweetness	-0.09	0.68***					
Acidity	-0.14	-0.08	-0.26				
Bitterness	0.35	0.71***	0.46*	-0.45*			
Umami	-0.34	-0.14	-0.13	0.67***	-0.70***		
Intensity	-0.20	0.40	0.26	0.64***	-0.12	0.59**	
Overall Preference	-0.03	0.60**	0.47*	0.43*	-0.02	0.53**	0.61**

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: SARE Project Tomatoes							
	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.31						
Sweetness	0.28	0.27					
Acidity	0.42**	0.44**	-0.26				
Bitterness	-0.17	-0.38*	-0.45**	0.27			
Umami	0.24	0.30	0.43**	0.22	0.19		
Intensity	0.57***	0.72***	0.60***	0.34	-0.21	0.72***	
Overall Preference	0.47**	0.74***	0.63***	0.39*	-0.31	0.49**	0.83***

*** $p < 0.01$ **$p < 0.05$ *$p < 0.10$

2019 SKC Flavor Correlations: All Tomatoes							
	Appearance	Texture	Sweetness	Acidity	Bitterness	Umami	Intensity
Appearance							
Texture	0.43***						
Sweetness	0.35***	0.65***					
Acidity	0.37***	0.32***	0.03				
Bitterness	0.13	0.23**	0.04	0.18*			
Umami	0.18*	0.41***	0.44***	0.24**	0.06		
Intensity	0.40***	0.70***	0.71***	0.37***	0.10	0.65***	
Overall Preference	0.44***	0.68***	0.70***	0.30***	-0.03	0.45***	0.74***

**** p < 0.01 **p < 0.05 *p < 0.10*

2019 SKC Flavor Correlations: Large Butternut Squash						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.08					
Sweetness	0.20	0.56				
Acidity	0.58	0.13	-0.14			
Bitterness	-0.46	-0.3	-0.39	-0.58		
Intensity	0.04	0.56	0.79**	-0.1	-0.14	
Overall Preference	0.32	0.65	0.94***	-0.06	-0.57	0.68*

**** p < 0.01 **p < 0.05 *p < 0.10*

2019 SKC Flavor Correlations: Mini Butternut Squash						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.80**					
Sweetness	0.32	0.69*				
Acidity	0.12	0.60	0.85**			
Bitterness	0.18	-0.05	-0.51	-0.32		
Intensity	0.43	0.80**	0.96***	0.83**	-0.34	
Overall Preference	0.80**	0.92***	0.75*	0.60	-0.32	0.78**

**** p < 0.01 **p < 0.05 *p < 0.10*

2019 SKC Flavor Correlations: All Butternut Squash						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.45					
Sweetness	0.27	0.63**				
Acidity	0.19	0.38	0.41			
Bitterness	-0.2	-0.1	-0.45	-0.01		
Intensity	0.28	0.70***	0.92***	0.35	-0.32	
Overall Preference	0.57**	0.75***	0.77***	0.08	-0.52*	0.73***

**** p < 0.01 **p < 0.05 *p < 0.10*

2019 SKC Flavor Correlations: Blue Green *maxima* Squash						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.76*					
Sweetness	0.48	0.78*				
Acidity	0.03	-0.05	-0.39			
Bitterness	-0.58	-0.90**	-0.64	0.31		
Intensity	0.55	0.71	0.97***	-0.46	-0.56	
Overall Preference	0.67	0.80*	0.93***	-0.14	-0.54	0.93***

**** $p < 0.01$ **$p < 0.05$ *$p < 0.10$*

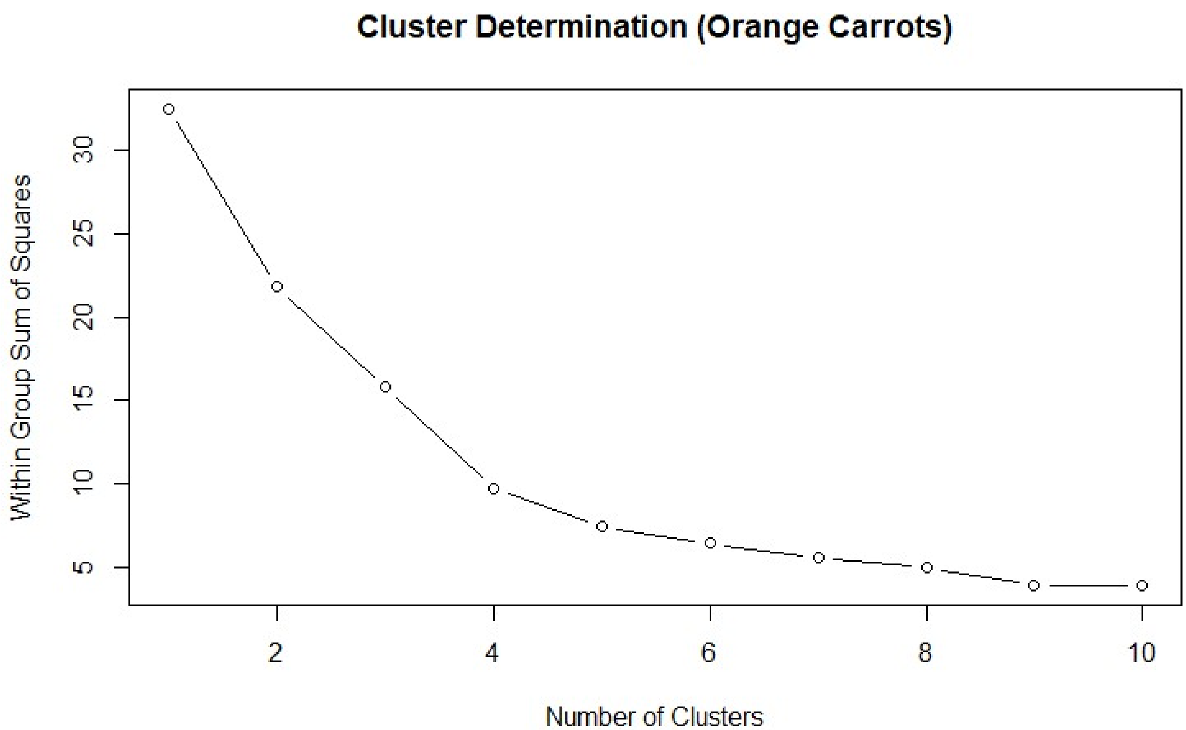
2019 SKC Flavor Correlations: Red Pink *maxima* Squash						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.33					
Sweetness	0.82**	0.79**				
Acidity	0.55	0.00	0.45			
Bitterness	0.00	-0.23	-0.11	0.34		
Intensity	0.76**	0.67*	0.87**	0.22	-0.2	
Overall Preference	0.66	0.84**	0.93***	0.33	-0.22	0.92***

**** $p < 0.01$ **$p < 0.05$ *$p < 0.10$*

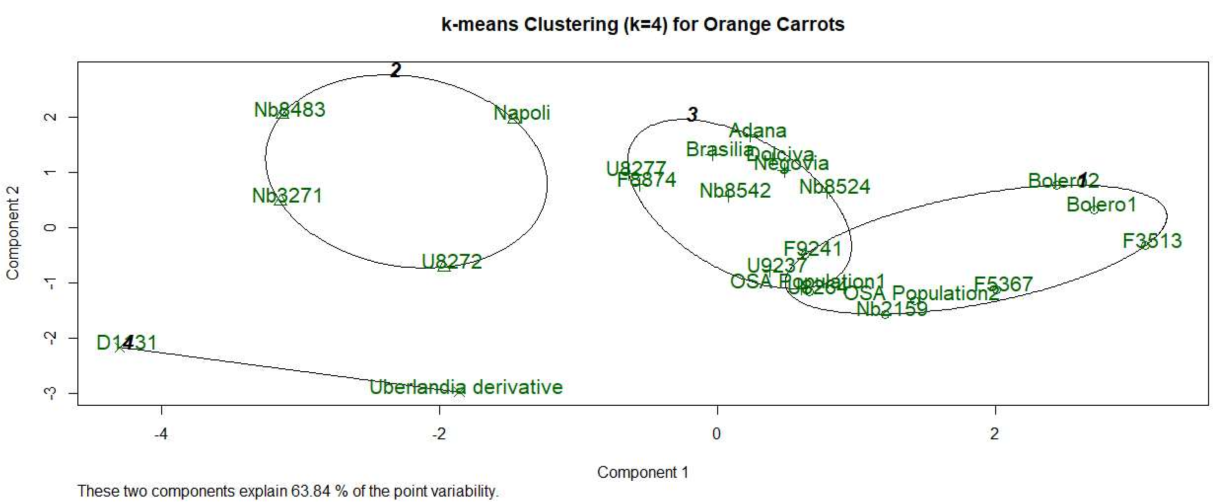
2019 SKC Flavor Correlations: All *maxima Squash*						
	Appearance	Texture	Sweetness	Acidity	Bitterness	Intensity
Appearance						
Texture	0.53*					
Sweetness	0.61**	0.77***				
Acidity	0.32	0.08	0.16			
Bitterness	-0.19	-0.61**	-0.38	0.16		
Intensity	0.60**	0.70***	0.89***	0.11	-0.44	
Overall Preference	0.62**	0.83***	0.92***	0.19	-0.44	0.90***

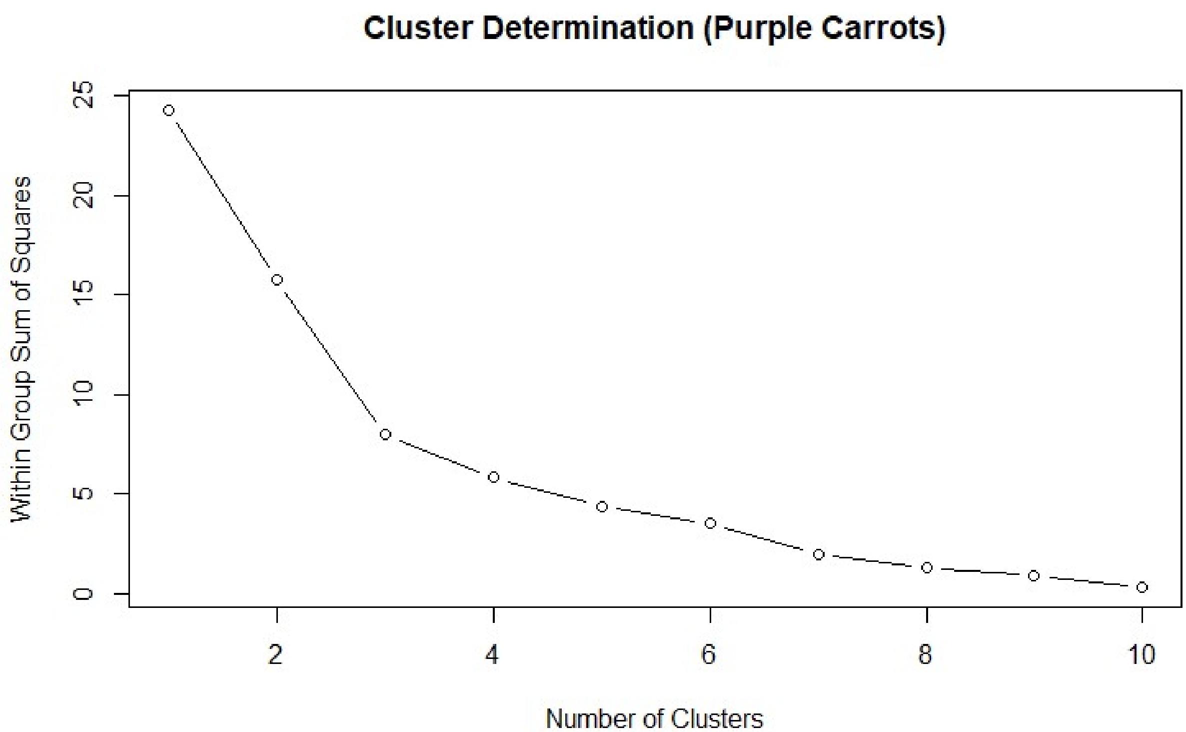
**** $p < 0.01$ **$p < 0.05$ *$p < 0.10$*

Appendix G – k-Means Clustering and Cluster Determination

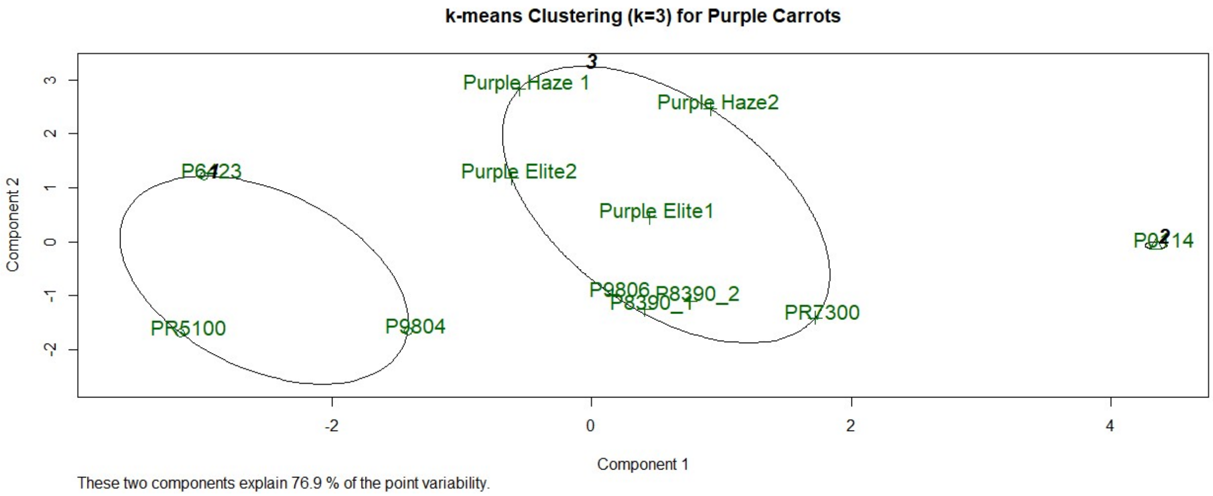


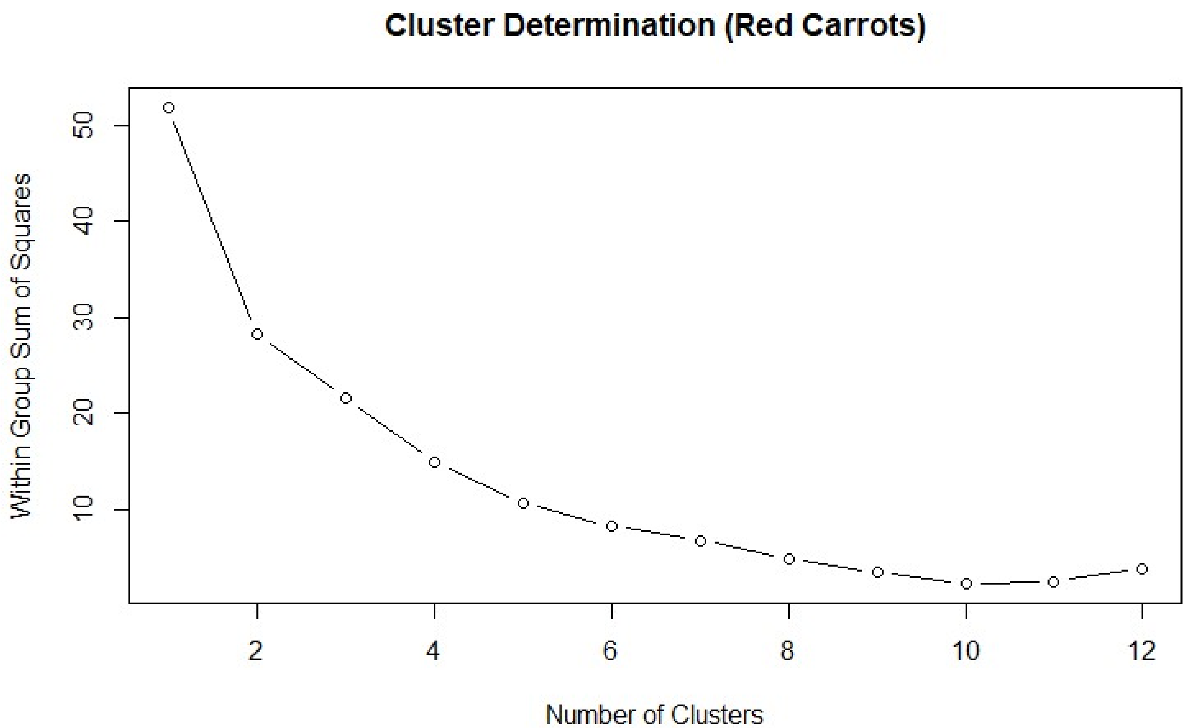
Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.09.10	2019.10.23	Carrot	NVM	Negovia	Orange	Bejo Seeds	WMARS	Field
2019.09.10	2019.10.23	Carrot	PSJ	Dolciva	Orange	High Mowing	WMARS	Field
2019.09.10	2019.10.23	Carrot	IDP	Adana	Orange	Bejo Seeds	WMARS	Field
2019.09.10	2019.10.23	Carrot	JXE	Bolero1	Orange	Johnny's	WMARS	Field
2019.09.10	2019.10.23	Carrot	HKJ	Bolero2	Orange	Johnny's	WMARS	Field
2019.09.10	2019.10.23	Carrot	XQM	Napoli	Orange	Bejo Seeds	WMARS	Field
2019.09.10	2019.10.23	Carrot	XKA	OSA Population 1	Orange	CIOA	WMARS	Field
2019.09.10	2019.10.23	Carrot	DHF	F3513	Orange	CIOA	WMARS	Field
2019.09.10	2019.10.23	Carrot	RXI	OSA Population 2	Orange	CIOA	WMARS	Field
2019.09.10	2019.10.23	Carrot	GHK	Uberlandia derivative	Orange	CIOA	WMARS	Field
2019.09.10	2019.10.23	Carrot	IKR	Nb8524	Orange	CIOA	WMARS	Field
2019.09.10	2019.10.23	Carrot	JVX	Nb2159	Orange	CIOA	WMARS	Field
2019.09.10	2019.10.23	Carrot	FXV	F5367	Orange	CIOA	WMARS	Field
2019.09.10	2019.11.26	Carrot	TRM	U8277	Orange	CIOA	WMARS	Field
2019.09.10	2019.11.26	Carrot	ZCL	U9237	Orange	CIOA	WMARS	Field
2019.09.10	2019.11.26	Carrot	ARX	U8264	Orange	CIOA	WMARS	Field
2019.09.10	2019.11.26	Carrot	BHE	Nb8542	Orange	CIOA	WMARS	Field
2019.09.10	2019.11.26	Carrot	PDM	Brasilia	Orange	CIOA	WMARS	Field
2019.09.10	2019.11.26	Carrot	NVM	F9241	Orange	CIOA	WMARS	Field
2019.09.10	2019.11.26	Carrot	PSJ	F8874	Orange	CIOA	WMARS	Field
2019.09.10	2019.11.26	Carrot	IDP	Nb8483	Orange	CIOA	WMARS	Field
2019.09.10	2019.11.26	Carrot	JXE	D1131	Orange	CIOA	WMARS	Field
2019.09.10	2019.11.26	Carrot	HKJ	Nb3271	Orange	CIOA	WMARS	Field
2019.09.10	2019.11.26	Carrot	XQM	U8272	Orange	CIOA	WMARS	Field



