Weed Removal Efficacy and Labor Implications of an Intelligent Cultivator in Vegetable Crops Marked with Machine Vision Detectable Signals

By

HANNAHJOY KENNEDY

B.S. Purdue University, 2013 (HannahJoy Pheasant)
M.S. University of California, Davis, 2018

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Approved:

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Steve Fennimore, Chair

_____

Rachael Goodhue

_____

Brad Hanson

Committee in Charge
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Abstract

Increasing weed control costs threaten vegetable crop grower profitability due to labor shortages, increasing costs per hour of labor, as well as a small and decreasing number of registered herbicides. A grower has some control of the weed seed bank but little control of herbicide availability and efficacy or labor shortages. Farmers, however, can contain labor costs by reducing the amount of hand-weeding needed by using an intelligent intra-row cultivator. Traditional inter-row mechanical cultivation has limited reach because it does not remove weeds within the seed line during early growth periods when competition for nutrients, water, and light is critical. Thus, intra-row hand weeding is necessary to remove weeds left by the traditional cultivator. In the face of these challenges, automated weed control systems can help to manage weed control costs by making intra-row cultivation feasible, reducing the amount of labor needed to hand-weed.

The main technical challenge automated intra-row cultivation must overcome is a computer's ability to differentiate between crop and weeds. The complexity of field conditions, including variable lighting and visual occlusion, continue to challenge machine learning. A novel "plant signaling" approach to weed and crop differentiation was tried in lettuce and processing tomatoes. Results from field trials in 2016-2018 show no significant difference in yield between rows cultivated with the intelligent cultivator or standard cultivator. This suggests that the intelligent cultivator was as safe for the crop as the standard cultivator. Substantial improvements in weed control efficacy and reduction in time spent hand-weeding were seen in the 2016-2018 field trials. Efficacy was defined as the difference between pre-cultivation weed counts and post-cultivation weed counts.

The minimum production area required for the adoption of the intelligent cultivator to increase profits is a modest 12 hectares for lettuce and 86 hectares for tomatoes. This assumes two lettuce cycles and one tomato cycle annually. Given the almost 50% reduction in hand-weeding costs per hectare per crop cycle and thus the relatively small production area needed for the intelligent cultivator to increase profits, switching from a standard inter-row cultivator to an intelligent intra-row cultivator would have a positive economic impact for vegetable producers in California

Keywords: Robotic weeding, robotic cultivation, automated cultivation, weed control, crop signaling, crop detection, high weed density, weed-crop differentiation.

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Chapter 1: Introduction and Literature Review

Introduction.

Any plant that is not wanted in its current location is considered a weed (Adams 1909, Fennimore and Bell 2014, Maxwell n.d.). Weeds can compete with desired plants for water and nutrients thus reducing yields and causing economic loss. They can also be hosts to insects and pathogens which can infect crops (Fennimore et al. 2014b, Lati et al. 2016, Lechenet et al. 2017, Slaughter et al. 2008b). In crops like lettuce (*Lactuca sativa*), which are minimally processed before consumption, the tolerance for weeds is close to zero as they are a possible contaminate of bagged lettuce (Fennimore et al. 2010, Lati et al. 2016, *Pest Management Strategic Plan for California and Arizona Lettuce Production* 2003, Slaughter et al. 2008b).

High-value specialty crops – crops grown on less than 122,000 ha – are a significant part of agricultural production in California. They are 61% of a $46 billion-dollar industry in California (California Department of Food and Agriculture 2017). However, there are limited options for weed control due to few herbicides being registered for use in most specialty crops. The herbicides that are available generally only control a few weed species (Fennimore et al. 2010, 2016c, Fennimore and Doohan 2008, Lati et al. 2016, Van Der Weide et al. 2008). Additionally, there is growing demand for organic produce (Fennimore and Doohan 2008) and the few organic herbicides available are contact herbicides (Gramig 2018a, Melander et al. 2015, Pérez-Ruíz et al. 2014) . Consequently, mechanical weed control is an important part of weed management in vegetable crops. Traditional mechanical cultivation, however, only removes weeds between crop rows and leaves the weeds which are close to or in between the crop plants (Lati et al. 2016, Melander et al. 2015, 2017). The removal of remaining in-row weeds requires hand weeding which is tedious, time-consuming, and expensive work (Fennimore and Doohan

2008, Lati et al. 2016, Pérez-Ruíz et al. 2014, Rasmussen et al. 2012, Van Der Weide et al. 2008). With increasing wage rates in California, this puts California specialty crop producers at a disadvantage relative to locations with lower wage rates such as Mexico (Fennimore and Doohan 2008). As a result, automated mechanical weed control is being pursued by numerous researchers and companies (Fennimore et al. 2010, Lati et al. 2016, Melander et al. 2015, 2017, R. Gallandt and Brown 2018, Slaughter et al. 2008b). While the concept is promising, delivering consistently strong results in variable field conditions remains elusive due to current technical limitations such as weed recognition (Fennimore et al. 2016c, Fennimore and Doohan 2008, Melander et al. 2015, 2017, R. Gallandt and Brown 2018, Van Der Weide et al. 2008).

The purpose of this literature review is to describe current approaches to weed control, and challenges associated with them, in vegetable specialty crops grown in rows in California, to provide justification for a new approach to automated mechanical weed control. Two crops with different morphology, head lettuce and processing tomatoes, have been chosen as representative crops and will be discussed in more detail.

Preventing weeds from competing with the crop through minimizing the weed seed production and pre-plant weed control are important components of integrated weed management plans but for the purpose of this review, the focus will be on mechanical weed control after planting.

Importance of specialty crops.

The term “specialty crops” includes fruits, nuts, vegetables, cut flowers, and ornamental plants (USDA Agricultural Marketing Service n.d.). The specialty crop designation means that the crop is grown on less than 122,000 ha (300,000 acres) in the whole country irrespective of

economic importance ("Specialty Crops and the IR-4 Project" 2018). In fact, specialty crops comprised 27% of the value of United States agriculture in 2012 (Johnson 2014). In California, they were 61% percent of the state's total agricultural production value of $46 billion in 2016 (California Department of Food and Agriculture 2017).

Lettuce.