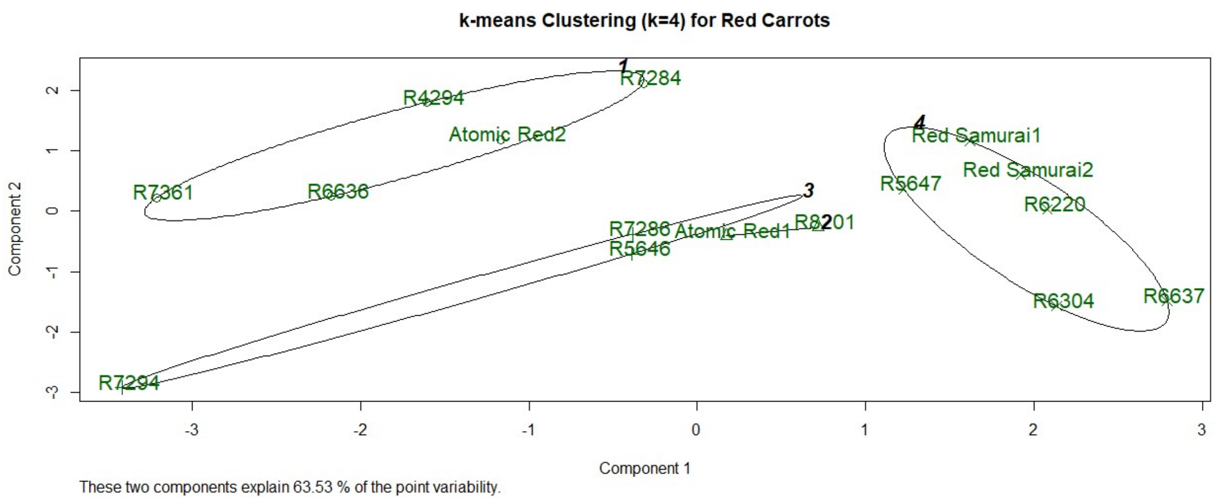


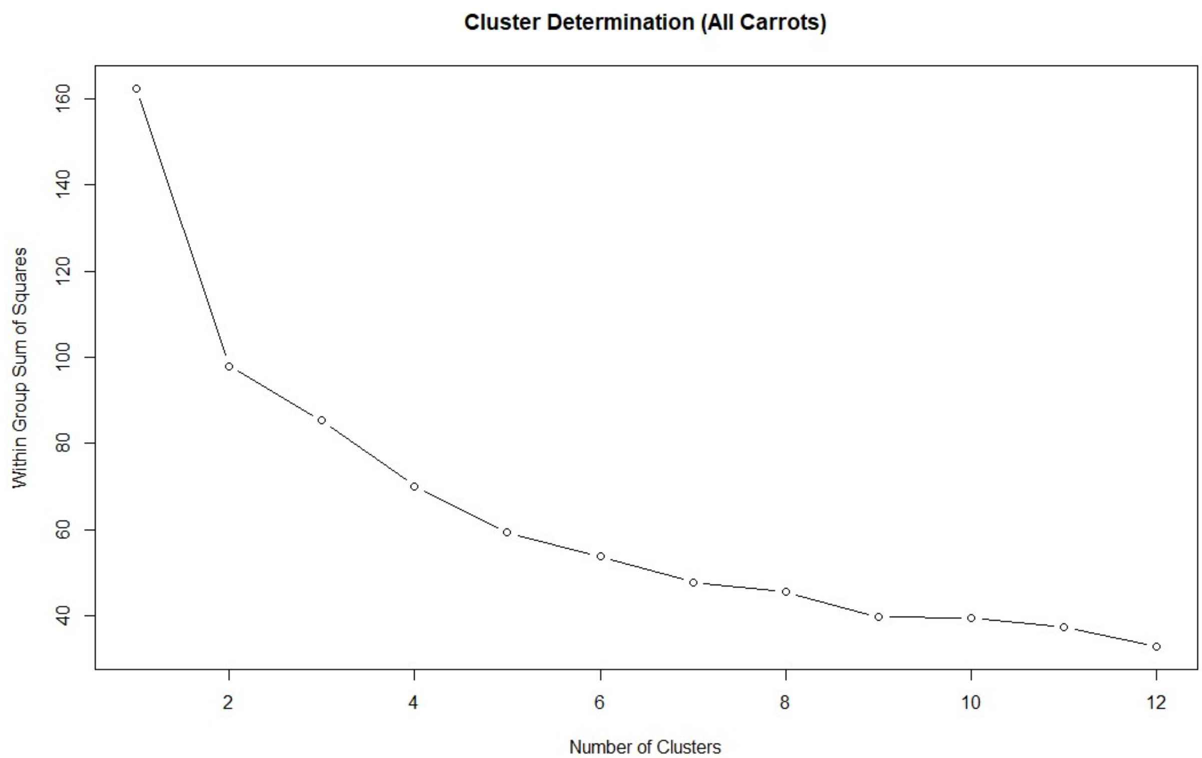
Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.09.10	2019.11.06	Carrot	ERP	Purple Elite1	Purple	Johnny's	WMARS	Field
2019.09.10	2019.11.06	Carrot	KHV	Purple Haze1	Purple	Johnny's	WMARS	Field
2019.09.10	2019.11.06	Carrot	OBE	Purple Haze2	Purple	Johnny's	WMARS	Field
2019.09.10	2019.11.06	Carrot	LPM	P0114	Purple	CIOA	WMARS	Field
2019.09.10	2019.11.06	Carrot	FJN	Purple Elite2	Purple	Johnny's	WMARS	Field
2019.09.10	2019.11.06	Carrot	SNH	P6423	Purple	CIOA	WMARS	Field
2019.09.10	2019.11.11	Carrot	NVM	P9806	Purple	CIOA	WMARS	Field
2019.09.10	2019.11.11	Carrot	PSJ	P8390	Purple	CIOA	WMARS	Field
2019.09.10	2019.11.11	Carrot	IDP	P8390	Purple	CIOA	WMARS	Field
2019.09.10	2019.11.11	Carrot	JXE	P9804	Purple	CIOA	WMARS	Field
2019.09.10	2019.11.11	Carrot	HKJ	PR7300	Purple	CIOA	WMARS	Field
2019.09.10	2019.11.11	Carrot	XQM	PR5100	Purple	CIOA	WMARS	Field


k-means Clustering (k=3) for Purple Carrots
Purple Haze 1
Purple Haze2
P6423
Purple Elite2
Purple Elite1
P0214
P9806
P8390_2
P8390_1
PR7300
PR5100
P9804
Component 1
Component 2
These two components explain 76.9 % of the point variability.

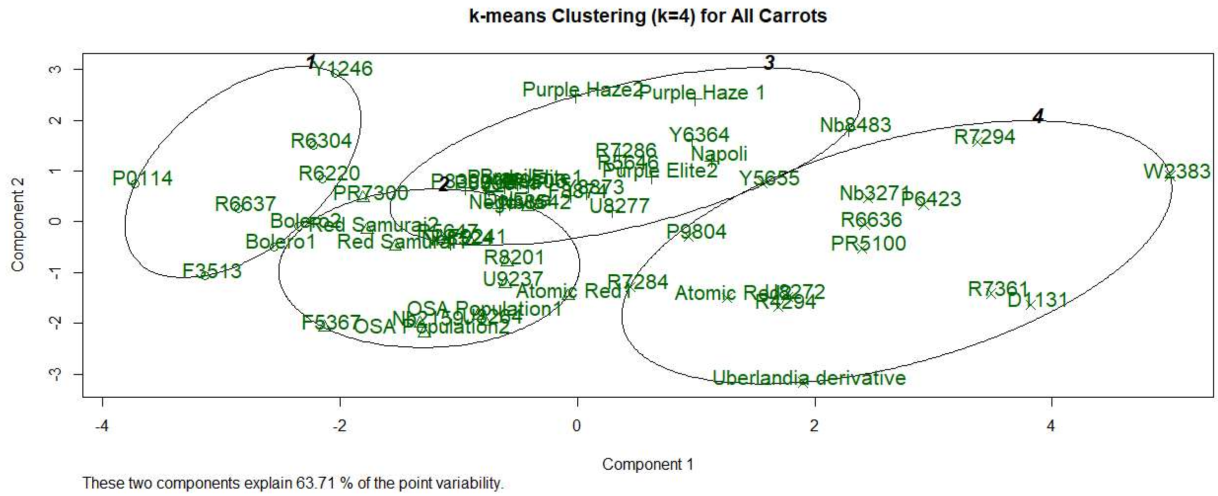

Cluster Determination (Red Carrots)
Within Group Sum of Squares
Number of Clusters

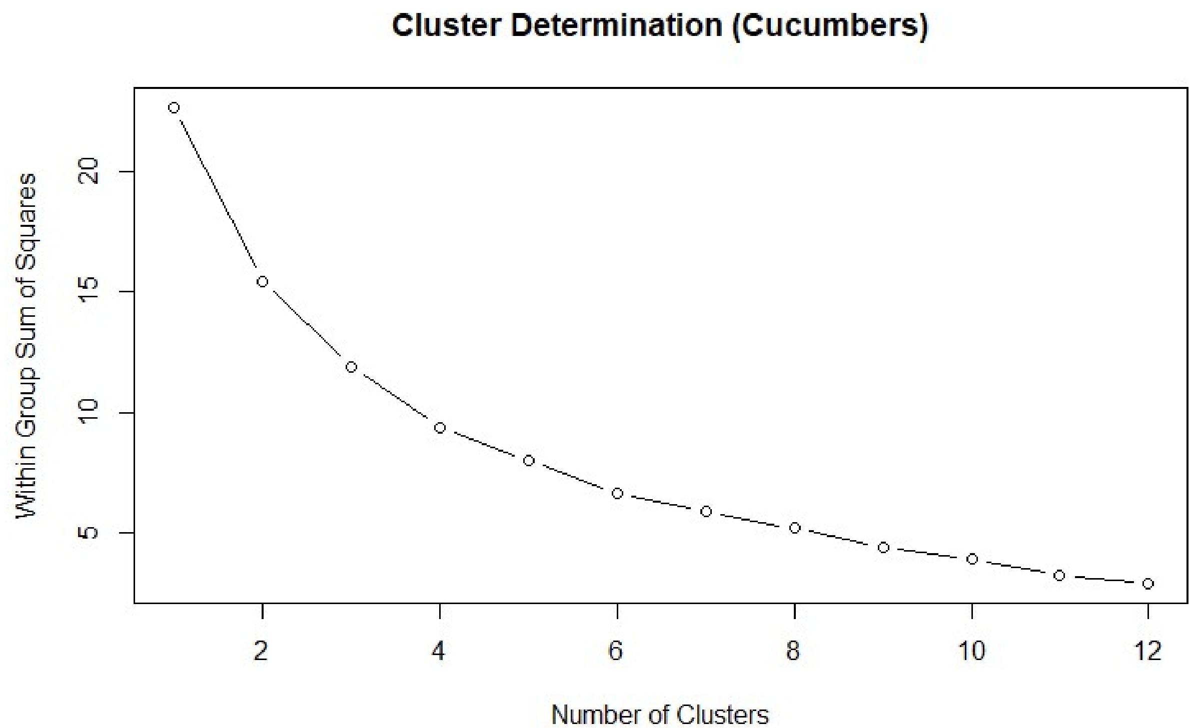
Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.09.10	2019.11.11	Carrot	TRM	R7286	Red	CIOA	WMARS	Field
2019.09.10	2019.11.11	Carrot	ZCL	R7361	Red	CIOA	WMARS	Field
2019.09.10	2019.11.11	Carrot	ARX	R6637	Red	CIOA	WMARS	Field
2019.09.10	2019.11.11	Carrot	BHE	R6304	Red	CIOA	WMARS	Field
2019.09.10	2019.11.11	Carrot	PDM	R7294	Red	CIOA	WMARS	Field
2019.09.10	2019.11.06	Carrot	NVM	Red Samurai1	Red	Territorial	WMARS	Field
2019.09.10	2019.11.06	Carrot	PSJ	R6636	Red	CIOA	WMARS	Field
2019.09.10	2019.11.06	Carrot	IDP	Atomic Red1	Red	Fedco	WMARS	Field
2019.09.10	2019.11.06	Carrot	JXE	Atomic Red2	Red	Fedco	WMARS	Field
2019.09.10	2019.11.06	Carrot	HKJ	R5647	Red	CIOA	WMARS	Field
2019.09.10	2019.11.06	Carrot	XQM	Red Samurai2	Red	Territorial	WMARS	Field





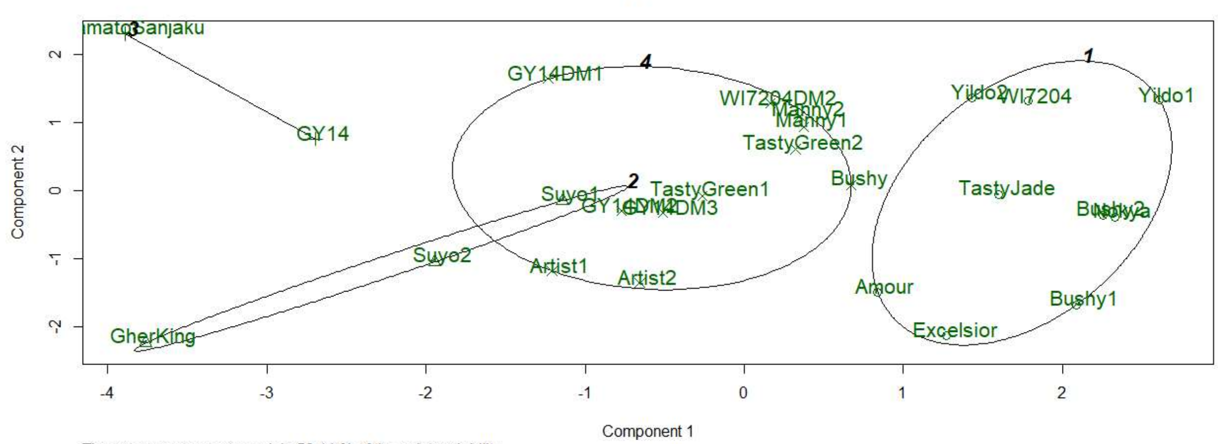
Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.09.10	2019.11.06	Carrot	XKA	Rainbow	WhiteYellow	Bejo Seeds	WMARS	Field
2019.09.10	2019.11.06	Carrot	DHF	Y1246	WhiteYellow	CIOA	WMARS	Field
2019.09.10	2019.11.06	Carrot	RXI	W2383	WhiteYellow	CIOA	WMARS	Field
2019.09.10	2019.11.06	Carrot	GHK	Rainbow	WhiteYellow	Bejo Seeds	WMARS	Field
2019.09.10	2019.11.06	Carrot	IKR	Y5655	WhiteYellow	CIOA	WMARS	Field
2019.09.10	2019.11.06	Carrot	JVX	Y6364	WhiteYellow	CIOA	WMARS	Field
2019.09.10	2019.11.06	Carrot	FXV	Y8873	WhiteYellow	CIOA	WMARS	Field


k-means Clustering (k=4) for All Carrots
Component 2
Component 1
These two components explain 63.71 % of the point variability.
Y1246
Purple Haze2
Purple Haze 1
Nb8483
R7294
W2383
R6304
R6220
P0114
R6637
PR7300
R7286
Y6364
Napoli
Purple Elite2
Y5655
U8277
Nb3271
P6423
R6636
PR5100
P9804
Bolero1
F3513
R8201
U9237
R7284
R7361
D1131
R4294
F5367
Uberlandia derivative
-4
-2
0
2
4
-3
-2
-1
0
1
2
3

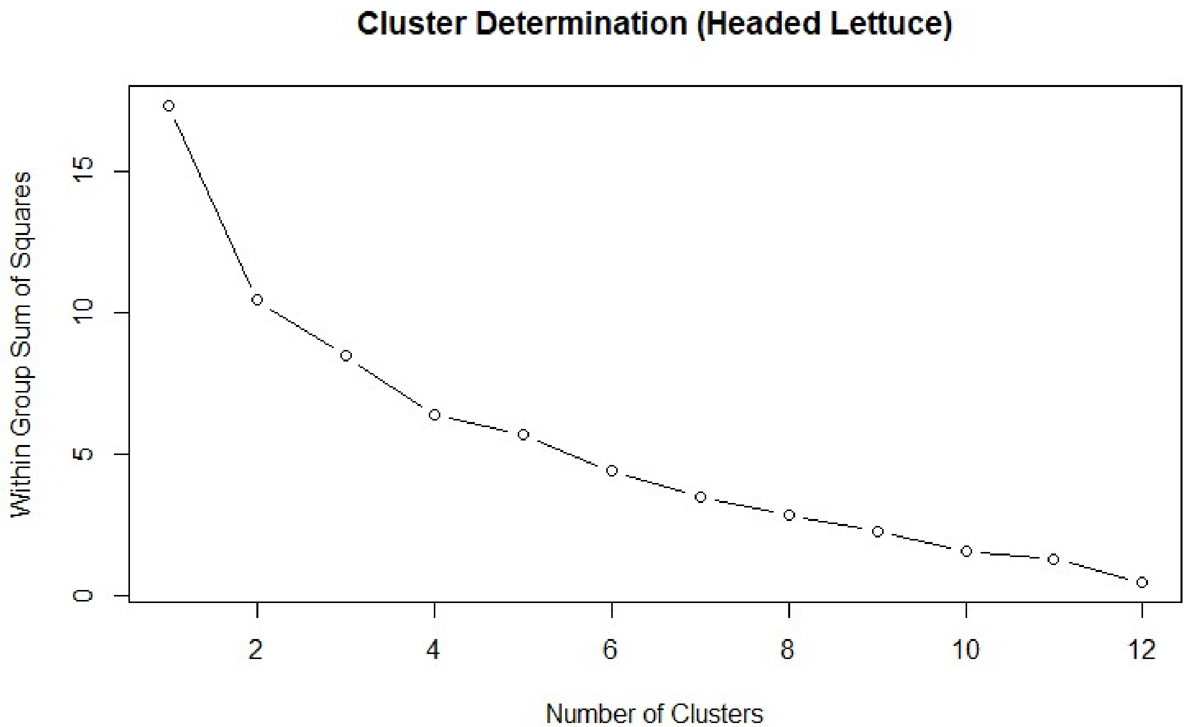

Cluster Determination (Cucumbers)
Within Group Sum of Squares
Number of Clusters
5
10
15
20
2
4
6
8
10
12

Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.07.19	2019.07.19	Cucumber	XKA	Tasty Green1	Asian	High Mowing	WMARS	Field
2019.07.19	2019.07.19	Cucumber	DHF	Suyo1	Asian	Fedco	WMARS	Field
2019.07.19	2019.07.19	Cucumber	RXI	Yamato Sanjaku Japanese	Asian	Hudson Valley	WMARS	Field
2019.07.19	2019.07.19	Cucumber	GHK	Tasty Jade	Asian	Johnny's	WMARS	Field
2019.07.19	2019.07.19	Cucumber	IKR	Suyo2	Asian	Fedco	WMARS	Field
2019.07.19	2019.07.19	Cucumber	JVX	Nokya	Asian	Johnny's	WMARS	Field
2019.07.19	2019.07.19	Cucumber	FXV	Tasty Green2	Asian	High Mowing	WMARS	Field
2019.07.19	2019.07.19	Cucumber	TRM	Amour	Pickling	Bejo Seeds	WMARS	Field
2019.07.19	2019.07.19	Cucumber	ZCL	Artist1	Pickling	Bejo Seeds	WMARS	Field
2019.07.19	2019.07.19	Cucumber	ARX	GherKing	Pickling	PanAmerican	WMARS	Field
2019.07.19	2019.07.19	Cucumber	BHE	Excelsior	Pickling	Vitalis	WMARS	Field
2019.07.19	2019.07.19	Cucumber	PDM	Artist2	Pickling	Bejo Seeds	WMARS	Field
2019.07.19	2019.07.19	Cucumber	ZCN	Bushy	Pickling	Seed Savers	WMARS	Field
2019.07.19	2019.07.19	Cucumber	LPB	GY14	Pickling	UW Wang Lab	WMARS	Field
2019.07.19	2019.07.19	Cucumber	CDQ	GY14DM1	Pickling	UW Wang Lab	WMARS	Field
2019.07.19	2019.07.19	Cucumber	WQB	GY14DM2	Pickling	UW Wang Lab	WMARS	Field
2019.07.19	2019.07.19	Cucumber	HKW	GY14DM3	Pickling	UW Wang Lab	WMARS	Field
2019.07.19	2019.07.19	Cucumber	NVM	Manny1	Mini	High Mowing	WMARS	Field
2019.07.19	2019.07.19	Cucumber	PSJ	WI7204	Mini	UW Wang Lab	WMARS	Field
2019.07.19	2019.07.19	Cucumber	IDP	Manny2	Mini	High Mowing	WMARS	Field
2019.07.19	2019.07.19	Cucumber	JXE	WI7204DM2	Mini	UW Wang Lab	WMARS	Field
2019.07.19	2019.07.19	Cucumber	HKJ	Yildo1	Mini	Bejo Seeds	WMARS	Field
2019.07.19	2019.07.19	Cucumber	XQM	Yildo2	Mini	Bejo Seeds	WMARS	Field

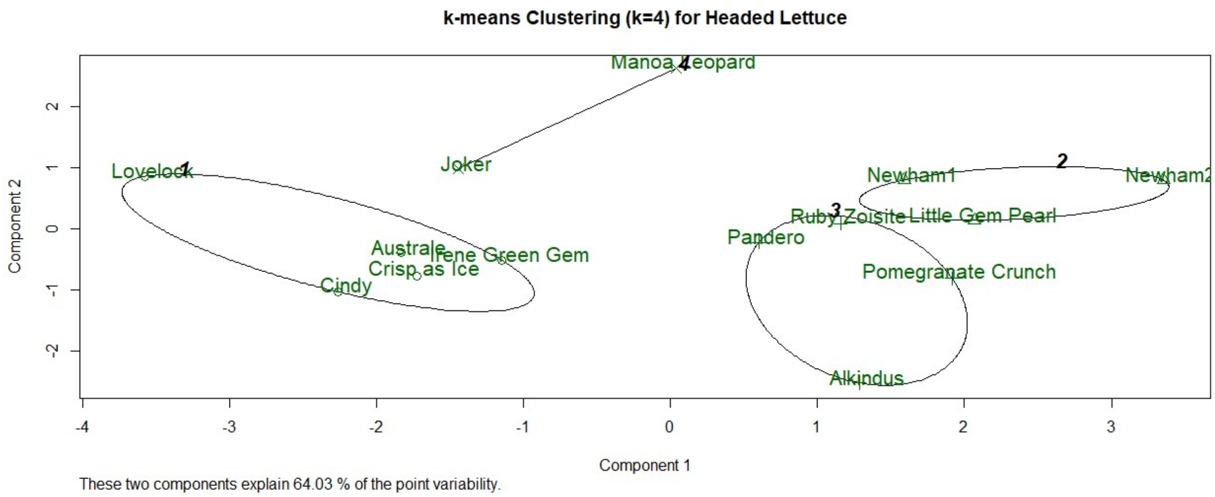
k-means Clustering (k=4) for All Cucumbers

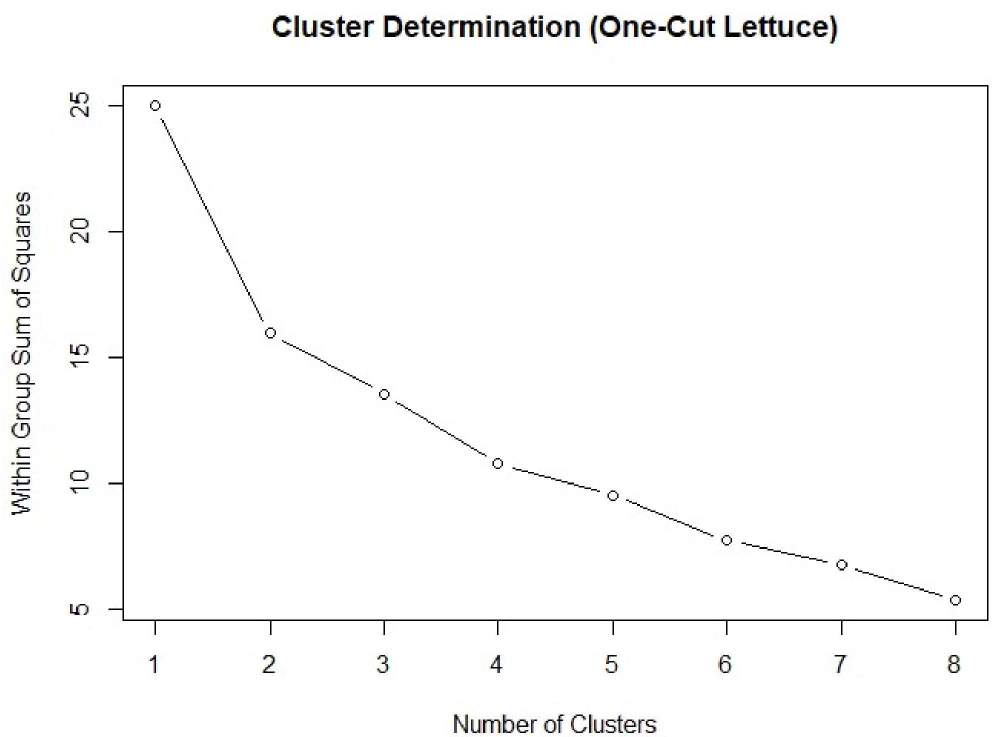


These two components explain 58.11 % of the point variability.

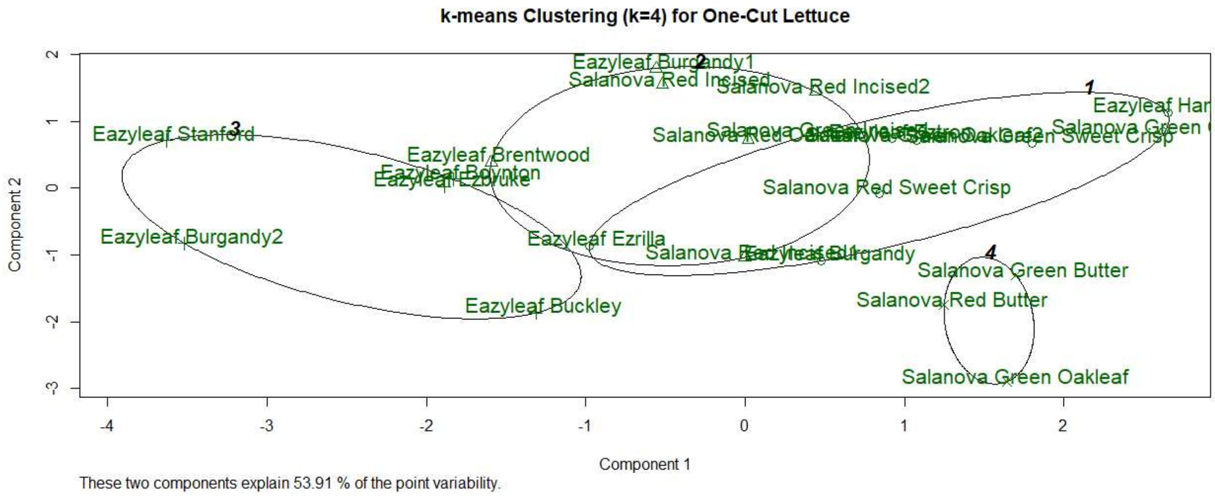


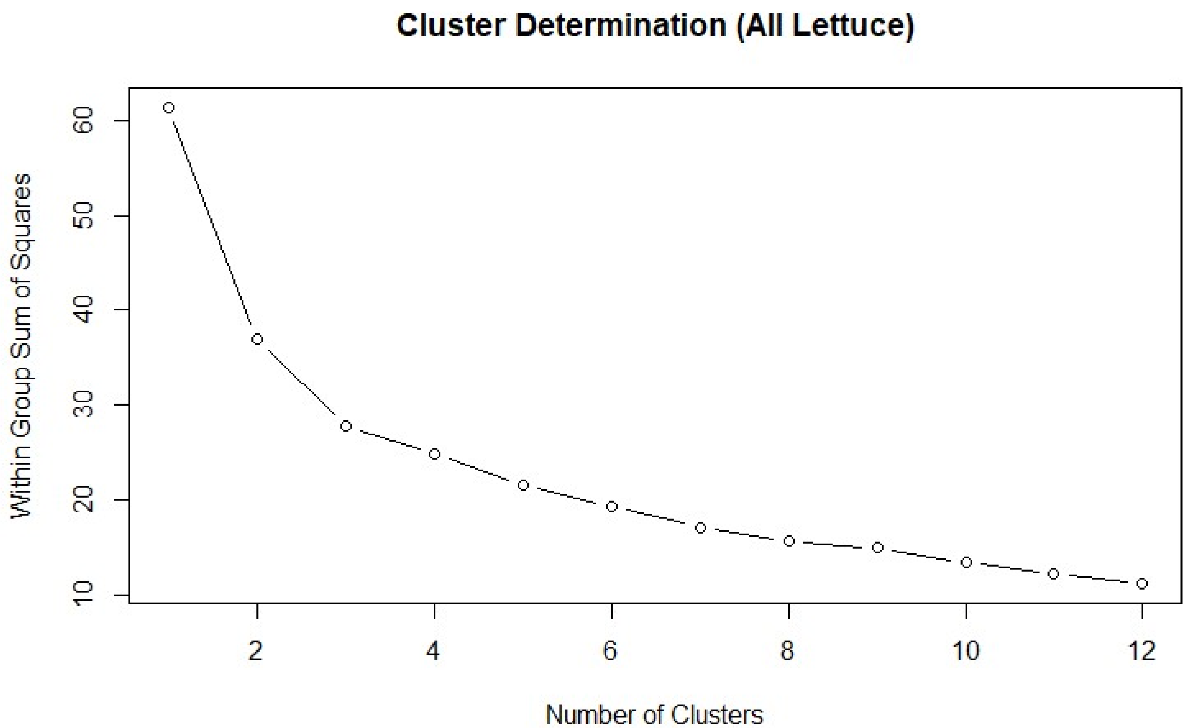
Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.06.26	2019.06.27	Lettuce	XKA	Joker	Butterhead	Wild Garden	WMARS	Field
2019.06.26	2019.06.27	Lettuce	DHF	Alkindus	Butterhead	Vitalis	WMARS	Field
2019.06.26	2019.06.27	Lettuce	RXI	Australe	Butterhead	High Mowing	WMARS	Field
2019.06.26	2019.06.27	Lettuce	GHK	Crisp as Ice	Butterhead	Seed Savers	WMARS	Field
2019.06.26	2019.06.27	Lettuce	IKR	Cindy	Butterhead	Adaptive Seeds	WMARS	Field
2019.06.26	2019.06.27	Lettuce	JVX	Lovelock	Butterhead	Vitalis	WMARS	Field
2019.06.26	2019.06.27	Lettuce	FXV	Manoa Leopard	Butterhead	Wild Garden	WMARS	Field
2019.06.24	2019.06.24	Lettuce	NVM	Newham1	LittleGem	Vitalis	WMARS	Field
2019.06.24	2019.06.24	Lettuce	PSJ	Little Gem Pearl	LittleGem	Adaptive Seeds	WMARS	Field
2019.06.24	2019.06.24	Lettuce	IDP	Pomegranate Crunch	LittleGem	Vitalis	WMARS	Field
2019.06.24	2019.06.24	Lettuce	JXE	Pandero	LittleGem	Adaptive Seeds	WMARS	Field
2019.06.24	2019.06.24	Lettuce	HKJ	Newham2	LittleGem	Vitalis	WMARS	Field
2019.06.24	2019.06.24	Lettuce	XQM	Ruby Zoisite	LittleGem	Wild Garden	WMARS	Field
2019.06.24	2019.06.24	Lettuce	CTQ	Irene Green Gem	LittleGem	Wild Garden	WMARS	Field

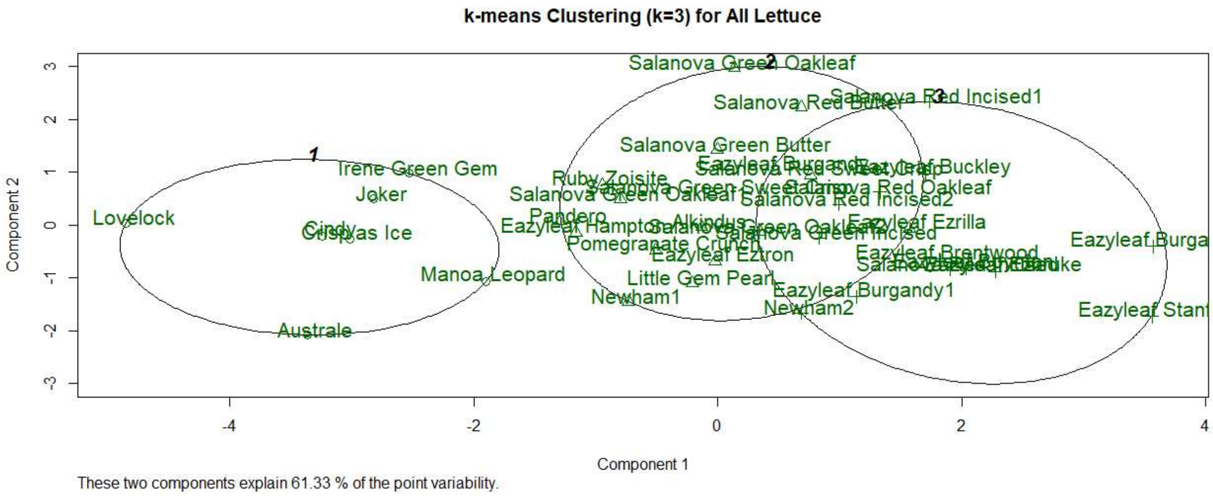

k-means Clustering (k=4) for Headed Lettuce
Manoa Leopard
Lovelock
Joker
Newham1
Newham2
Ruby Zoisite
Little Gem Pearl
Pandero
Australe
Irene Green Gem
Crisp as Ice
Cindy
Pomegranate Crunch
Alkindus
Component 1
Component 2
These two components explain 64.03 % of the point variability.