Lettuce production worth $2 billion, in 2016, was 4% percent of California agriculture production value that year (California Department of Food and Agriculture 2017). Lettuce production is composed of three main types: leaf lettuce (20,100 ha / 49,800 acres in 2016), iceberg type head lettuce (36,400 ha / 90,000 acres in 2016), and romaine type head lettuce (28,700 ha / 70,900 acres in 2016) (California Department of Food and Agriculture 2017, Smith et al. 2011, Turini et al. 2011). In 2016 there were 13,000 ha (32,000 acres) of organic lettuce (all types) grown in California (National Agricultural Statistics Service 2017).

Head lettuce is typically grown in 1 m (40-inch) beds with two seed lines or 2 m (80-inch) wide beds with six seed lines (Koike et al. 2011, Smith et al. 2017b). For field establishment, lettuce producers use both transplanted and direct seeding methods with direct seeding being most common (Turini et al. 2011). Lettuce is weeded about a month after planting (Turini et al. 2011). Lettuce has a short growing cycle (60-90 days) so multiple crops can be grown a year, depending on the growing region (Samtani et al. 2014, Turini et al. 2011).

Tomatoes.

Processing tomato production in California had a $1.3 billion value in 2016, which is 94% of United States production and comprised 2% of California total agriculture production

value in 2016 (California Department of Food and Agriculture 2017). Processing tomatoes are used in value added products such as pizza, sauce, catsup, salsa, etc. This study focuses on processing tomatoes because they are a significant part of California agriculture (106,000 ha / 262,000 acres in 2006) while fresh market tomatoes only account for $300 million (in 2016) (California Department of Food and Agriculture 2017, Hartz et al. 2010). Although organic tomato production is not differentiated between fresh and processing tomatoes in the USDA's Certified Organic Survey – California (National Agricultural Statistics Service 2017), an estimated three-fourths of the 4,400 ha (10,800 acres) of organic tomato production in California are processing tomatoes (Johnson 2015, Processing Tomato Advisory Board 2017).

Tomatoes are typically started in greenhouses and transplanted into 1.5 m (60-inch) wide beds with one or two plant lines (Fennimore and Bell 2014, Hartz et al. 2010). The growing season typically lasts three months after transplanting (Harris Moran Seed Company 2016, Schrader 2000).

Weed control in specialty crops.

Why it is necessary.

There are many reasons weeds are undesirable in a field. Weeds can harbor insects and pathogens, compete for nutrients, water, or even sunlight leading to reduced crop yields (Fennimore et al. 2014b, Lati et al. 2016, Samtani et al. 2014, Slaughter et al. 2008b). Additionally, weeds could contaminate the crop at harvest requiring the weeds to be removed before the crop can be processed. In crops such as lettuce which can be packaged in the field, there are few opportunities to remove the weeds before the produce reaches consumers (*Pest*

Management Strategic Plan for California and Arizona Lettuce Production 2003). Weed contamination of lettuce or tomato cannot be tolerated by either industry.

While the best method of weed control is prevention, it is not totally possible because of weed seeds in the soil, i.e. the seedbank (Gramig 2018a, Smith et al. 2018). Prevention means avoiding the introduction of new weeds from outside the field as well as minimizing the reproduction of weeds already in the field. An integrated approach to prevention and control is needed to achieve profitable crop production (Brown and Gallandt 2018, Gramig 2018a, Lechenet et al. 2017, Melander et al. 2017, Riemens et al. 2007).

An overview of the typical approach to weed management in California agricultural production is to keep the seed bank low, use tillage and other methods to remove weeds that emerge prior to crop planting, and then to use selective physical and chemical methods to remove weeds after the crop has been planted. The weed control methods used before and after planting are generally different due to crop safety concerns and are elaborated upon below (*Pest Management Strategic Plan for California and Arizona Lettuce Production* 2003, Slaughter et al. 2008b, Smith et al. 2017b, 2017c).

Chemical weed control.

While herbicides are vital to crop production, in specialty crops, there are fewer herbicides available compared to agronomic crops like field corn (Fennimore et al. 2010, 2016c, Fennimore and Doohan 2008, Lati et al. 2016, Van Der Weide et al. 2008). The development cost of an herbicide averages $240 to $300 million, and thus a large market is required to provide the returns on this investment (Fennimore et al. 2016a, Phillips McDougall 2016). Due to the small number of hectares specialty crops are grown on, and the wide variety of crop species,

agro-chemical companies do not have a sufficient economic incentive to develop new herbicides for such specialized use (Lati et al. 2016, Samtani et al. 2014).

The three most widely used herbicides in lettuce are all preplant incorporated (PPI) or preemergence (PRE) (Table 1.1). Bensulide is mostly used to control purslane and pigweed while pronamide has the broadest spectrum for use on broadleaf weeds and benefin primarily controls grasses. There are two herbicides registered for use in lettuce postemergence (POST) in California, sethoxydim and clethodim (Fennimore and Bell 2014, Smith et al. 2017d). They are only used on a small number of hectares due to their efficacy only on grass weeds, which are uncommon problems in lettuce fields.

The United States market for organic lettuce was $262 million in 2015 (Greene et al. 2017) and the demand for organic produce is growing. There is one herbicide, 'Suppress', registered for use in organic lettuce (Rusnak 2014). However, 'Suppress' is a non-selective contact herbicide, with limited utility because tillage performs the same tasks and thus this herbicide is not commonly used commercially (Gramig 2018b).

Tomatoes have more registered herbicides available than lettuce. See Table 1.2 for the five most commonly used herbicides. Tomatoes have seven herbicides registered for post-emergence use in California (Lanini et al. 2016a). However, the herbicides that are available typically target a limited number of weed species (Fennimore et al. 2016a, 2010, Fennimore and Doohan 2008, Lati et al. 2016). The market for organic processing tomatoes is quite small (less than 3% of total processing tomato market) but growing (Hartz et al. 2010). 'Suppress' is again the only organic herbicide available and it is used on 0.09% of tomato production area.

Table 1.1. The three most common herbicides used in lettuce in California, as well as the two POST herbicides, and the single organic herbicide available[a].

Herbicide	Brand name	Treatment timing	% of production area treated[b]
Pronamide	Kerb	PRE	53
Bensulide	Prefar	PRE	28
Benefin	Balan	PRE	6
Clethodim	Select Max	POST	2
Sethoxydim	Poast	POST	0.7
Capric acid	Suppress	Organic, POST	0.01

[a] (Samtani et al. 2014, Smith et al. 2017a)
[b] Data from (California Department of Pesticide Regulation 2016)

Table 1.2. Five most common herbicides used in tomatoes in California and the single organic herbicide available[a].