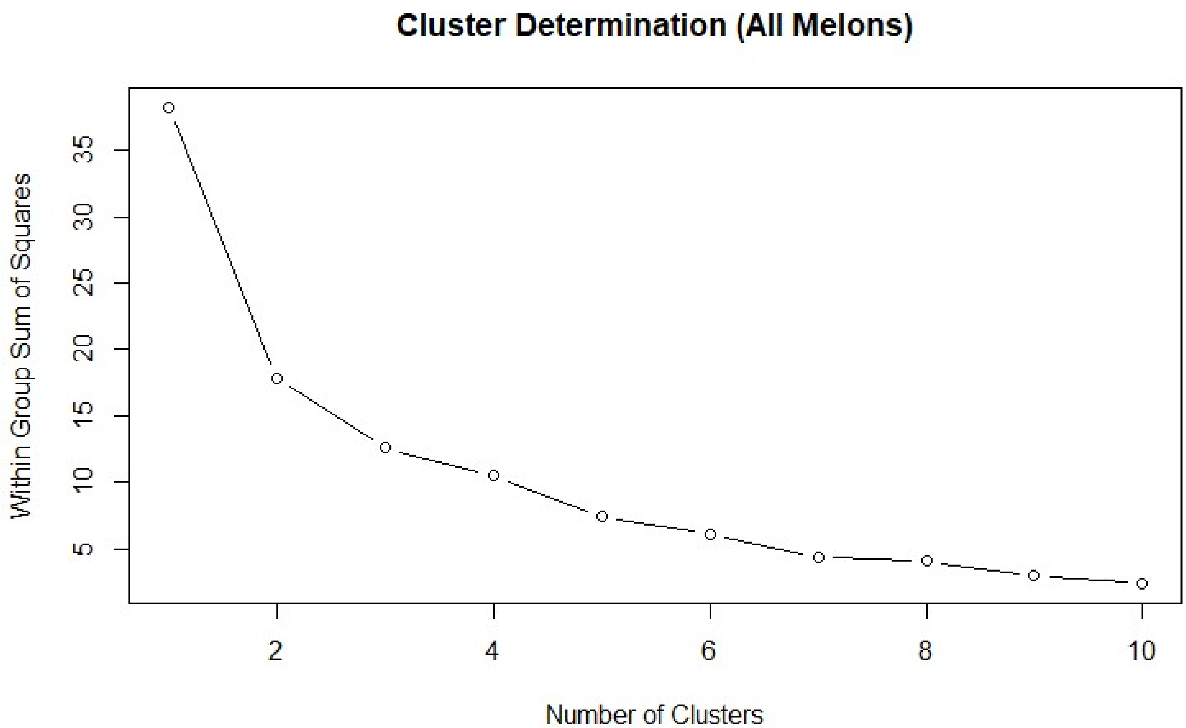

Cluster Determination (One-Cut Lettuce)
Within Group Sum of Squares
Number of Clusters

Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.06.24	2019.06.24	Lettuce	ERP	Salanova Green Sweet Crisp	OnecutGreen	Johnny's	WMARS	Field
2019.06.24	2019.06.24	Lettuce	KHV	Salanova Green Incised	OnecutGreen	Johnny's	WMARS	Field
2019.06.24	2019.06.24	Lettuce	OBE	Eazyleaf Hampton	OnecutGreen	Vitalis	WMARS	Field
2019.06.24	2019.06.24	Lettuce	LPM	Salanova Green Oakleaf1	OnecutGreen	Johnny's	WMARS	Field
2019.06.24	2019.06.24	Lettuce	FJN	Salanova Green Butter	OnecutGreen	Johnny's	WMARS	Field
2019.06.24	2019.06.24	Lettuce	SNH	Salanova Green Oakleaf2	OnecutGreen	Johnny's	WMARS	Field
2019.06.24	2019.06.24	Lettuce	ITF	Eazyleaf Ezrilla	OnecutGreen	Vitalis	WMARS	Field
2019.06.24	2019.06.24	Lettuce	VCJ	Eazyleaf Eztron	OnecutGreen	Vitalis	WMARS	Field
2019.06.24	2019.06.24	Lettuce	ZCN	Eazyleaf Burgandy1	OnecutRed	Vitalis	WMARS	Field
2019.06.24	2019.06.24	Lettuce	LPB	Salanova Red Sweet Crisp	OnecutRed	Johnny's	WMARS	Field
2019.06.24	2019.06.24	Lettuce	CDQ	Eazyleaf Burgandy2	OnecutRed	Vitalis	WMARS	Field
2019.06.24	2019.06.24	Lettuce	WQB	Eazyleaf Brentwood	OnecutRed	Vitalis	WMARS	Field
2019.06.24	2019.06.24	Lettuce	HKW	Salanova Red Incised	OnecutRed	Johnny's	WMARS	Field
2019.06.24	2019.06.24	Lettuce	TRM	Eazyleaf Stanford	OnecutRed	Vitalis	WMARS	Field
2019.06.24	2019.06.24	Lettuce	ZCL	Salanova Red Butter	OnecutRed	Johnny's	WMARS	Field
2019.06.24	2019.06.24	Lettuce	ARX	Eazyleaf Ezbruke	OnecutRed	Vitalis	WMARS	Field
2019.06.24	2019.06.24	Lettuce	BHE	Eazyleaf Boynton	OnecutRed	Vitalis	WMARS	Field
2019.06.24	2019.06.24	Lettuce	PDM	Salanova Red Oakleaf	OnecutRed	Johnny's	WMARS	Field

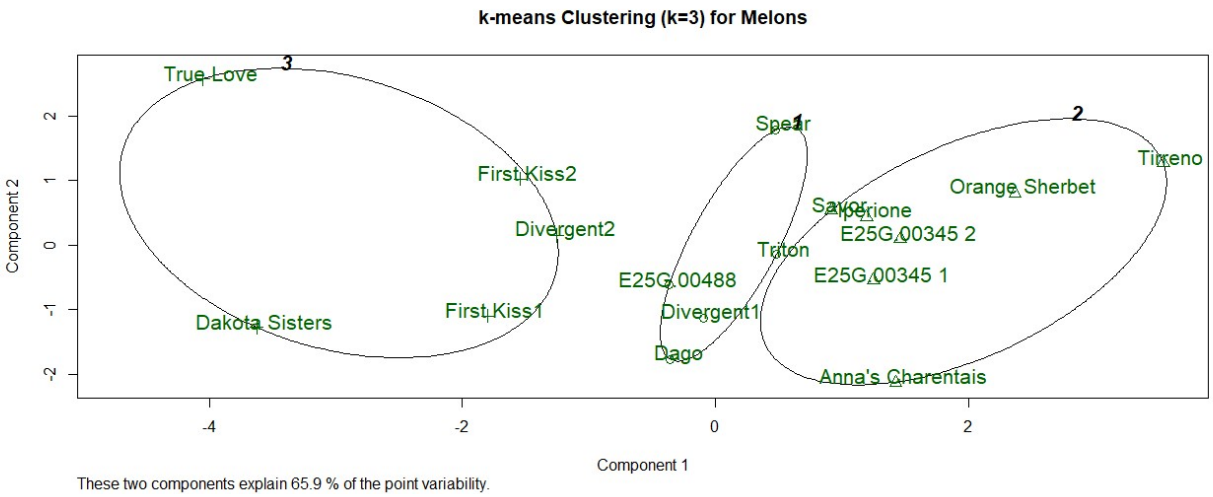

k-means Clustering (k=4) for One-Cut Lettuce
Eazyleaf Burgandy1
Salanova Red Incised2
Eazyleaf Stanford
Eazyleaf Brentwood
Eazyleaf Boynton
Salanova Red Sweet Crisp
Eazyleaf Burgandy2
Eazyleaf Ezrilla
Salanova Green Butter
Salanova Red Butter
Eazyleaf Buckley
Salanova Green Oakleaf
Component 1
Component 2
These two components explain 53.91 % of the point variability.

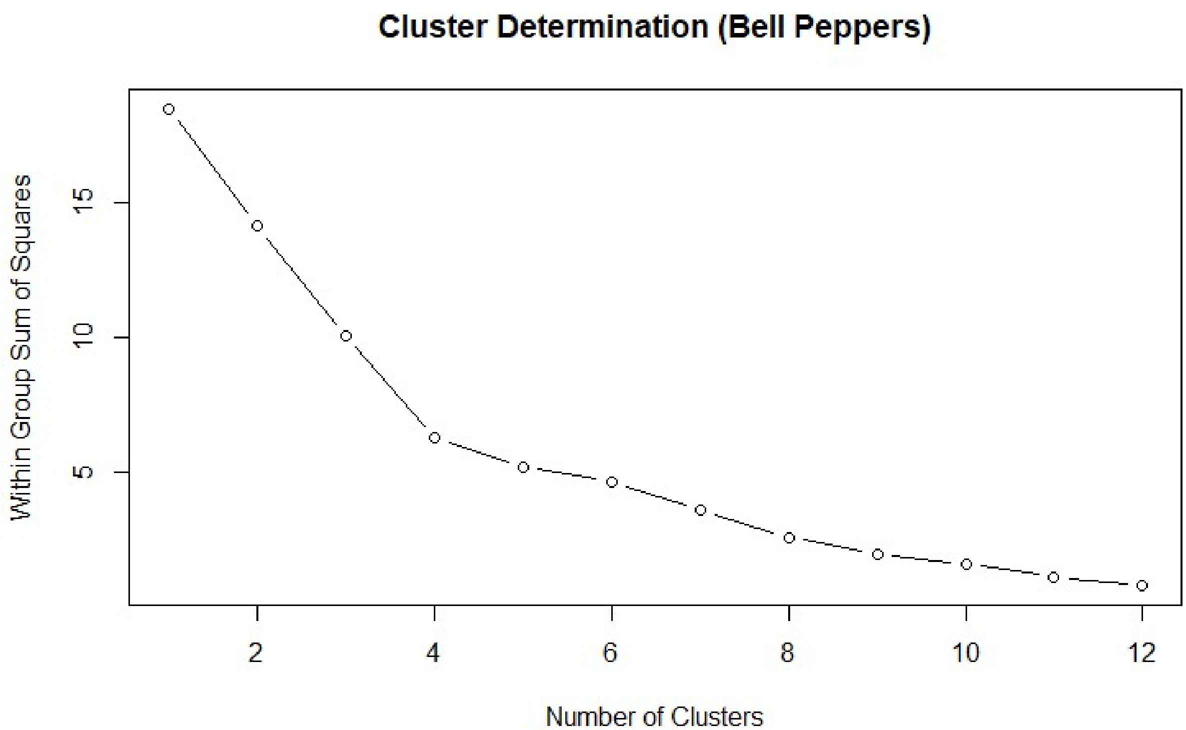

Cluster Determination (All Lettuce)
Within Group Sum of Squares
Number of Clusters


k-means Clustering (k=3) for All Lettuce
Component 2
Component 1
These two components explain 61.33 % of the point variability.
1
2
3
Salanova Green Oakleaf
Salanova Red Butter
Salanova Red Incised1
Salanova Green Butter
Irene Green Gem
Joker
Lovelock
Cindy
Manoa Leopard
Australe
Ruby Zoisite
Pandero
Pomegranate Crunch
Eazyleaf Eztron
Little Gem Pearl
Newham1
Eazyleaf Buckley
Salanova Red Incised2
Eazyleaf Ezrilla
Eazyleaf Brentwood
Eazyleaf Burgandy1
Newham2
Eazyleaf Stant
-4
-2
0
2
4
-3
-2
-1
0
1
2
3

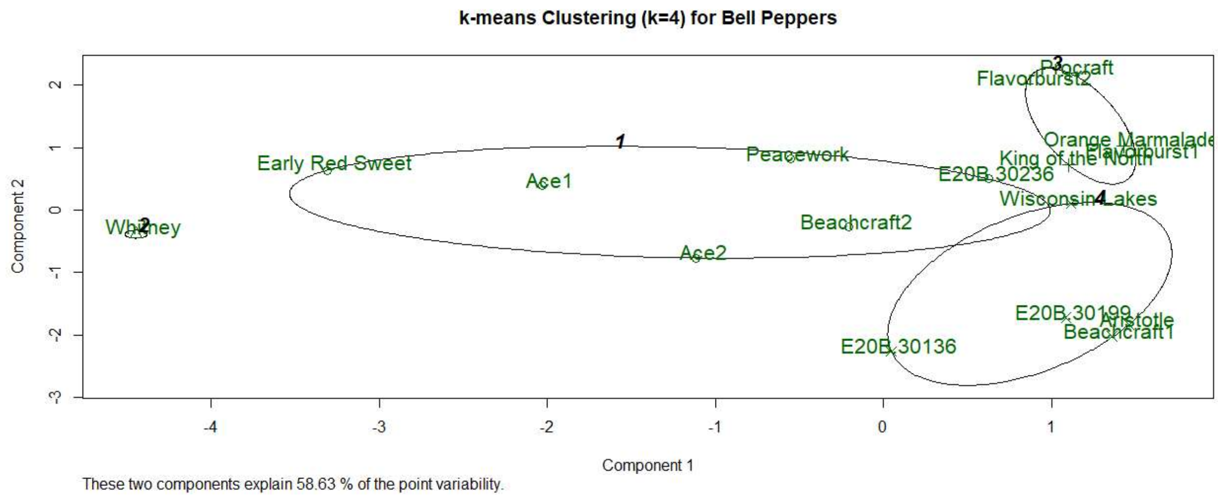

Cluster Determination (All Melons)
Within Group Sum of Squares
Number of Clusters
5
10
15
20
25
30
35
2
4
6
8
10

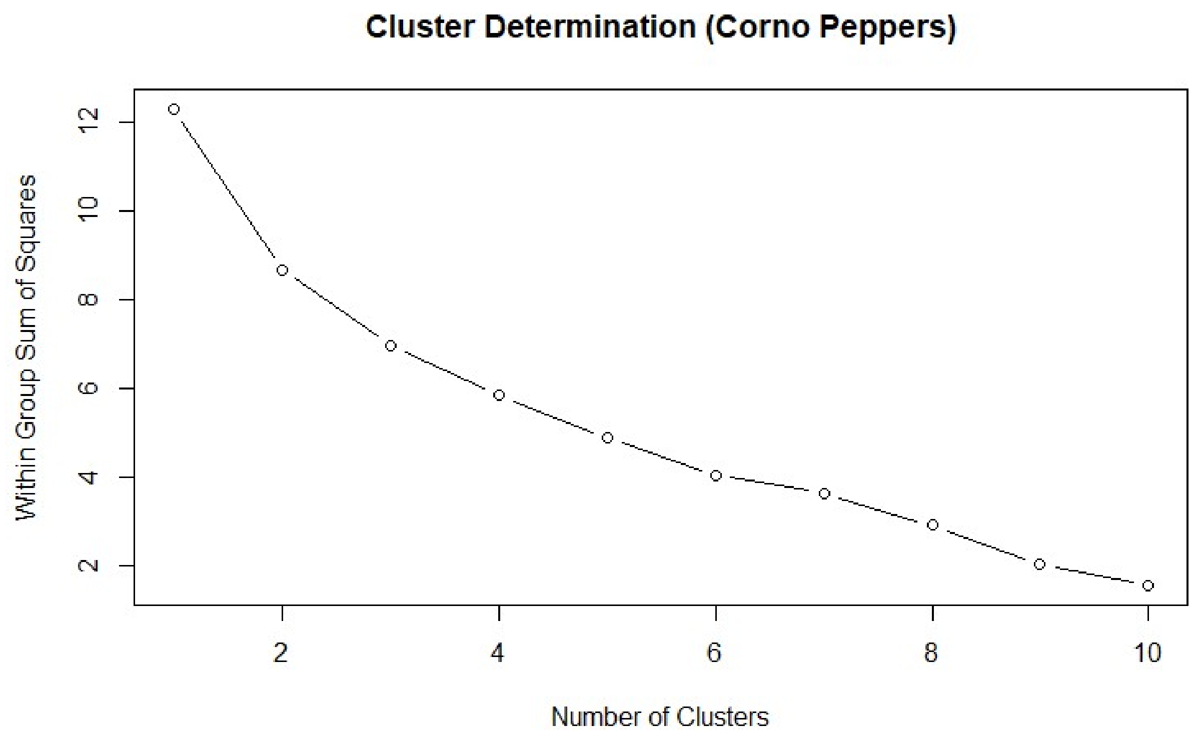
Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.08.27	2019.08.28	Melon	ZCN	E25G.00488	Galia	Vitalis	WMARS	Field
2019.08.27	2019.08.28	Melon	LPB	E25G.00345_1	Galia	Vitalis	WMARS	Field
2019.08.27	2019.08.28	Melon	CDQ	E25G.00345_2	Galia	Vitalis	WMARS	Field
2019.08.27	2019.08.28	Melon	ERP	Iperione	Cantaloupe	Vitalis	WMARS	Field
2019.08.27	2019.08.28	Melon	KHV	Savor	Cantaloupe	Johnny's	WMARS	Field
2019.08.27	2019.08.28	Melon	OBE	Divergent1	Cantaloupe	Vitalis	WMARS	Field
2019.08.27	2019.08.28	Melon	LPM	Tirreno	Cantaloupe	Vitalis	WMARS	Field
2019.08.27	2019.08.28	Melon	FJN	Spear	Cantaloupe	Seed Savers	WMARS	Field
2019.08.27	2019.08.28	Melon	SNH	Divergent2	Cantaloupe	Vitalis	WMARS	Field
2019.08.27	2019.08.28	Melon	ITF	Triton	Cantaloupe	EarthWork Seed	WMARS	Field
2019.08.27	2019.08.28	Melon	XKA	First Kiss1	Cantaloupe	High Mowing	WMARS	Field
2019.08.27	2019.08.28	Melon	DHF	Anna's Charentais	Cantaloupe	EarthWork Seed	WMARS	Field
2019.08.27	2019.08.28	Melon	RXI	Dakota Sisters	Cantaloupe	Prairie Road	WMARS	Field
2019.08.27	2019.08.28	Melon	GHK	True Love	Cantaloupe	High Mowing	WMARS	Field
2019.08.27	2019.08.28	Melon	IKR	Dago	Cantaloupe	Seed Savers	WMARS	Field
2019.08.27	2019.08.28	Melon	JVX	Orange Sherbet	Cantaloupe	High Mowing	WMARS	Field
2019.08.27	2019.08.28	Melon	FXV	First Kiss2	Cantaloupe	High Mowing	WMARS	Field


k-means Clustering (k=3) for Melons
True Love
First Kiss2
Divergent2
First Kiss1
Dakota Sisters
Spear
E25G 00488
Divergent1
Dago
Triton
Savor
Alperione
Orange Sherbet
Tirreno
E25G 00345 2
E25G 00345 1
Anna's Charentais
1
2
3
Component 1
Component 2
These two components explain 65.9 % of the point variability.

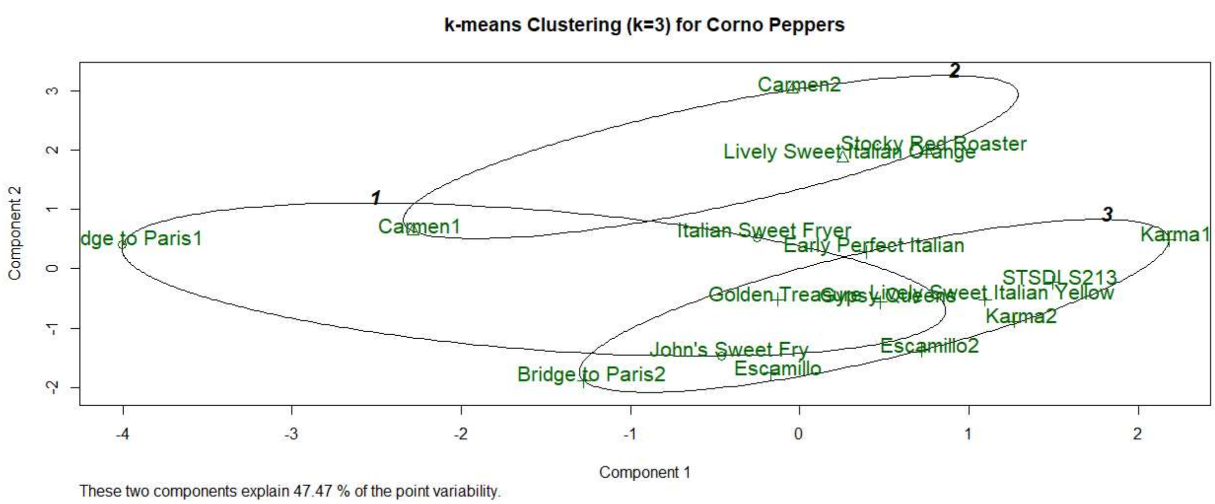

Cluster Determination (Bell Peppers)
Within Group Sum of Squares
Number of Clusters

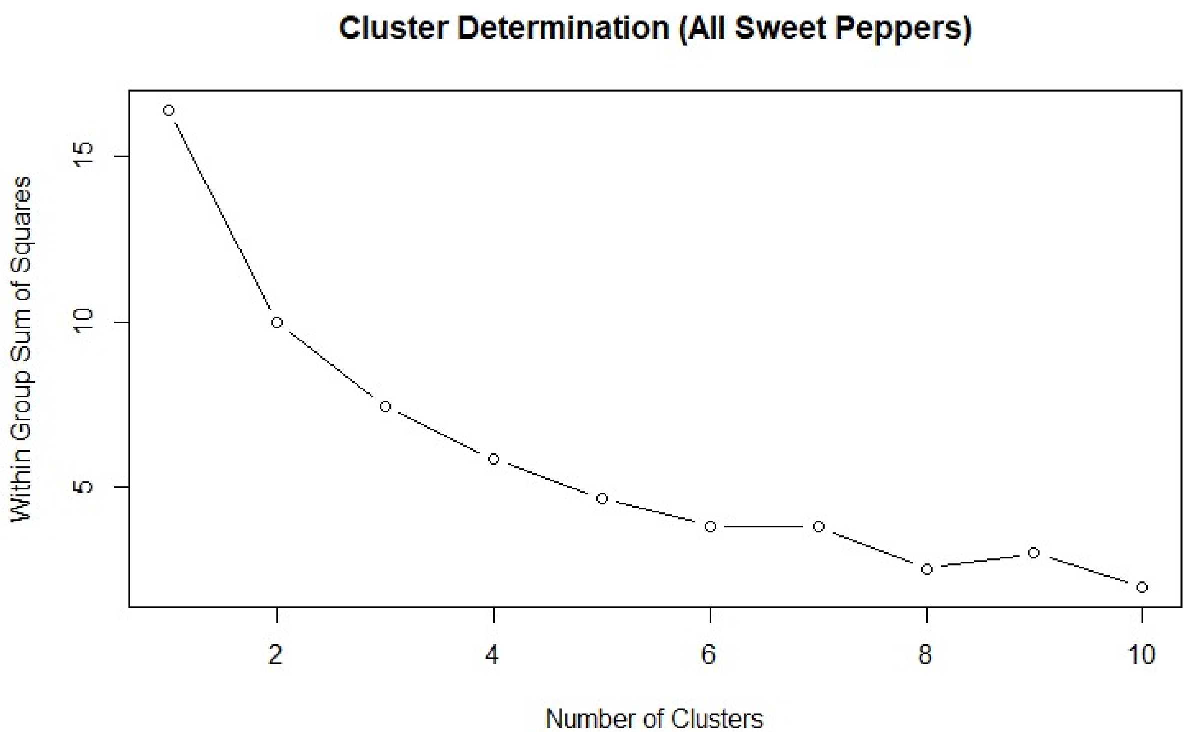
Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.09.06	2019.09.09	Pepper	NVM	King of the North	Red	Hudson Valley	WMARS	Field
2019.09.06	2019.09.09	Pepper	PSJ	Early Red Sweet	Red	Turtle Tree	WMARS	Field
2019.09.06	2019.09.09	Pepper	IDP	Wisconsin Lakes	Red	Nature and Nurture	WMARS	Field
2019.09.06	2019.09.09	Pepper	JXE	Ace1	Red	Johnny's	WMARS	Field
2019.09.06	2019.09.09	Pepper	HKJ	Peacework	Red	Fruition Seeds	WMARS	Field
2019.09.06	2019.09.09	Pepper	XQM	Ace2	Red	Johnny's	WMARS	Field
2019.09.06	2019.09.09	Pepper	XKA	Beachcraft1	Red	Vitalis	WMARS	Field
2019.09.06	2019.09.09	Pepper	DHF	Procraft	Red	Vitalis	WMARS	Field
2019.09.06	2019.09.09	Pepper	RXI	E20B.30236	Red	Vitalis	WMARS	Field
2019.09.06	2019.09.09	Pepper	GHK	E20B.30136	Red	Vitalis	WMARS	Field
2019.09.06	2019.09.09	Pepper	IKR	Aristotle	Red	Seminis	WMARS	Field
2019.09.06	2019.09.09	Pepper	JVX	Beachcraft2	Red	Vitalis	WMARS	Field
2019.09.06	2019.09.09	Pepper	ZCN	Flavorburst1	Yellow	Bejo Seeds	WMARS	Field
2019.09.06	2019.09.09	Pepper	LPB	Flavorburst2	Yellow	Bejo Seeds	WMARS	Field
2019.09.06	2019.09.09	Pepper	CDQ	Whitney	Orange	Bejo Seeds	WMARS	Field
2019.09.06	2019.09.09	Pepper	WQB	Orange Marmalade	Orange	PanAmerican	WMARS	Field
2019.09.06	2019.09.09	Pepper	HKW	E20B.30199	Yellow	Vitalis	WMARS	Field

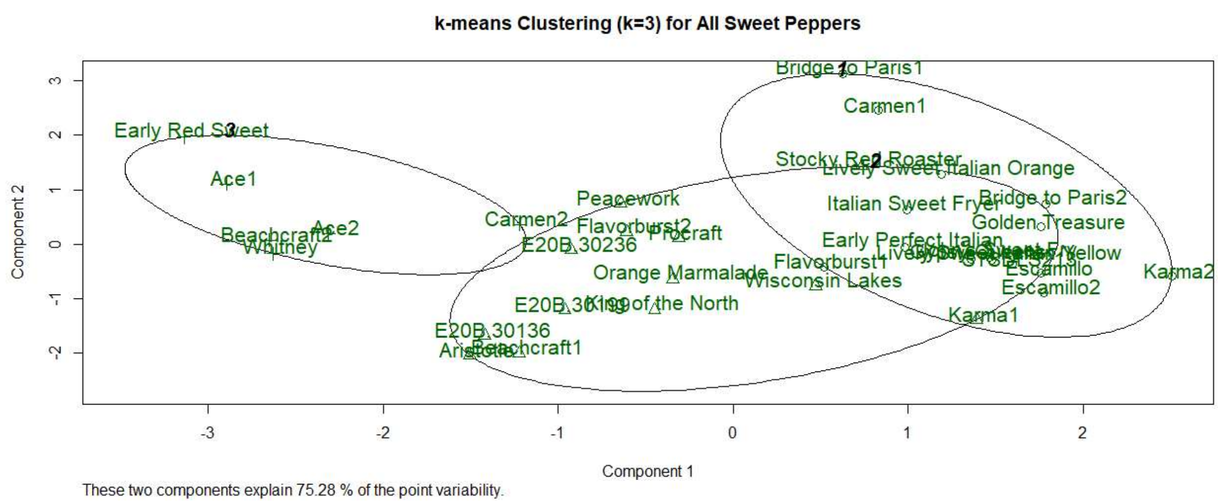

k-means Clustering (k=4) for Bell Peppers
Component 2
Component 1
Whitney
Early Red Sweet
Ace1
Peacework
Ace2
Beachcraft2
E20B.30236
King of the North
Orange Marmalade
Flavorburst1
Flavorburst2
Procraft
Wisconsin Lakes
E20B.30199
Aristotle
Beachcraft1
E20B.30136
These two components explain 58.63 % of the point variability.

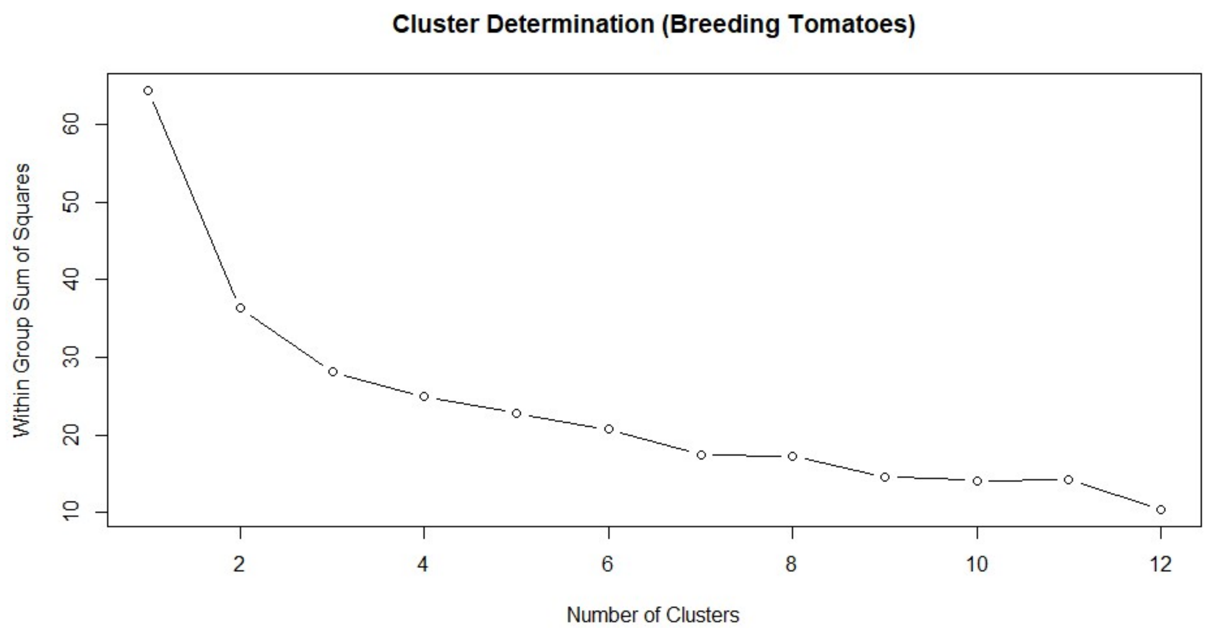

Cluster Determination (Corno Peppers)
Within Group Sum of Squares
Number of Clusters

Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.09.06	2019.09.10	Pepper	ZCN	Golden Treasure	Orange	Seed Savers	WMARS	Field
2019.09.06	2019.09.10	Pepper	LPB	Escamillo1	Yellow	Johnny's	WMARS	Field
2019.09.06	2019.09.10	Pepper	CDQ	Escamillo2	Yellow	Johnny's	WMARS	Field
2019.09.06	2019.09.10	Pepper	WQB	Lively Sweet Italian Orange	Orange	High Mowing	WMARS	Field
2019.09.06	2019.09.10	Pepper	HKW	Lively Sweet Italian Yellow	Yellow	High Mowing	WMARS	Field
2019.09.06	2019.09.10	Pepper	NVM	Stocky Red Roaster	Red	Wild Garden	WMARS	Field
2019.09.06	2019.09.10	Pepper	PSJ	Early Perfect Italian	Red	Wild Garden	WMARS	Field
2019.09.06	2019.09.10	Pepper	IDP	Gypsy Queens	Red	Adaptive Seeds	WMARS	Field
2019.09.06	2019.09.10	Pepper	JXE	Karma1	Red	Wild Garden	WMARS	Field
2019.09.06	2019.09.10	Pepper	HKJ	Karma2	Red	Wild Garden	WMARS	Field
2019.09.06	2019.09.10	Pepper	XQM	John's Sweet Fry	Red	Seed Savers	WMARS	Field
2019.09.06	2019.09.10	Pepper	XKA	STSDLS213	Red	PanAmerican	WMARS	Field
2019.09.06	2019.09.10	Pepper	DHF	Carmen1	Red	Johnny's	WMARS	Field
2019.09.06	2019.09.10	Pepper	RXI	Italian Sweet Fryer	Red	Seed Savers	WMARS	Field
2019.09.06	2019.09.10	Pepper	GHK	Carmen2	Red	Johnny's	WMARS	Field
2019.09.06	2019.09.10	Pepper	IKR	Bridge to Paris1	Red	Hudson Valley	WMARS	Field
2019.09.06	2019.09.10	Pepper	JVX	Bridge to Paris2	Red	Hudson Valley	WMARS	Field

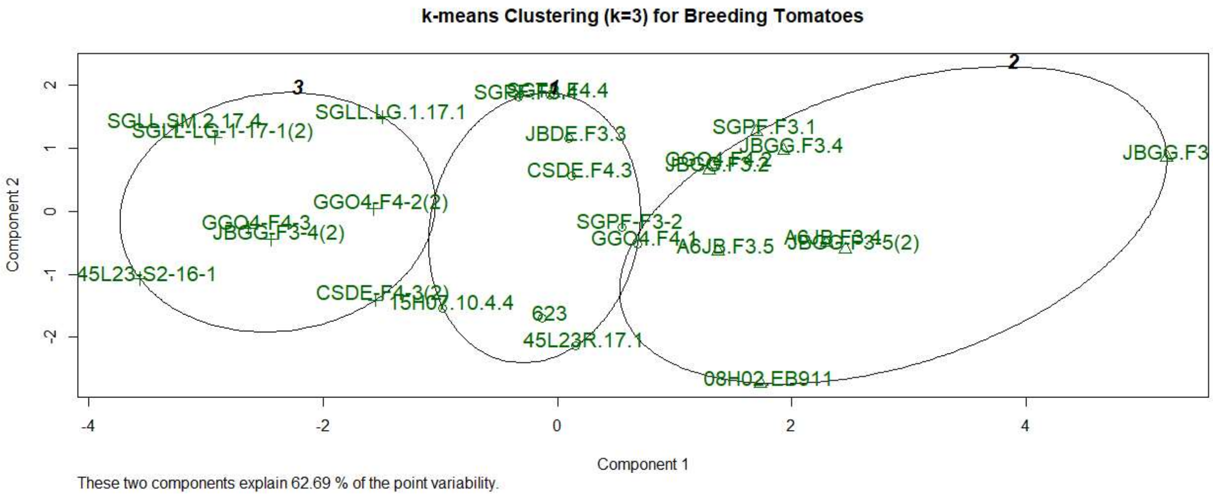


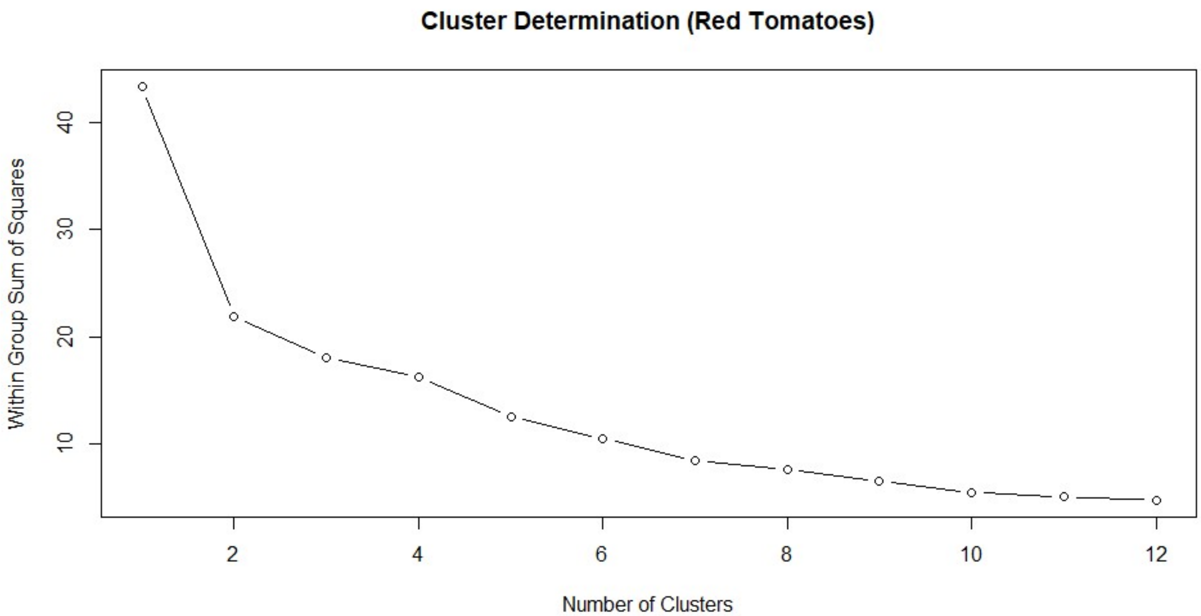

Cluster Determination (All Sweet Peppers)
Within Group Sum of Squares
5
10
15
2
4
6
8
10
Number of Clusters


k-means Clustering (k=3) for All Sweet Peppers
Component 2
Component 1
Bridge to Paris1
Carmen1
Early Red Sweet
Ace1
Stocky Red Roaster
Lively Sweet Italian Orange
Peacework
Italian Sweet Fryer
Bridge to Paris2
Golden Treasure
Carmen2
Flavorburst2
Procraft
Beachcraft2
Ace2
Whitney
E20B 30236
Early Perfect Italian
Orange Marmalade
Flavorburst1
Wisconsin Lakes
Escamillo
Escamillo2
Karma2
E20B 30199
King of the North
Karma1
E20B 30136
Aristotle
Beachcraft1
These two components explain 75.28 % of the point variability.