Herbicide	Brand name	Treatment timing	% of production area treated[b]
Trifluralin	Triflurex HF	PRE	58
S-metolachlor	Dual Magnum	PRE	47
Glyphosate	Roundup UltraMax	PRE	38
Rimsulfuron	Matrix SG	POST	21
Metolachlor	Dual	POST	16
Capric acid	Suppress	Organic, POST	0.09

[a] According to (California Department of Pesticide Regulation 2015)
[b] Data from (California Department of Pesticide Regulation 2016)

Physical weed control.

Due to the limitations of chemical weed control, physical methods are a critical part of weed management plans in specialty crops. Physical weed control includes hand pulling or hoeing weeds and cultivators. Cultivation is shallow tillage with the goal of promoting crop growth through increased soil aeration and infiltration as well as reduced competition from weeds (American Society of Agricultural Engineers 2005). The term is “used synonymously

with physical or mechanical weed control" (R. Gallandt and Brown 2018). It specifically occurs during early stages of crop growth with the goal of uprooting, burying, or cutting weed seedlings to reduce competition (Melander et al. 2017, R. Gallandt and Brown 2018).

Traditional mechanical cultivators were equipped with metal tools of various shapes which were pulled through the soil by animals, and later tractors, to uproot weeds as the soil was tilled. This method has been employed in some form for hundreds of years (Alstrom 1990, Bell 2015). Common mechanical cultivators include rotary hoes, chisel plow, cultivator sweeps, spring tine harrows, spider weeders, basket weeders, torsion weeders, and finger weeders (Fennimore et al. 2014a, Gramig 2018b, Kelly et al. 2007, Melander et al. 2015, 2017, R. Gallandt and Brown 2018).

The main drawbacks with traditional cultivators are that they: 1) only remove weeds between the plant rows, with the exception of finger and torsion weeders, 2) that they are not selective about the plants they remove, both crops and weeds, including the finger and torsion weeders, and 3) that the crop can be damaged by the cultivator coming too close to the crop (Melander et al. 2015, 2017, R. Gallandt and Brown 2018). Cultivating between the plant rows is called inter-row cultivation as opposed to intra-row cultivation; in intra-row cultivation the implement is moved around the crop plants to remove weeds within the crop row (Lati et al. 2016). The selectivity of a weed control method is its ability to destroy weeds while not damaging the crop. Simply considering the percentage of weeds removed is insufficient without also considering crop damage (R. Gallandt and Brown 2018). Weed control efficacy and crop damage are highly correlated (Melander et al. 2015, 2017). While efficacy is greater when more of the field is weeded by the cultivator, if the cultivator tools come too close to the crop plants, the crop could be injured by root pruning, burial, or uprooting (R. Gallandt and Brown 2018).

Reduced yield or quality could also result from cultivation because of adverse effects on soil quality such as soil compaction and increased wind erosion (R. Gallandt and Brown 2018).

Achieving weed control effectiveness while avoiding crop injury takes considerable skill on the part of the operator to combine the ideal cultivation implement, implement adjustments, cultivation timing, crop disturbance tolerance, and operating speed (Gramig 2018b, Kelly et al. 2007, Melander et al. 2015). As a result, in current California lettuce and tomato production, hand labor is used to remove remaining weeds in between crop plants after a mechanical inter-row cultivator has gone through a field (Fennimore et al. 2016a, Fennimore and Doohan 2008, Lati et al. 2016, Slaughter et al. 2008b). Some crops, such as high-density spinach or baby leaf lettuce, which have as little as 3.8 cm (1.5 in) space between plant lines, are entirely weeded by hand labor (Fennimore and Bell 2014).

Current weed control practices in California.

A standard weed control management program in iceberg and romaine lettuce includes pre-plant herbicide (benefin or glyphosate) and cultivation, preemergence herbicides band applied (pronamide with bensulide), cultivation (sled-mounted cultivator), and hand-weeding crew (Table 1.3) (Smith et al. 2017a, Tourte et al. 2015, 2017, Turini et al. 2011)

A standard weed control management program in processing tomatoes includes pre-plant herbicides incorporated (trifluralin with *S*-metolachlor) or sprayed (glyphosate with oxyfluorfen) and cultivation, post-emergent herbicide spray (rimsulfuron), cultivation (sled-mounted cultivator), layby herbicide application, and hand-weeding crew (Table 1.4) (Hartz et al. 2010, Lanini et al. 2016b, Miyao et al. 2017).

Table 1.3. Typical weed control management program and costs per hectare for Central Coast romaine and iceberg lettuce production[a].

Operation	Herbicide or implement	Amount	Operation time	Cost
		ha^{-1}	hr ha^{-1}	\$ ha^{-1}
Pre-plant cultivation and bed preparation	Disc, roll, bed shape, list	N/A	6.4	591
Pre-plant herbicides	benefin	1.1–1.7 kg ai	0	106-227
Preemergance herbicide -band	pronamide with bensulide	0.6–2.2 kg ai 5.6–6.7 kg ai	0	106-227
Cultivate/break bottoms	Sled with cultivator sweeps, curved sweep knives, and squirrel cages	N/A	1.3-1.5	84-99
Hand hoe crew	Hand hoe	N/A	23.5	378-398
Total weed control cost	-	-	-	1265-1542

[a] UC Agriculture and Natural Resources "*Sample costs to and harvest iceberg lettuce - 2017* (Tourte et al. 2017) and "*Sample costs to and harvest romaine hearts – 2015"* (Tourte et al. 2015)

Table 1.4. Typical weed control management program and costs per hectare for Sacramento Valley processing tomato production[a].

Operation	Herbicide or implement	Amount	Equipment time	Cost
		ha^{-1}	hr ha^{-1}	\$ ha^{-1}
Pre-plant cultivation and bed preparation	Disc, bed shape, roll, list	N/A	0.7	178
Pre-plant herbicides 2x	trifluralin with *S*-metolachlor	0.6–1.1 kg ai 1.1–1.78 kg ai	0.49	62
Post-transplant herbicide spray-band	rimsulfuron	36.5–73 ml ai	0.44	30
Close cultivate sled	Sled with cultivator sweeps, curved sweep knives, and squirrel cages	N/A	0.57	30
Layby herbicide	trifluralin	0.6–1.1 kg ai	0.25	32
Hand hoe crew	Hand hoe	N/A	0	297
Total weed control cost	-	-	-	629

[a] UC Agriculture and Natural Resources "*Sample costs to produce processing tomatoes: sub-surface, drop irrigated, in the Sacramento Valley and Northern Delta - 2017* (Miyao et al. 2017)

Intelligent mechanical weed control.