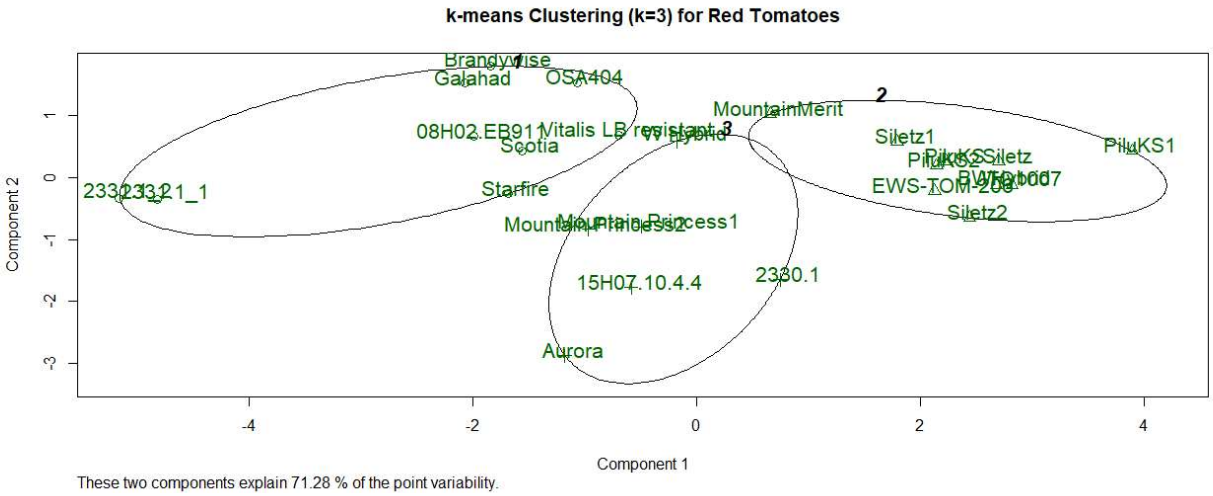

Cluster Determination (Breeding Tomatoes)
Within Group Sum of Squares
10
20
30
40
50
60
2
4
6
8
10
12
Number of Clusters

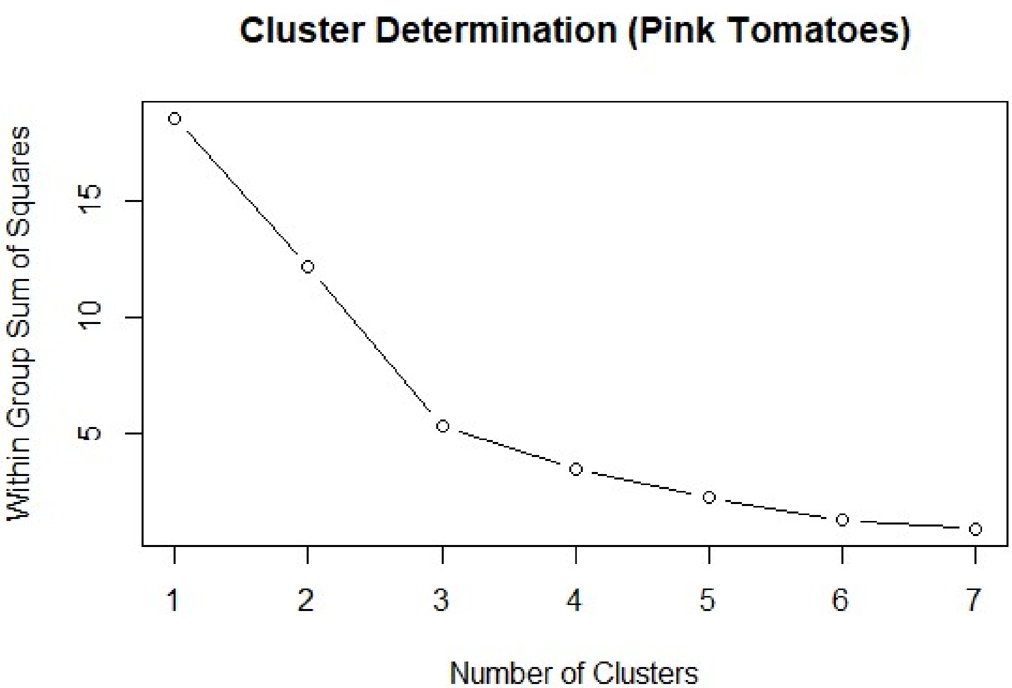
Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.08.14	2019.08.15	Tomato	NVM	SGLL.LG.1.17.1	Breeding	SKC	WMARS	High Tunnel
2019.08.14	2019.08.15	Tomato	PSJ	45L23R.17.1	Breeding	SKC	WMARS	High Tunnel
2019.08.14	2019.08.15	Tomato	IDP	GGO4.F4.1	Breeding	SKC	WMARS	High Tunnel
2019.08.14	2019.08.15	Tomato	JXE	GGO4.F4.2	Breeding	SKC	WMARS	High Tunnel
2019.08.14	2019.08.15	Tomato	HKJ	SGTA.F4.4	Breeding	SKC	WMARS	High Tunnel
2019.08.14	2019.08.15	Tomato	XQM	SGPF.F3.1	Breeding	SKC	WMARS	High Tunnel
2019.08.14	2019.08.15	Tomato	CTQ	SGPF.F3.4	Breeding	SKC	WMARS	High Tunnel
2019.08.14	2019.08.15	Tomato	XKA	CSDE.F4.3	Breeding	SKC	WMARS	High Tunnel
2019.08.14	2019.08.15	Tomato	DHF	JBGG.F3.4	Breeding	SKC	WMARS	High Tunnel
2019.08.14	2019.08.15	Tomato	RXI	JBDE.F3.3	Breeding	SKC	WMARS	High Tunnel
2019.08.14	2019.08.15	Tomato	GHK	A6JB.F3.4	Breeding	SKC	WMARS	High Tunnel
2019.08.14	2019.08.15	Tomato	IKR	JBGG.F3.5	Breeding	SKC	WMARS	High Tunnel
2019.08.14	2019.08.15	Tomato	JVX	JBGG.F3.2	Breeding	SKC	WMARS	High Tunnel
2019.08.14	2019.08.15	Tomato	FXV	A6JB.F3.5	Breeding	SKC	WMARS	High Tunnel
2019.08.21	2019.08.22	Tomato	NVM	SGLL.SM.2.17.4	Breeding	SKC	WMARS	High Tunnel
2019.08.21	2019.08.22	Tomato	PSJ	15H07.10.4.4	Breeding	KCTomato	WMARS	High Tunnel
2019.08.21	2019.08.22	Tomato	IDP	SGPF-F3-2	Breeding	SKC	WMARS	High Tunnel
2019.08.21	2019.08.22	Tomato	JXE	CSDE-F4-3	Breeding	SKC	WMARS	High Tunnel
2019.08.21	2019.08.22	Tomato	HKJ	623	Breeding	KCTomato	WMARS	High Tunnel
2019.08.21	2019.08.22	Tomato	XQM	GGO4-F4-3	Breeding	SKC	WMARS	High Tunnel
2019.08.21	2019.08.22	Tomato	XKA	JBGG-F3-4	Breeding	SKC	WMARS	High Tunnel
2019.08.21	2019.08.22	Tomato	DHF	GGO4-F4-2	Breeding	SKC	WMARS	High Tunnel
2019.08.21	2019.08.22	Tomato	RXI	08H02.EB911	Breeding	KCTomato	WMARS	High Tunnel
2019.08.21	2019.08.22	Tomato	GHK	45L23-S2-16-1	Breeding	SKC	WMARS	High Tunnel
2019.08.21	2019.08.22	Tomato	IKR	SGLL-LG-1-17-1	Breeding	SKC	WMARS	High Tunnel
2019.08.21	2019.08.22	Tomato	JVX	JBGG-F3-5	Breeding	SKC	WMARS	High Tunnel


k-means Clustering (k=3) for Breeding Tomatoes
Component 1
Component 2
These two components explain 62.69 % of the point variability.
SGLL.SM.2.17.4
SGLL-LG-1-17-1(2)
SGLL.LG.1.17.1
GGO4-F4-2(2)
GGO4-F4-3
JBGG-F3-4(2)
45L23-S2-16-1
CSDE-F4-3(2)
15H07.10.4.4
623
45L23R.17.1
JBDE.F3.3
CSDE.F4.3
SGPF-F3-2
GGO4.F4.1
A6JB.F3.5
SGPF.F3.1
JBGG.F3.4
JBGG.F3
08H02.EB911

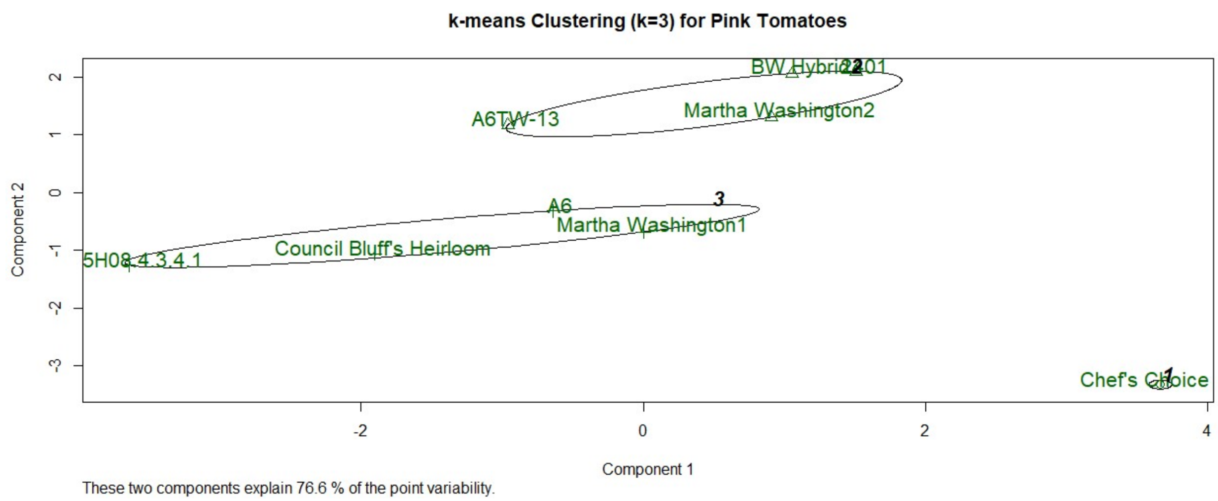

Cluster Determination (Red Tomatoes)
Within Group Sum of Squares
Number of Clusters

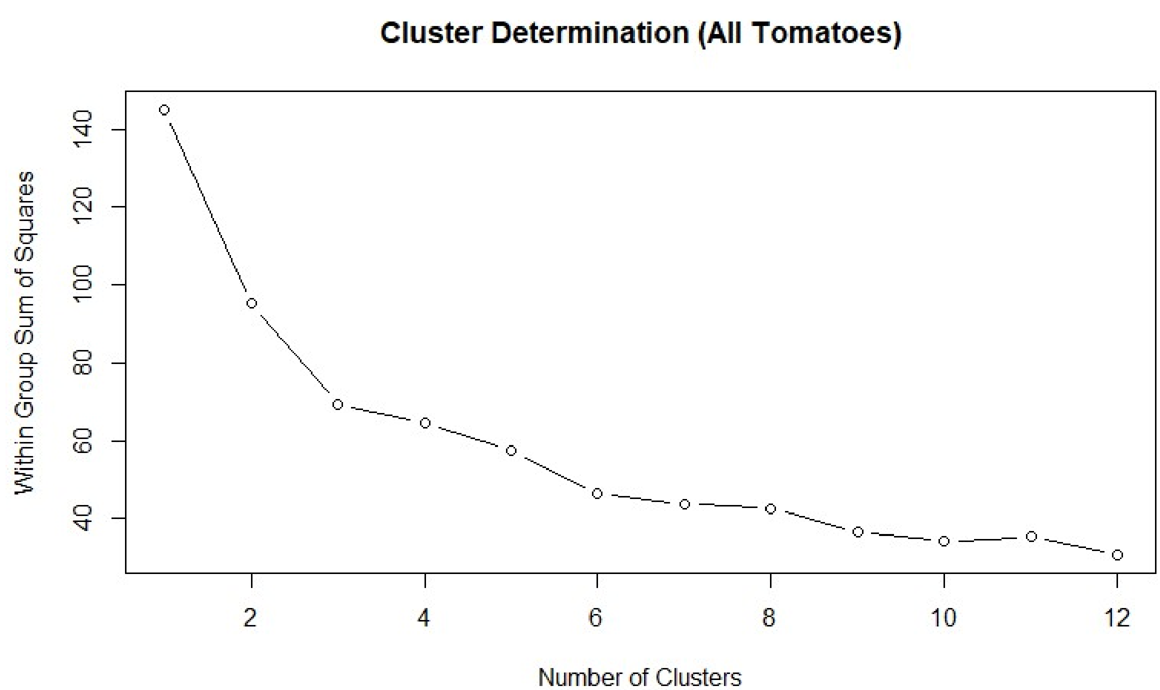
Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.07.29	2019.07.30	Tomato	TRM	Siletz1	Red	Adaptive Seeds	WMARS	High Tunnel
2019.07.29	2019.07.30	Tomato	ZCL	Pilu KS	Red	Adaptive	WMARS	High Tunnel
2019.07.29	2019.07.30	Tomato	ARX	2330.1	Red	PanAmerican	WMARS	High Tunnel
2019.07.29	2019.07.30	Tomato	BHE	JTO1007	Red	Johnny's	WMARS	High Tunnel
2019.07.29	2019.07.30	Tomato	PDM	Siletz2	Red	Adaptive Seeds	WMARS	High Tunnel
2019.08.06	2019.08.07	Tomato	NVM	Mountain Merit	Red	Bejo Seeds	WMARS	High Tunnel
2019.08.06	2019.08.07	Tomato	PSJ	EWS-TOM-206	Red	EarthWork Seed	WMARS	High Tunnel
2019.08.06	2019.08.07	Tomato	IDP	JTO1007	Red	Johnny's	WMARS	High Tunnel
2019.08.06	2019.08.07	Tomato	JXE	2330.1	Red	PanAmerican	WMARS	High Tunnel
2019.08.06	2019.08.07	Tomato	HKJ	Siletz	Red	Adaptive Seeds	WMARS	High Tunnel
2019.08.06	2019.08.07	Tomato	XQM	Pilu KS	Red	Adaptive Seeds	WMARS	High Tunnel
2019.08.19	2019.08.20	Tomato	XKA	Pilu KS1	Red	Adaptive	WMARS	High Tunnel
2019.08.19	2019.08.20	Tomato	DHF	BW Hybrid	Red	University of Florida	WMARS	High Tunnel
2019.08.19	2019.08.20	Tomato	RXI	JTO1007	Red	Johnny's	WMARS	High Tunnel
2019.08.19	2019.08.20	Tomato	GHK	Pilu KS2	Red	Johnny's	WMARS	High Tunnel
2019.08.19	2019.08.20	Tomato	IKR	Mountain Merit	Red	Bejo Seeds	WMARS	High Tunnel
2019.08.19	2019.08.20	Tomato	JVX	Siletz	Red	Adaptive	WMARS	High Tunnel
2019.08.19	2019.08.20	Tomato	FXV	EWS-TOM-206	Red	EarthWork Seed	WMARS	High Tunnel
2019.08.28	2019.08.30	Tomato	XKA	2331.1_1	Red	PanAmerican	WMARS	Field
2019.08.28	2019.08.30	Tomato	DHF	2331.1_2	Red	PanAmerican	WMARS	Field
2019.08.28	2019.08.30	Tomato	RXI	Galahad	Red	EarthWork Seed	WMARS	Field
2019.08.28	2019.08.30	Tomato	GHK	Brandywise	Red	Fruition Seeds	WMARS	Field
2019.08.28	2019.08.30	Tomato	IKR	Vitalis LB resistant	Red	Vitalis	WMARS	Field
2019.08.28	2019.08.30	Tomato	JVX	W Hybrid	Red	University of Florida	WMARS	Field
2019.08.28	2019.08.30	Tomato	FXV	15H07.10.4.4	Red	KCTomato	WMARS	Field
2019.08.28	2019.08.30	Tomato	ERP	08H02.EB911	Red	KCTomato	WMARS	Field
2019.08.28	2019.08.30	Tomato	KHV	OSA404	Red	OSA	WMARS	Field
2019.08.28	2019.08.30	Tomato	OBE	Scotia	Red	Deep Harvest	WMARS	Field
2019.08.28	2019.08.30	Tomato	LPM	Mountain Princess1	Red	High Mowing	WMARS	Field
2019.08.28	2019.08.30	Tomato	FJN	Mountain Princess2	Red	High Mowing	WMARS	Field
2019.08.28	2019.08.30	Tomato	SNH	Aurora	Red	Adaptive	WMARS	Field
2019.08.28	2019.08.30	Tomato	ITF	Starfire	Red	Adaptive	WMARS	Field


k-means Clustering (k=3) for Red Tomatoes
Component 1
Component 2
-4
-2
0
2
4
1
0
-1
-2
-3
1
2
3
Brandywise
Galahad
OSA404
08H02.EB911
Vitalis LB resistant
Scotia
Starfire
MountainMerit
Siletz1
PiluKS1
EWS-TOM-208
Siletz2
15H07.10.4.4
2330.1
Aurora
These two components explain 71.28 % of the point variability.