Intelligent guidance of the cultivator refers to a machine-vision system that controls the cultivator tracking, so that it precisely follows the row (Fennimore et al. 2010, Fennimore and Doohan 2008, Lati et al. 2016, Slaughter et al. 2008b). However, machine guidance of cultivator steering is also an important component of intelligent intra-row cultivation (Figure 1.1). Intelligent cultivator guidance systems can be applied to inter-row cultivation so that the cultivator tools can be set at a narrower uncultivated band around the crop and increase cultivation speed. This can be done because the guidance system reacts more quickly and precisely than a human operator (Fennimore and Doohan 2008, Slaughter et al. 2008b). Examples of this approach include the Eco-Dan (Eco-Dan A/S, Kvistgaard, Denmark, http://www.eco-dan.dk/), Robocrop Guided Hoes (Garford, England, http://www.garford.com/products_robocrop.html), and Steketee IC-Light Steering System (Steketee, The Netherlands, http://steketee.com/en/steketee-ic-light/).

Intelligent intra-row cultivation requires three more technologies; a machine-vision system that detects crop plants and weeds, an image classification and decision algorithm that differentiates crop plants and weeds, and control over the actuator so that it uproots the weed while protecting the crop (Christensen et al. 2009, Slaughter et al. 2008a, 2008b). Precision guidance systems, decision algorithms, and precision in-row weed control devices are commercially available or are at an advanced level of development (Christensen et al. 2009, Fennimore et al. 2016b, Slaughter et al. 2008a, 2008b). Weed detection and differentiation from crop plants, requiring a high level of correctness at real-time speeds, are the remaining obstacles to commercial level intelligent intra-row cultivators (Fennimore et al. 2016a, Slaughter et al. 2008b).

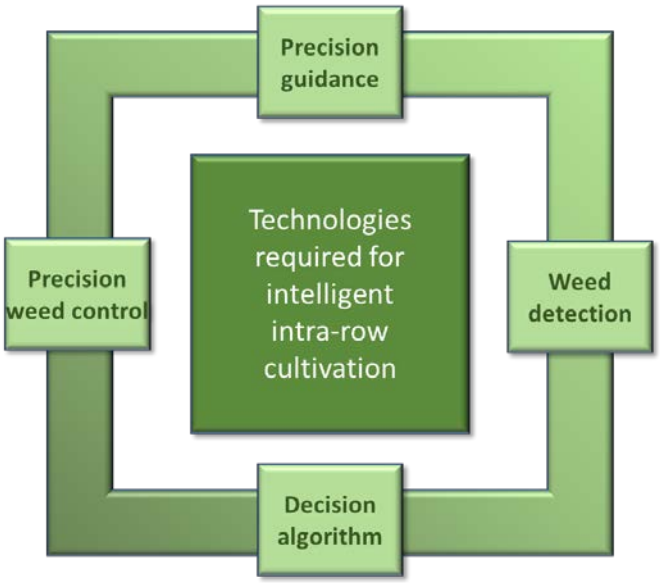

Figure 1.1. Technologies required for a fully-functional intelligent intra-row cultivator.

Approaches to crop and weed differentiation.

Methods to differentiate crops from weeds fall into three main categories and the methods are often used in combination:

1. Identifying crop plant location based on systems level information such as real-time kinematic (RTK) global positioning system (GPS) coordinates of planting location (Fennimore et al. 2016a, Rasmussen et al. 2012, Van Der Weide et al. 2008).

2. Using context or pattern detection to follow the crop row and assuming weeds are randomly scattered while the crop is planted at a defined spacing (Christensen et al. 2009, Hemming et al. 2011, Slaughter et al. 2008b).

3. Differentiating between crop and weed plants via plant characteristics such as color, reflectance, leaf or plant shape, leaf or plant texture, leaf or plant size, or size differential (i.e. a transplanted crop plant will be much larger than a weed) (Christensen et al. 2009, Fennimore et al. 2016b, Lati et al. 2016, Rasmussen et al. 2012, Slaughter et al. 2008b, Tillett et al. 2008).

Challenges.

These approaches have had some success but not at the level needed for widespread commercial adoption (Pérez-Ruíz et al. 2014, Van Der Weide et al. 2008). To reach a commercial level of viability, weed removal must consistently be greater than 95% under variable field conditions (Lati et al. 2016) at a speed of at least 0.45 meters per second (1 mile $hour^{-1}$) (Fennimore, unpublished). This would at least match human speeds; a crew of 10 people takes about 2.5 hours to hand-weed a hectare of lettuce (23.5 labor hours ha^{-1}) or almost two hours to hand-weed a hectare of tomatoes (18.3 labor hours ha^{-1}) (Miyao et al. 2017, Tourte et al. 2015, 2017).

The row-pattern recognition systems are problematic where weed populations are high and the row pattern cannot be detected. In these weedy situations, the machines cease to function or cause damage to the crop (Melander et al. 2017).

Correct weed verses crop classification results have been as high as 95% in limited crop/weed/field conditions but the average is 66% with a range from 21% to 95% (R. Gallandt and Brown 2018, Slaughter et al. 2008a). Machine learning remains challenged by the complexity of field conditions. The lighting is variable, leaves overlap (occlusion), and row patterns can be difficult to detect at high weed densities, requiring complex sensors and high computational power (Pérez-Ruíz et al. 2014).

Table 1.5. Methods used by commercial intelligent mechanical cultivators to differentiate weeds from crops.