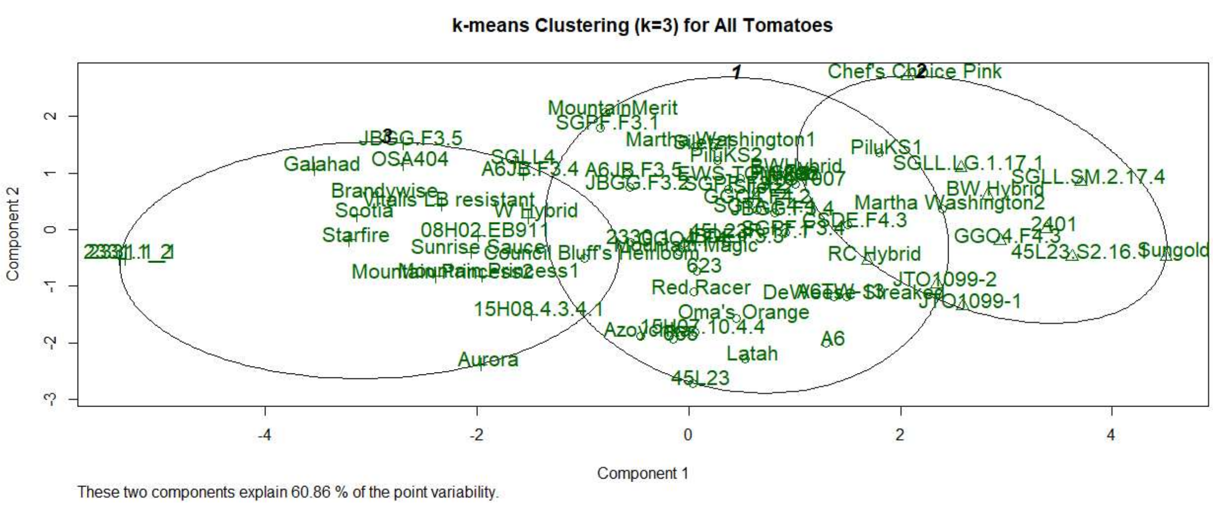

Cluster Determination (Pink Tomatoes)
Within Group Sum of Squares
Number of Clusters
5
10
15
1
2
3
4
5
6
7

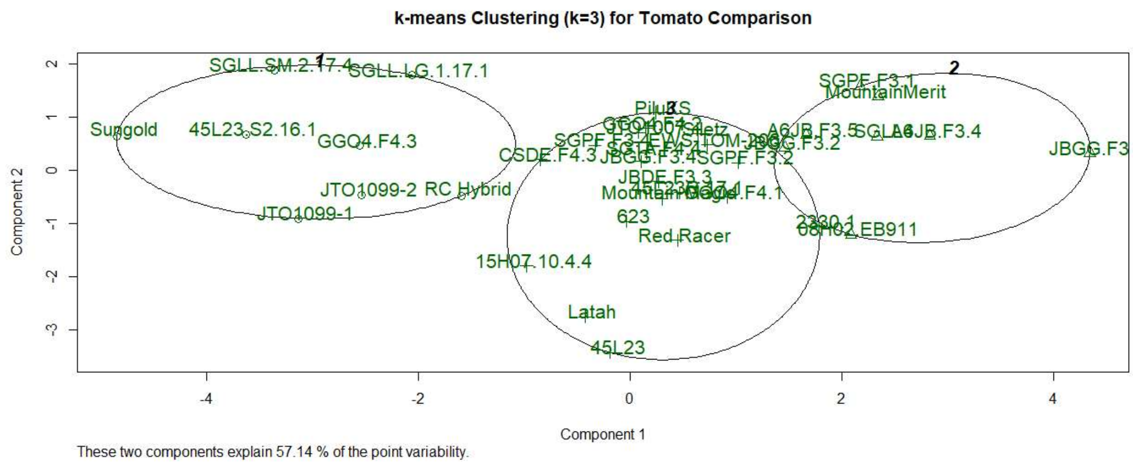
Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.08.06	2019.08.07	Tomato	TRM	2401	Pink	PanAmerican	WMARS	High Tunnel
2019.08.06	2019.08.07	Tomato	ZCL	BW Hybrid	Pink	University of Florida	WMARS	High Tunnel
2019.08.06	2019.08.07	Tomato	ARX	Martha Washington1	Pink	Johnny's	WMARS	High Tunnel
2019.08.06	2019.08.07	Tomato	BHE	Martha Washington2	Pink	Johnny's	WMARS	High Tunnel
2019.08.06	2019.08.07	Tomato	PDM	Chef's Choice Pink	Pink	Johnny's	WMARS	High Tunnel
2019.08.28	2019.08.29	Tomato	TRM	A6	Pink	Craig Grau	WMARS	Field
2019.08.28	2019.08.29	Tomato	ZCL	A6TW-13	Pink	Craig Grau	WMARS	Field
2019.08.28	2019.08.29	Tomato	ARX	Council Bluff's Heirloom	Pink	Seed Savers	WMARS	Field
2019.08.28	2019.08.29	Tomato	BHE	15H08.4.3.4.1	Pink	KCTomato	WMARS	Field

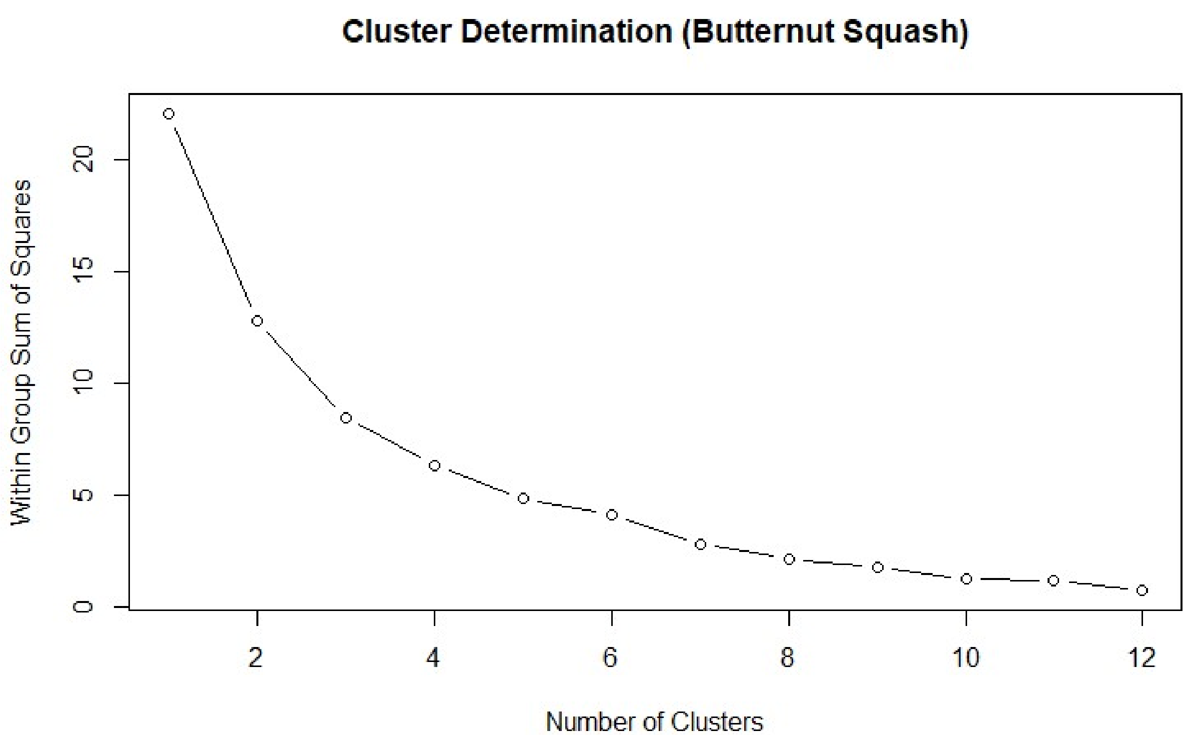

k-means Clustering (k=3) for Pink Tomatoes
BW Hybrid 201
A6TW-13
Martha Washington2
A6
Martha Washington1
5H08.4.3.4.1
Council Bluff's Heirloom
Chef's Choice
Component 2
Component 1
These two components explain 76.6 % of the point variability.


Cluster Determination (All Tomatoes)
Within Group Sum of Squares
Number of Clusters

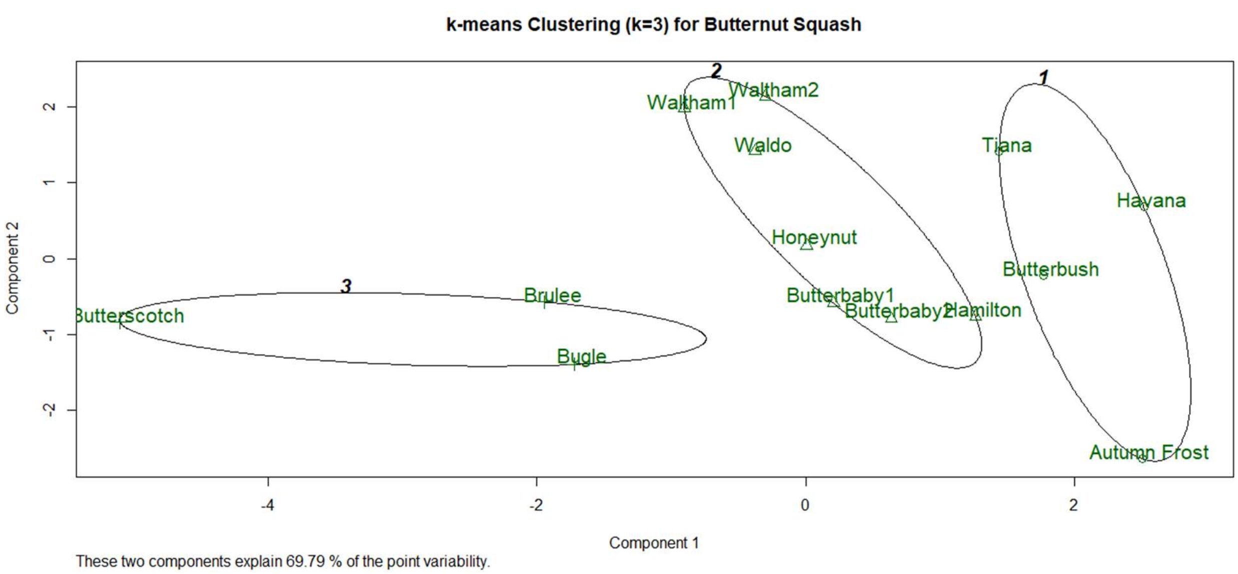
Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.08.28	2019.08.29	Tomato	NVM	DeWeese Streaked	Orange Yellow	Seed Savers	WMARS	Field
2019.08.28	2019.08.29	Tomato	PSJ	Oma's Orange	Orange Yellow	Seed Savers	WMARS	Field
2019.08.28	2019.08.29	Tomato	IDP	665	Orange Yellow	KCTomato	WMARS	Field
2019.08.28	2019.08.29	Tomato	JXE	623	Orange Yellow	KCTomato	WMARS	Field
2019.08.28	2019.08.29	Tomato	HKJ	Sunrise Sauce	Orange Yellow	PanAmerican	WMARS	Field
2019.08.28	2019.08.29	Tomato	XQM	Azoychka	Orange Yellow	Adaptive Seeds	WMARS	Field
2019.08.28	2019.08.29	Tomato	ZCN	JTO1099_1	Cherry	Johnny's	WMARS	Field
2019.08.28	2019.08.29	Tomato	LPB	JTO1099_2	Cherry	Johnny's	WMARS	Field
2019.08.28	2019.08.29	Tomato	CDQ	Sungold	Cherry	Johnny's	WMARS	Field
2019.08.28	2019.08.30	Tomato	NVM	Latah	Cocktail	Uprising Seeds	WMARS	Field
2019.08.28	2019.08.30	Tomato	PSJ	SGLL4	Cocktail	KCTomato	WMARS	Field
2019.08.28	2019.08.30	Tomato	IDP	45L23	Cocktail	KCTomato	WMARS	Field
2019.08.28	2019.08.30	Tomato	JXE	Red Racer	Cocktail	EarthWork Seed	WMARS	Field
2019.08.28	2019.08.30	Tomato	HKJ	Mountain Magic	Cocktail	Bejo Seeds	WMARS	Field
2019.08.28	2019.08.30	Tomato	XQM	RC Hybrid	Cocktail	EarthWork Seed	WMARS	Field

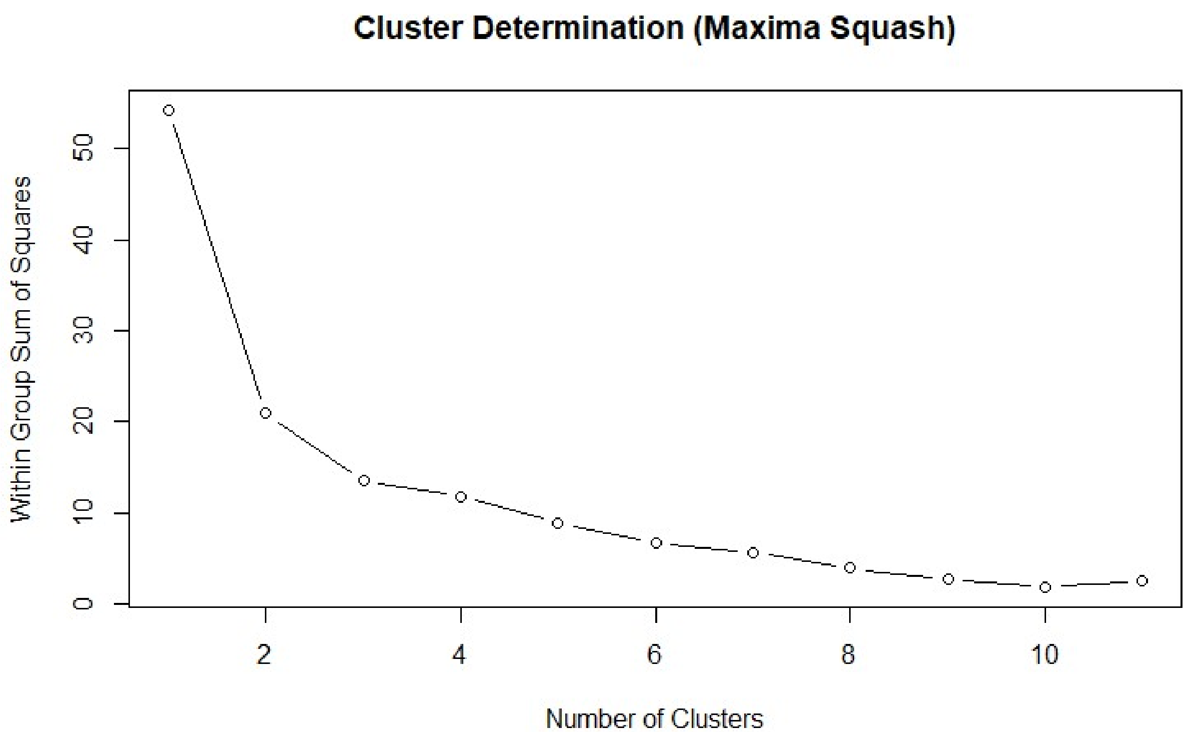



k-means Clustering (k=3) for Tomato Comparison
Component 1
Component 2
These two components explain 57.14 % of the point variability.
Sungold
45L23.S2.16.1
GGQ4.F4.3
SGLL.SM.2.17.4
SGLL.LG.1.17.1
JTO1099-2
RC Hybrid
JTO1099-1
CSDE.F4.3
Piluss
JBDE.F3.3
623
Red Racer
15H07.10.4.4
Latah
45L23
SGPF.F3.1
MountainMerit
JBGG.F3
2330.1
EB911

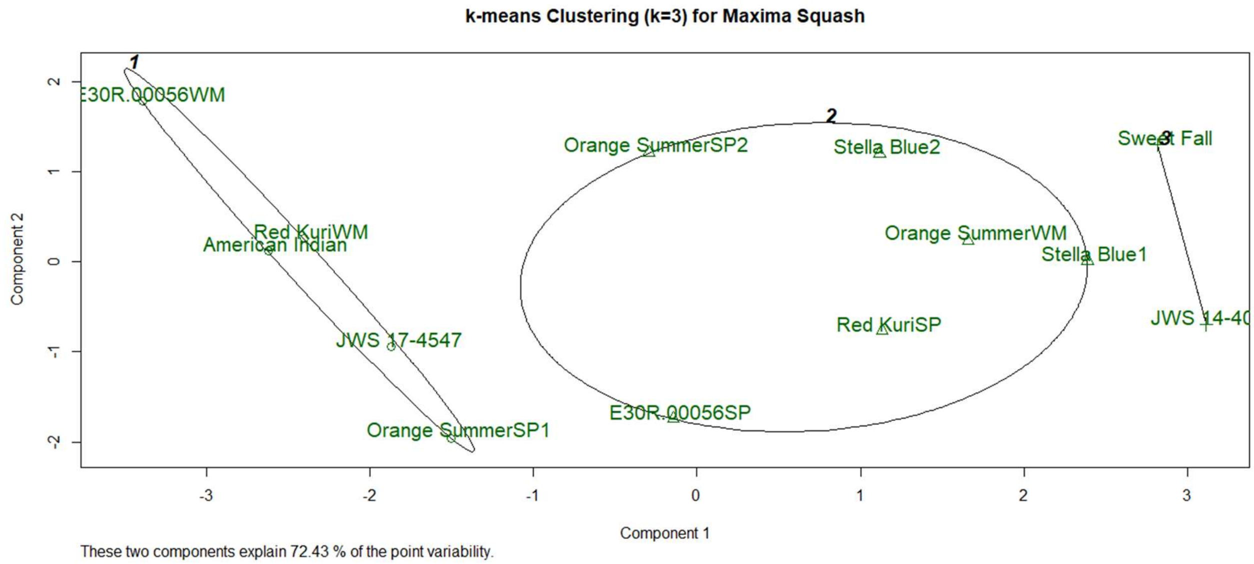

Cluster Determination (Butternut Squash)
Within Group Sum of Squares
Number of Clusters

Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.09.26	2019.10.18	Squash	ERP	Havana	Large	Vitalis	WMARS	Field
2019.09.26	2019.10.18	Squash	KHV	Waldo	Large	Johnny's	WMARS	Field
2019.09.26	2019.10.18	Squash	OBE	Butterbush	Large	Seed Savers	WMARS	Field
2019.09.26	2019.10.18	Squash	LPM	Waltham1	Large	Johnny's	WMARS	Field
2019.09.26	2019.10.18	Squash	FJN	Bugle	Large	Rupp	WMARS	Field
2019.09.26	2019.10.18	Squash	SNH	Tiana	Large	Vitalis	WMARS	Field
2019.09.26	2019.10.18	Squash	ITF	Waltham2	Large	Johnny's	WMARS	Field
2019.09.26	2019.10.18	Squash	XKA	Brulee	Mini	High Mowing	WMARS	Field
2019.09.26	2019.10.18	Squash	DHF	Autumn Frost	Mini	PanAmeric an	WMARS	Field
2019.09.26	2019.10.18	Squash	RXI	Honeynut	Mini	High Mowing	WMARS	Field
2019.09.26	2019.10.18	Squash	GHK	Hamilton	Mini	EarthWork Seed	WMARS	Field
2019.09.26	2019.10.18	Squash	IKR	Butterbaby1	Mini	PanAmeric an	WMARS	Field
2019.09.26	2019.10.18	Squash	JVX	Butterbaby2	Mini	PanAmeric an	WMARS	Field
2019.09.26	2019.10.18	Squash	FXV	Butterscotch	Mini	Johnny's	WMARS	Field





Harvest Date	Taste Date	Crop	Code	Variety	Market	Seed Source	Location	Management
2019.09.26	2019.11.13	Squash	XKA	Stella Blue1	Blue Green	Siskiyou Seeds	Spooner	Field
2019.09.26	2019.11.13	Squash	DHF	American Indian	Blue Green	Seed Savers	Spooner	Field
2019.09.26	2019.11.13	Squash	RXI	Sweet Fall	Blue Green	Seed Savers	Spooner	Field
2019.09.26	2019.11.13	Squash	GHK	Stella Blue2	Blue Green	Siskiyou Seeds	Spooner	Field
2019.09.26	2019.11.13	Squash	IKR	JWS 17-4547	Blue Green	Johnny's	Spooner	Field
2019.09.26	2019.11.13	Squash	JVX	JWS 14-4069	Blue Green	Johnny's	Spooner	Field
2019.09.26	2019.11.13	Squash	ERP	Red KuriSP	Red Pink	Vitalis	Spooner	Field
2019.09.26	2019.11.13	Squash	KHV	Red KuriWM	Red Pink	Vitalis	WMARS	Field
2019.09.26	2019.11.13	Squash	OBE	Orange SummerSP1	Red Pink	High Mowing	Spooner	Field
2019.09.26	2019.11.13	Squash	LPM	Orange SummerSP2	Red Pink	High Mowing	Spooner	Field
2019.09.26	2019.11.13	Squash	FJN	Orange SummerWM	Red Pink	High Mowing	WMARS	Field
2019.09.26	2019.11.13	Squash	SNH	E30R.00056SP	Red Pink	Vitalis	Spooner	Field
2019.09.26	2019.11.13	Squash	ITF	E30R.00056WM	Red Pink	Vitalis	WMARS	Field


k-means Clustering (k=3) for Maxima Squash
1
2
3
E30R.00056WM
Red KuriWM
American Indian
JWS 17-4547
Orange SummerSP1
Orange SummerSP2
Stella Blue2
Orange SummerWM
Stella Blue1
Red KuriSP
E30R.00056SP
Sweet Fall
JWS 14-40
Component 1
Component 2
These two components explain 72.43 % of the point variability.

Appendix H: 2019 SKC Stakeholder Survey Questions and Responses

2019 SKC Breeder/Seed Co. Survey: Summary Questions and Responses

How many years have you contributed varieties to the Seed to Kitchen trials (first year of trials was 2014)?

4 or more	3years	2years	1year
6	0	0	0

How important are the different parts of Seed to Kitchen in your decision-making?

	Extremely important	Very important	Somewhat important	Slightly important	Not at all important
Connecting with UW researchers	1	2	2	0	1
Connecting with farmers	1	2	1	2	0
Connecting to breeders/seed cos.	1	2	1	1	1
Connecting to chefs	1	3	1	1	0
Research station data	3	1	0	1	1
Flavor data	4	1	1	0	0
Midwest on-farm trial results	2	0	2	1	1

How likely are you to share results of the Seed to Kitchen trials with someone in your organization?

Very likely	Somewhat likely	Not likely
5	1	0

Have you shared Seed to Kitchen trial results with any of the following people outside your organization? (Check all that apply)

Farmers	Chefs	Other breeders/seed cos.	Other
2	1	1	seed distributor

How much do the Seed to Kitchen trial results affect your variety/selection decisions?

A great deal	Moderately	A little	Not at all
0	4	1	1

How useful have the professional connections you have made through the trials been?

	Extremely useful	Very useful	Somewhat useful	Slightly useful	Not at all useful
Connections with UW researchers	2	1	2	1	0
Connections with farmers	1	0	2	1	2
Connections to breeders/seed cos.	1	1	1	2	1
Connections to chefs	1	1	0	1	3

Have there been particular varieties where you feel Seed to Kitchen trials have been particularly useful in decisions about commercialization?

Yes	No
4	2

If yes, which varieties?

Autumn Frost Squash
JWS 14-4069
Salvaterra's Select tomato
Italia pepper
John's Sweet Fry pepper

What do you think is the best part of Seed to Kitchen?

Detailed yield data, flavor analysis
The connection of food to farmers to chefs and the practical partnerships
Connection to chefs
Getting comprehensive flavor data from chefs.
The broad number of farms engaged with trials
attending the field day

How would you rate your overall experience with the Seed to Kitchen trials?

Extremely satisfied	Somewhat satisfied	Neither satisfied or dissatisfiec	Somewhat dissatisfied	Extremely dissatisfied
3	2	0	1	0

How likely are you to continue to participate in the Seed to Kitchen Variety Trials?

Extremely likely	Somewhat likely	Neither likely nor unlikely	Somewhat unlikely	Extremely unlikely
4	1	0	1	0

Please list below any specific crops you would like to see added to the trials that are not currently included.

Herbs (basil)
Collards
onions
Melon
Watermelon

How many years have you been a plant breeder or working in the seed industry?

5
12
10
6
8

Who are your primary customers?

Wholesale growers	Market growers	Home gardeners	Retail seed companies	Companies who license my varieties
1	3	4	4	0

What predominant geographic area are your customers in? (Can select multiple)

Global	USA,MEX,CAN	Midwest USA	Northeast USA	Northwest USA
2	2	1	1	1

How can Seed to Kitchen improve for breeders/seed companies?

increase the number of plants/rep in trials

Getting at least some data back to researchers more quickly (I know it's hard!)

The data results need to be collated and distributed more quickly. Plot sizes are too small to feel confident in results (especially for the cucurbits, which often have just 4 plants/plot). Also, clarity during the submission process on how many locations the varieties will be planted. This led to some surprises in the total entry fee at the end of year, when plots were included in Hancock that were not anticipated.

2019 Chef Survey: Questions and Responses

How many years have you participated in the Seed to Kitchen trials (first year of trials was 2014)?

4 or more	3years	2years	1year
3	1	1	1

How did you first hear about Seed to Kitchen?

From a fellow chef	Social media	Attended a presentation	Approached by university as	Approached by farmer
3	0	0	3	0

What parts of Seed to Kitchen were most motivating or important for you joining?

	Extremely important	Very important	Moderately important	Slightly important	Not at all important
Connecting with fellow chefs	3	1	1	1	0
Connecting with local farmers/growers	5	1	0	0	0
Connecting with University researchers	3	2	1	0	0
Tasting different varieties of commercially a	5	1	0	0	0
Participating in the breeding process of new	5	0	1	0	0

When it comes to tastings, which group is most exciting for you?

	Extremely exciting	Very exciting	Moderately exciting	Slightly exciting	Not at all exciting
Varieties currently available to farmers	1	4	1	0	0
Varieties soon to be available to farmers (1-:	3	2	1	0	0
Early generations in breeding process (5-8 ye	2	4	0	0	0
Historic or heirloom varieties not available c	5	1	0	0	0

What has been a favorite experience or memory from your time working with Seed to Kitchen?

Meeting at the West Side Ag Center and walking through the fields. It was a pleasure seeing where all the varieties are grown. Loved taking all that produce back to the restaurant to play with. Additionally all the times someone drops off a big variety to our kitchen, it's one thing to taste the raw product and comment on the nuance, but to get to work with the different varieties and see how they respond to seasoning and cooking side-by-side is the real pleasure for me.

It is great to taste genetically different types of the same thing to really notice the nuances between varieties.
too many to narrow down. I have loved them all.
the carrot tasting at forequarter, the squash tasting at pifc and the pepper tasting at the ufc commissary.

How much has participating with Seed to Kitchen affected the following:

	A great deal	A lot	Somewhat	A little	None at all
Sourcing for your restaurant	2	0	2	2	0
Exposure/outreach for your restaurant	2	1	1	2	0
Understanding of plant breeding/variety dev	2	4	0	0	0
Relationships with farmers	1	2	2	1	0
Relationships with other chefs	2	1	2	1	0
Relationships with plant breeders	2	1	3	0	0

Please tell how your participation with Seed to Kitchen has impacted you the most?

Anytime I am able to step out of the kitchen and connect with the source of our produce I become a slightly better chef. It has made me more conscientious and more dedicated to moving away form commodity farming.

We have been buying over 80% of our product locally for 20 years so I'm excited to see some of our farmers involved.
learned so much about plant breeding and vegetable flavors.

How often do you talk about your Seed to Kitchen participation with others?

Always	Frequently	Sometimes	Occasionally	Never
1	3	1	1	0

To whom do you mention your work with Seed to Kitchen?

Other chefs	Farmers/growers	Family and friends	Produce sellers	Other
5	4	5	3	0

How well is Seed to Kitchen doing when it comes to:

	Extremely well	Very well	Moderately well	Slightly well	Not well at all
Communicating overall goals	0	4	1	0	0
Delivering relevant information	2	3	0	0	0
Monthly chef tastings	2	3	0	0	0
Farm to Flavor event	2	3	0	0	0

Which of the following changes are most important for improving Seed to Kitchen for chefs going forward?

	Extremely important	Very important	Moderately important	Slightly important	Not at all important
Tasting more breeding lines	2	1	2	0	0
Field trips to visit trials or farms	1	1	2	1	0
More information on variety history	3	1	1	0	0
More interaction with farmers	1	1	3	0	0
More interaction with breeders	2	0	3	0	0
Flavor wheel/lexicon development	0	2	2	0	1

Please give any details or other ideas you have as to how Seed to Kitchen can improve?

I think having more opportunity to cook with the produce and give feedback to the qualities as the product is cooked. While I can speculate how a vegetable will cook or respond to various preparations, until I get the vegetables in the kitchen I'm mostly guessing.

Other chefs including myself are confused by the wheel. I've been involved in tasting for the Slow Food Ark of Taste and the process was much clearer.

2019 Farmer/Grower Survey: Summary of Questions and Responses

How many years have you participated in the Seed to Kitchen trials (first year of trials was 2014)?

4 or more	3years	2years	1year
10	4	4	1

How satisfied are you with your overall experience working with Seed to Kitchen?

Extremely satisfied	Very satisfied	Somewhat satisfie	Slightly satisfied	Not at all satisfied
4	12	2	1	0

How likely are you to continue participating in SKC trials?

Extremely likely	Somewhat likely	Neither likely nor u	Somewhat unlikely	Extremely unlikely
11	6	2		

Please share your favorite experience or memory as a member of Seed to Kitchen?

Ruth came and visited our farm a few years ago. It was interesting to chat with her.

We appreciated that we trialed some carrots we did not have interest in and have really found some gems

Meeting at events w/ other farmers and chefs to discuss successes and favorites

The excitement of receiving seed and looking at the varieties

STK gave me the resources and reason to begin saving my own tomato seed. This was a first for me as a grower of 25 years.

Digging potatoes several years ago and being amazed at the variety within fingerling potatoes

I love trialing new varieties. Because of seed trials I was introduced to Italian sweet peppers which are by far our favorite peppers now. When I trialed beets some of my CSA members did a taste testing survey cooking the different varieties for a farm picnic. It was fun and I hope the member feedback was useful to SKC.

Growing out F2 potatoes from actual seed and seeing the genetic variability within that family of plants.

I really love trying out new varieties that aren't on the market yet.

being able to start potatoes from seed, saving the tubers, planting them nest season, then having them used in UW trials (Ruth Genger)

I had a visit the first year from an administrator of the program. He was accompanied by a young graduate student associated with the program and she was delightful in her keen interest in the success of the project.

The winter squash trial really inspired us in terms of the potential for new varieties, and exceptional flavors. This also gave us ideas and clarified some of our own priorities for the traits that suit our operation.

Being invited to the tasting event at the end of the season.

Was proud to be able to donate over 30 lbs of produce to a local food pantry. And totally enjoyed the seed to kitchen dinners.

Doing taste trial on the farm with the crew was a blast and informed our variety choices for the following year.

Discovering Badger Flame beets!

Best variety has been Orange Summer Red Kuri. Was introduced to this variety through SKC. Since introduction we now sell 5-10 thousand pounds every year to local grocers, restaurants and institutions.

Which parts of Seed to Kitchen are most important to you as a participant?

	Extremely important	Very important	Moderately import	Slightly important	Not at all import
Connecting with UW researchers	6	8	3	1	1
Connecting to breeders/seed cos.	6	2	5	5	0
Connecting with other farmers	1	7	7	4	0
Connecting to local chefs	2	3	7	4	2
Seeing new and upcoming varieties	13	4	1	0	1
Sharing trial results	5	11	2	0	0
Seeing how varieties perform on your farm	12	6	1	0	0

How much has your experience working with Seed to Kitchen impacted your work?

A great deal	Somewhat	A little	None at all
4	9	5	0

Which types of information are most influential for your decision-making on farm?

	Extremely important	Very important	Somewhat importa	Slightly important	Not at all import
Trial results from your farm specifically	8	9	2	0	0
Trial results as a whole (from all farms + research stati	3	7	8	0	0
Other farmers' recommendation	3	11	5	0	0
Visits to research stations	2	1	8	5	2
January stakeholder meeting in Madison	0	2	3	6	8

How likely are you to share what you have learned with others?

Very likely	Somewhat likely	Not at all likely
12	5	0

With whom are you most likely to share your experience with Seed to Kitchen? (Check all that apply)

Other farmers	Local chefs	Seed companies/b	Customers	Friends and famil	Other
16	10	4	9	8	2

Visitors to farmstay B&B, Soil Sisters Wisconsin, students in organic gardening classes
Donors for non-profit

How useful have the different professional connections you have made through the trials been?

	Extremely useful	Very useful	Somewhat useful	Slightly useful	Not at all useful
Connections with farmers	2	3	9	5	0
Connections with UW researchers	2	10	4	3	0
Connections to breeders/seed cos.	2	3	6	3	5
Connections to chefs	1	3	5	2	8

Have you found new varieties that you are now using because of the Seed to Kitchen trials?

Yes	No
16	1

Please list which varieties of which crops you are now using as a result of the Seed to Kitchen trials.

Various carrots and potatoes
Damsel tomato, Adana carrot, Carmen pepper
a few hot pepper varieties especially
red endeavor potato, papa cacho potato, sweet yellow dumpling potato
Carmen and Bridge to Paris peppers
Some as yet unnamed potato varieties, tasty jade cucumber.
various potatoes and kale
borega beets, cortland onion, daisy gold potato, Havana butternut squash, various Japanese cukes
Nutterbutter winter squash. Another one that I can't remember.
Butternut Squash--Autumn Frost, French Melon--D'artagnon, Corno di Toro Pepper--Escamillo
Blush red onion, Cortland yellow onion, Escamillo peppers, Napoli carrots, Daisy Gold and Aylesbury Gold potatos (and probably others I can't bring to mind)
Badger flame, Boro, heatless habanero (Numex Suave Orange?), Tiana, Pomegranate Crunch, Spretnak, sugarloaf variety (Virtus?)

Salt and pepper cucumbers, White beets
Badger Flame beet, Chocolate Sprinkles cherry tomato, Damsel tomato, Magic Molly potato, Newham Little Gem lettuce
Orange Summer-Red Kuri

Have you made any other changes on your farm based on Seed to Kitchen trials or connections you've made through the trials? (If yes, please tell what you've changed)

Yes	No
5	12

I do many more of my own trials now
Last year I grew russets for the first time. Honestly, I never thought that I'd like them so much. They grew exceptionally well.

We've started being more intentional about variety traits, flavor and explore new varieties r
Modified my HH tomatoes because of a field day visit, done more farm crew taste trails
I've changed some spacings for lettuce and potatoes

How well is Seed to Kitchen doing when it comes to the following:

	Extremely well	Very well	Moderately well	Slightly well	Not well at all
Communicating trial results	3	12	3	0	1
Addressing relevant crops for trialing	2	12	4	1	0
Sending trial materials in spring (seeds, etc.)	5	9	4	0	1
Making data collection easy	2	12	4	0	1

How many years have you been farming?

6
13
27
33
25
24
8
40
13
5
12
27
40
10
40
9
5

In your operation, how many acres are dedicated to vegetable production each year? (estimation is fine)

2
5.65
4.5
2
1
4
1
1
0.75
1
2
2
12
0.2
2.5
5
2
12

What is your farm's plant hardiness zone (for example, locations in WI range from 3a to 5b)?

5a
3b/4a
5a
5b
5b
3b
4
4b
4a
5a
5b
4
5b
4b (I think...)
4
5b
3
5b
5

What are your primary markets?

Farmers market	CSA	Restaurant	Local grocery	Wholesale
9	7	9	6	4

What would you change to improve Seed to Kitchen?

More seed for certain crops
trial result reporting - I haven't tried the app yet - I bet that will be much easier
Happy as things are
skip the platforms that load poorly in rural areas, find interesting open-pollinated varieties, send seeds in time for greenhouse propagation prior to transplant, especially where season is short

Some bugs still need to be worked out of the Seedlinked interface for entering data but otherwise, SKC is awesome
Receiving seeds sooner. Last year I recieved my onion seeds a month after I had started my other onions.
separate farmers from local gardeners in results and S2K data; your survey questions relate to farmers
not a thing. this is a well-run program. I appreciate the honest, hands-on approach.
Our farm is a few hours west of Madison so participating in off farm events is a challenge.
I would like to choose my trials, and know how many different seeds come with each trial, MUCH earlier in the process. My plan is finished in December. If I don't know which seeds I'm getting until March or April, I have to go back and change my plan in the middle of planting season to accommodate the new seeds.

Slightly more communication (and slightly more in advance) about expected dates for meetings, variety-choosing deadlines, expected seed delivery times, etc.

Resources/networking for people not farming in Madison area.
More on farm visits by researchers
More varieties from major breeders. There are a lot of new varieties that I would like to see included.