Name	Differentiation approach	Precision weed control implement	Results	Company	Notes
Struik WeedFix	Pattern detection	Moving tines	None Found	Struik, Wieringerwerf, The Netherlands. http://www.struikholland.nl/ShowContent.aspx?cid=60	Throws dirt into the row to bury intra-row weeds[f]
Robocrop InRow Weeder	Pattern detection and plant characteristics: Crop spacing, plant size, plant color. Requires crop to be much larger than weeds	Rotating disc with cutout	30-54% weed reduction in lettuce and 16-31% hand weeding time reduction[a]	Tillett and Hague Technology Ltd., Peterborough, UK. http://garford.com/products_robocropinrow.html	
Sarl Radis	Pattern detection and plant characteristics: Light interception and plant size, requires crop to be much larger than weeds	Reciprocating knife	Limitations in open structure crops such as onion[b]	France	No longer available
Bonirob	Plant characteristics: leaf color, shape, size	stamping rod	90% effective in carrots[c]	Deepfield Robotics, Ludwigsburg, Germany. https://spectrum.ieee.org/automaton/robotics/industrial-robots/bosch-deepfield-robotics-weed-control	Removed from Bosch website
Robovator	Plant characteristics: plant size i.e. requires crop to be much larger than weeds	Reciprocating knife	52-75% weed reduction in lettuce and 22-55% hand weeding time reduction[d]	F. Poulsen Engineering ApS, Hvalsø, Denmark. http://www.visionweeding.com/	

			27-41% weed reduction in lettuce and broccoli and 29-45% hand weeding time reduction[e]		
Steketee IC Weeder	Plant characteristics: height, width, color	Reciprocating knife, finger weeder	75% weed reduction in lettuce and 37% hand weeding time reduction[d]	Machinefabriek Steketee BV, Haringvliet, The Netherlands. https://www.steketee.com/en/steketee-ic-weeder/	
Remoweed	Infrared	Reciprocating knife	None found	Ferrari Costruzioni Meccaniche, Guidizzolo, Italy. https://ferraricostruzioni.com/en/automated-weeders/28-remoweed.html	No details available on how the IR detection works
Dino	RTK GPS	Plowshare, harrow	None found	Naio Technologies, Escalquens, France. https://www.naio-technologies.com/en/agricultural-equipment/large-scale-vegetable-weeding-robot/	Fully autonomous - can get intra-row weeds with "in-row plowshare"

[a] (Fennimore et al. 2014a)
[b] (Van Der Weide et al. 2008)
[c] Birgit Schulz, Deepfield communications lead, in (Gershgorn 2015)
[d] (Smith 2016)
[e] (Lati et al. 2016)
[f] (Schans et al. 2006)

Economics of weed control.

Weed control costs in head lettuce production in California have been estimated at between $533 and $724 per hectare ($216 - $293 acre^{-1}) in cost studies conducted by University of California Cooperative Extension (Tourte et al. 2015, 2017) with weed control costs in organic leaf lettuce reaching $803 per hectare ($325 acre^{-1}) (Tourte et al. 2009a). This is seven to ten percent of total production costs (Tourte et al. 2015, 2017). Production costs exclude harvest costs. In processing tomatoes, weed control costs are about $356 per hectare ($144 acre^{-1}). This is eight percent of total production costs (Miyao et al. 2017).

New minimum wage and overtime laws were passed in 2016 by the California legislature. The minimum wage will increase to $15 an hour by 2022 and the amount of overtime permitted will be reduced (Martin 2016). These changes in will increase the cost of weed control. Additionally, labor shortages are a concern due to fewer people wanting to work in agriculture (Martin 2007, Tourte et al. 2017). If farmers cannot find enough people willing to hand-weed at the right time for their crop, they will increasingly be vulnerable to crop losses to weeds.

Economic analysis of new equipment.

While weed control costs are a substantial part of production costs, the monetary cost of a new piece of farm equipment, such as an automated mechanical cultivator, and its potential savings are not the only factors a farmer considers (Bisschoff et al. 1994). The amount of land, suitability of crops to mechanical weed control, availability and reliability of hand-weeding labor, availability of skilled labor to use and repair the new equipment, and reliability and efficacy of the equipment are also factors which must be considered (Bisschoff et al. 1994, Gandonou et al. 2006).

Conclusion.

Increasing weed control costs threaten vegetable crop grower profitability due to labor shortages, rising labor expense, as well as lack of registered herbicides and loss of old herbicides. Traditional inter-row mechanical cultivation is not sufficient as it does not remove weeds within the seed line at early growth periods when competition for nutrients, water and light is critical. Thus, intra-row hand weeding is necessary, but increasingly expensive. Automated weed control systems can help to manage weed control costs by reducing dependence on hand-weeding.

Some intra-row cultivators commercially available differentiate between crops and weeds using row pattern recognition. The row-pattern recognition systems are problematic where weed populations are high and, consequently, the row pattern cannot be detected. In these weedy situations, the machines cease to function or cause damage to the crop. Other intra-row cultivators commercially available use machine learning to differentiate between crops and weeds based on a variety of classifiers. The complexity of field conditions, including variable lighting and occlusion, continue to challenge machine learning. The need remains for a novel approach to differentiate crop and weed plants that is practical, cost-effective, and robust to variable field conditions.

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Chapter 2: Plant Signaling Method with Automated Cultivator

Introduction.

The main area of difficulty that must be overcome for automated intra-row cultivation is to differentiate between crops and weeds using digital imagery and processing at field operation speeds of at least 0.45 meters per second (1 mile hour^{-1}). The complexity of field conditions, including variable lighting and visual occlusion, continue to challenge machine learning. The need remains for a novel approach for differentiating crop and weed plants which is practical, cost-effective, and robust to variable field conditions such as irregular lighting, different soil types, imprecise plant spacing, leaf overlap, variation in plant color or shape, etc.

Plant signaling approach.

The concept of "plant signaling" is a novel approach to crop and weed differentiation (Figure 2.1). It is based on the premise that the identity of the crop is known with certainty when it is planted, whether transplanted or seeded. Thus, if the crop was marked in some manner which is machine-readable, when the automated cultivator passes through the field it would recognize the crop signal and thus avoid it. Plants detected that lack the signal, are then classified as weeds and removed by the automated cultivator.

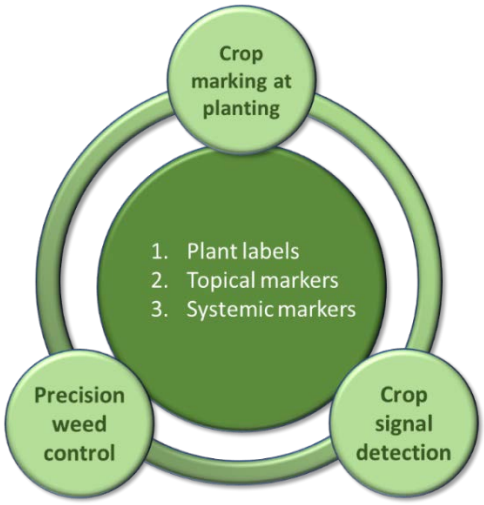

Figure 2.1. Plant signaling concept diagram.

Marking system descriptions.

Three methods of plant signaling were considered; physical plant labels, topical markers, and systemic markers (Figure 2.1).

A plant label is a physical, biodegradable, colored label. The physical label is transplanted together with the crop plant. For example, a physical plant label is picked up with a tomato seedling and placed into the transplanter together, so that the label is planted alongside the tomato seedling (Figure 2.2).

Figure 2.2a. Plant label being placed in tomato transplanter fingers

Figure 2.2b. Plant label in ground alongside tomato seedling

Paint is applied to the stem or leaves of the crop as a topical marker which allows the intelligent cultivator to recognize the marked crop plants as the cultivator moves through the field. The ideal topical marker would not stunt crop growth, would be biodegradable, and would not contaminate the harvested commodity.

Figure 2.3a. Lettuce seedling in soil with topical marker.

Figure 2.3b. Tomato seedling in soil with topical marker.

Systemic markers are compounds absorbed by the plant roots and translocated to the leaves such that it fluoresces in the leaves when light of a specific wavelength is focused on the crop, thus enabling the machine vision system to recognize the crop.

The marking compound would be incorporated into the crop seed coat or seed pellet and then absorbed by the crop roots as the seed germinates, continuing through the third leaf stage. The marking compound must be a xylem mobile molecule so that it can be taken up by the roots and translocated into the foliage. For optimal translocation to the shoot, the compound should have intermediate polarity with log Kow values between 0 and 2.0 (0-1.0 according to Nissen, Sterling, and Namuth (2017), 0.5-1.5 according to Hsu, Marxmiller, and Yang (1990), 1.5-2.0 according to Briggs, Bromilow, and Evans (1982)). The marker must fluoresce when exposed to a specific wavelength, and be safe for use on food crops, i.e., Food and Drug Administration approved. The marker concentrations in the leaves must be high enough for machine vision

detection in 5 milliseconds to permit normal travel speeds of 0.45 meters per second (1mile hour^{-1}) (Fennimore, unpublished).

Several lab and greenhouse experiments have been conducted on various compounds to explore their properties (Kennedy, unpublished). At this time, no marking compound has been found which meets the criteria, thus no field trials have been done with a systemic marker. Physical labels and topical markers have been used in field trials as described in the Materials and Methods section below.

Automated mechanical cultivator.

The automated mechanical cultivator used in this research was developed at University of California, Davis (UC Davis) by Dr. David Slaughter's lab. It uses a machine vision system to locate all the plants in its field of vision and detect the plant signals (physical labels and topical markers) on the crop. It then uproots all plants without the marker using mechanical cultivator knives which open and close to avoid the marked crop plants.

The machine vision system consists of a camera, six mirrors, and ultraviolet (UV) light emitting diodes (LEDs) (Nguyen and Slaughter, unpublished). The configuration of the system can be seen in Figure 4. The camera is an electrically-controlled, high-resolution, area-scan, single-lens, digital, color camera (Model Scout scA1600 gm/gc, Basler Inc., Ahrensburg, Germany). The mirrors are first-surface mirrors (Model 0.485 Thickness in Glass Sheets, Kaleidoscopes Inc., Iowa, USA). The two sets of six high efficacy UV LEDs (ultraviolet light-emitting diodes) (Model LZ4-00UA00 Ultraviolet 410 nm 10 Watt, LED Engin Inc., San Jose, California, USA) have LED lighting reflectors (Model C10437 Boomerang Hexagonal, Ledil Oy, Finland). The camera, capturing images with resolution of 1624 × 1230 pixels, was equipped with a fixed lens (Model Computer M0814-MP2 8mm 1:2.4 2/3", CBC Group Inc., Tokyo,

Japan) and it was positioned at a proper height from the ground to capture the plants and all the mirrors. The two set of mirrors were mounted on the left and right sides of travel direction, where each set had three 15 × 10 cm mirrors directed to three different view angles surrounding the target plant.

Figure 2.5 shows the mirror layout from the top. The mirror pairs of top-left and bottom-right mirrors (represented by yellow square-dot lines), middle-left and middle-right mirrors (represented by red solid lines), and bottom-left and top-right mirrors (represented by green dash-dot lines) were set up parallel to each other. This permitted estimating the location of the plant signal despite visual occlusion from some angles (Nguyen and Slaughter, unpublished).

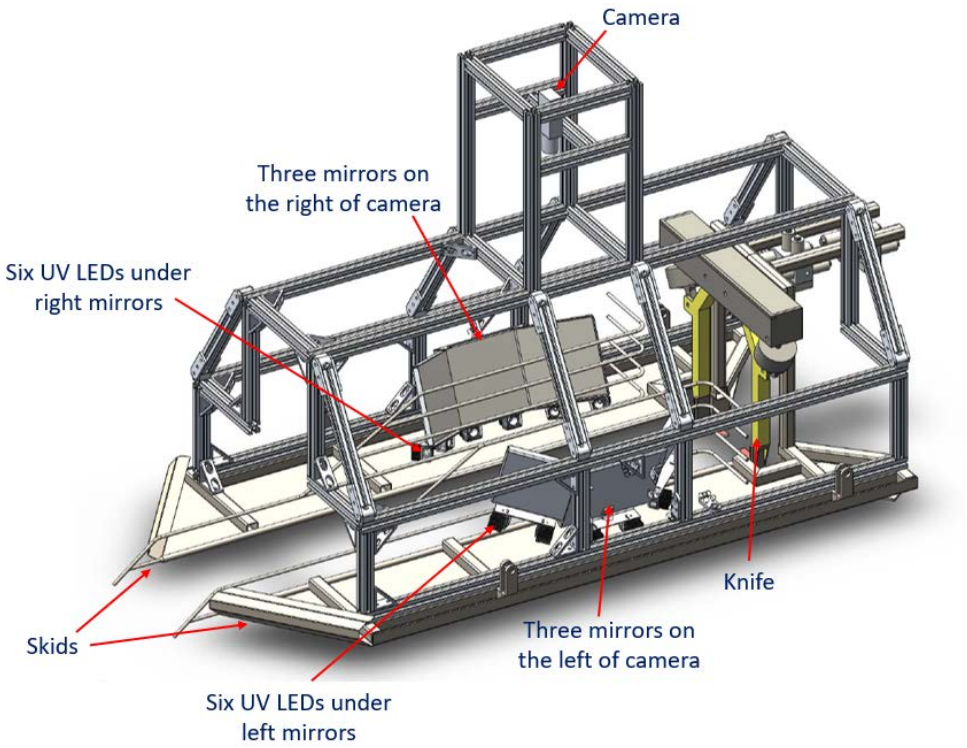

Figure 2.4. Mechanical structure of UC Davis weed knife control system, including a camera mounted on top, six first-surface mirrors, twelve UV LEDs, and an air-based mechanical cultivator knife (Nguyen and Slaughter, unpublished).

The twelve UV LEDs were mounted underneath the mirrors and used to illuminate the plant signals from the sides. The high intensity, controlled illumination system was developed to

be capable of activating the unique fluorescent and reflectance characteristics of the plant signals (Nguyen and Slaughter, unpublished). The LED brightness could be controlled by an adjustable power supply (Model HLG-185H-C1050B, MEAN WELL Enterprises Co., Guangzhou, China). Figure 2.6 shows a tomato plant with plant label (green straw), captured under direct sunlight in combination with UV light (Figure 2.6a) for color-based weed detection and visualization purposes, and under UV light only (Figure 2.6b) for fluorescent signaling. The imaging chamber was designed to be entirely dark when skids are set on the soil surface, to minimize the effects of sunlight from outside.

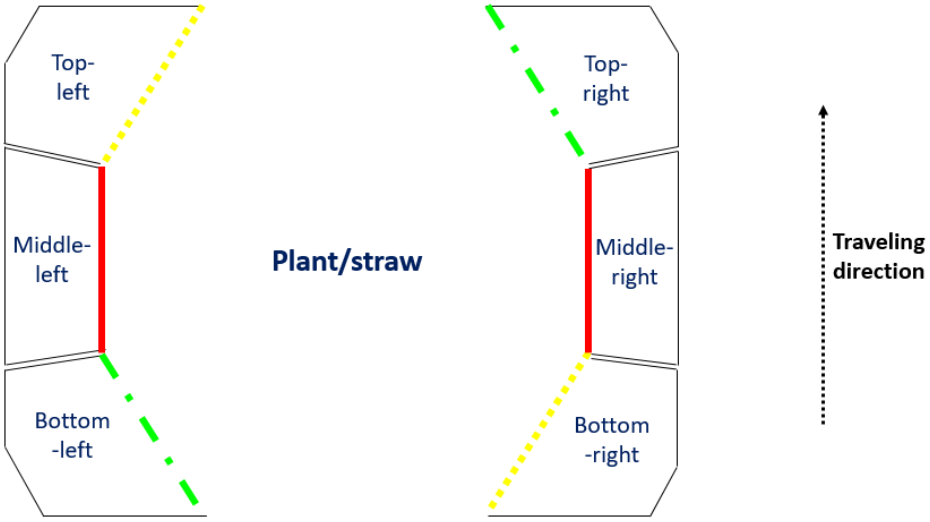

Figure 2.5. Layout from top view of six mirrors to support side views of the target plant. Top-left and bottom-right mirrors are set up parallel to each other, represented by the yellow square-dot lines. Middle-left and middle-right mirrors are set up parallel to each other, represented by the red solid lines. Bottom-left and top-right are set up parallel to each other, represented by the green dash-dot lines (Nguyen and Slaughter, unpublished).

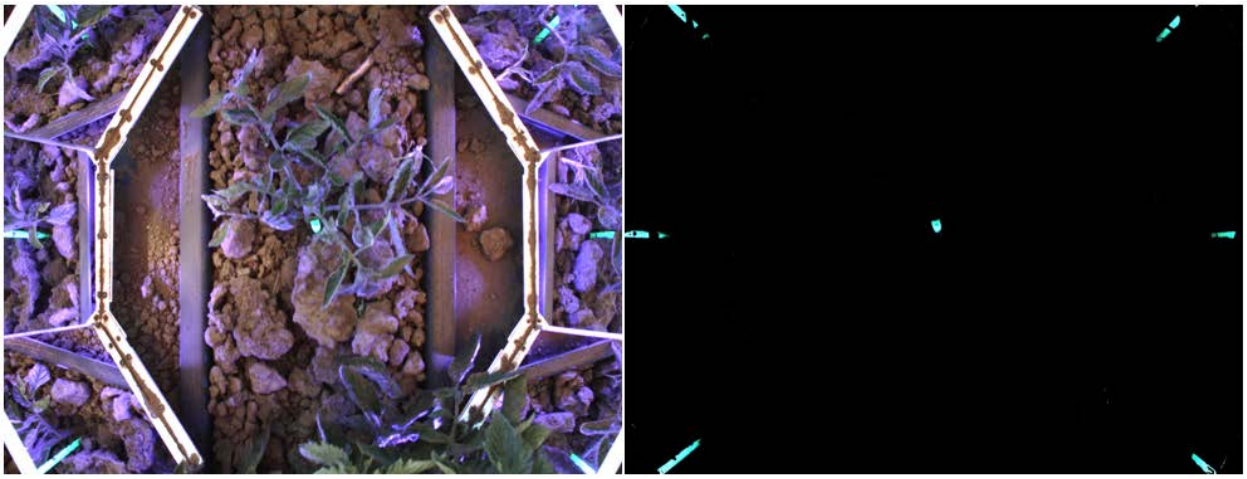

Figure 2.6. Image of a tomato plant with a green straw taken (a) under normal light plus UV light, and (b) under UV light only.

Each knife blade (red parts in Figure 2.7) was made from a 6.4 mm think plate of hardened tool steel (Model Aristocrat D-2, air hardened to Rockwell 60, Precision Marshall Steel, Washington, Pennsylvania, USA) and cut into a triangular shape, with a triangle base width of 7 cm and a triangle height of 3.2 cm. The cutting edge was created by sharpening the two forward pointing sides of the triangular plate. Two arms (yellow in Figure 2.7) were used to fasten the knife blades at their bottom, with the triangular blade tip and sharpened cutting edges facing the forward travel direction. The knife blades are set to cut at a depth of approximately 2 cm below the soil surface.

The cultivator knives are controlled by a pair of double acting pneumatic cylinders (Model CCD15-SBP-004, Ingersoll Rand plc., Dublin, Ireland). An electronically actuated solenoid air control valve (Model A212SD-024-D, Ingersoll Rand plc., Dublin, Ireland) was used to control knife motion with air pressure through the pneumatic cylinders.

Figure 2.7a. Weed knives closed
- uprooting weeds in seedline

Figure 2.7b. Weed knives open
- avoiding tomato plant

The solenoid received open/close signals based on the detection results obtained using the camera. An FPGA (field-programmable gate array) based real-time controller (Model NI CompactRIO-9014, National Instruments Corporation, Austin, Texas, USA) was used to control the knife via a digital I/O module (Model NI 9403 5V/TTL Bidirectional Digital I/O 32-channel Module, National Instruments Corporation, Austin, Texas, USA), a wheel encoder (Model 63RS64 Polarized connection, Grayhill Inc., La Grange, Illinois, USA) via a digital input module (Model NI 9411 ±5 to 24 V Differential Digital Input 6-channel Module, National Instruments Corporation, Austin, Texas, USA), and a personal computer via CAT 5e Ethernet connection. The wheel encoder was utilized to determine the location of the weed control system with respect to travel direction and to interpret the relative distance between the knife and the detect crop signal. The camera connected directly to the computer via CAT 5e Ethernet connection. Camera intrinsic parameters, including focal length, focus, aperture, exposure time, and white balance, and UV LEDs brightness, were manually set to achieve the best quality images at the commercial tractor speed of 3.2 km hr^{-1} (2 miles hr^{-1}).

LabVIEW (National Instruments Corporation, Austin, Texas, USA) code was used for all implementation from camera image acquisition, object detection, to wheel encoder read and knife control. Once an image was acquired of a fluorescent plant signal, LabVIEW based software algorithms estimated plant location and determined when to open and close the cultivator knives while the system was traveling in the field (Nguyen and Slaughter, unpublished). Figure 2.8 shows an example of cultivator knives removing weeds around tomato plants.

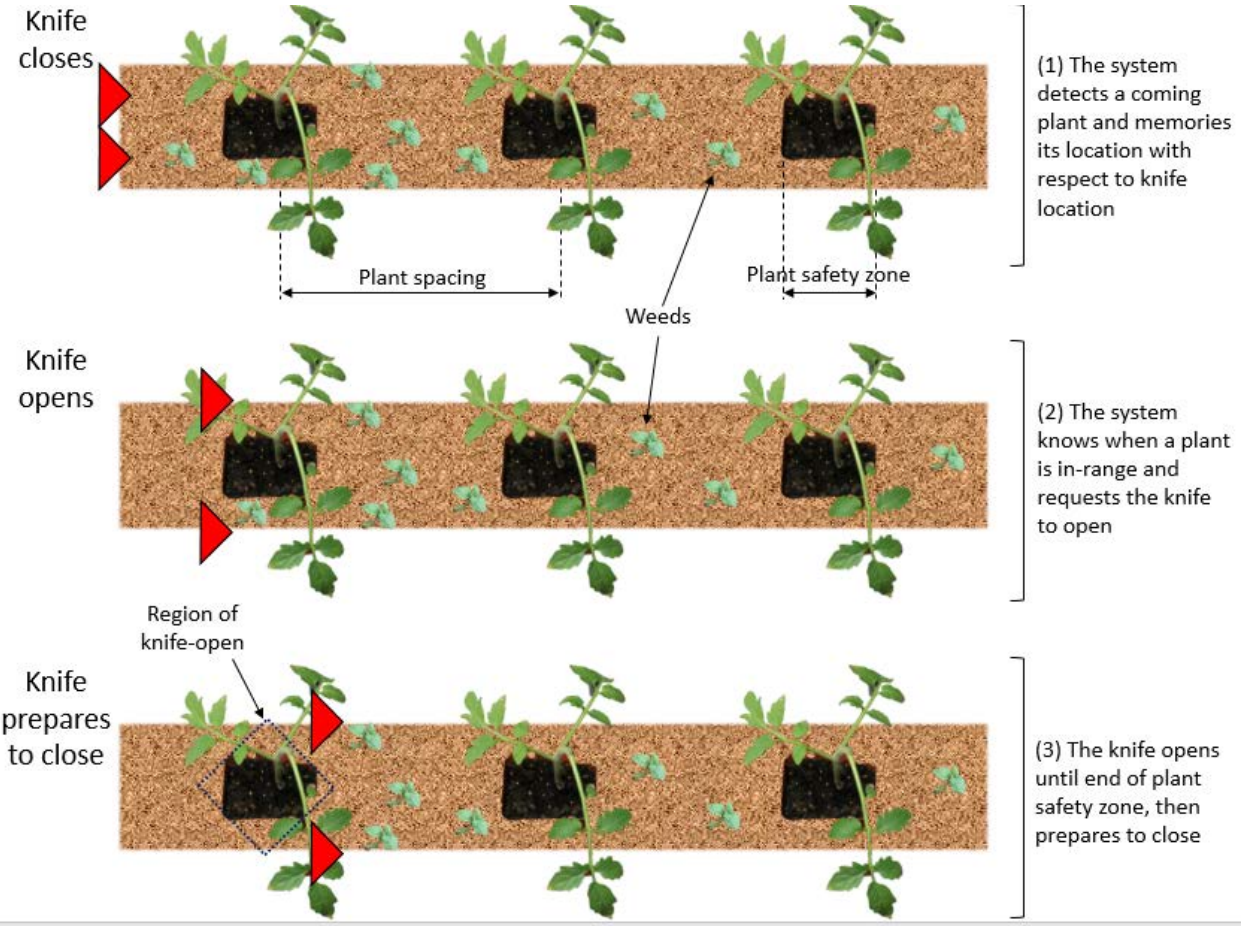

Figure 2.8. An example of knife cutting weeds for tomato plants with two operating states (open and close) of the knife.

First, the system approaches and detects a plant (based on its plant label), then it estimates the plant's location in correspondence to the location of the knife. Second, the knife opens when plant is approached and stays open for a set distance (the plant safety zone). Third, the knife closes when the plant safety zone ends and prepars for the next plant. Plant spacing (i.e. distance between two adjacent plants) can be defined as a constant or automatically estimated while traveling.

Materials and Methods.

Six field trials in romaine lettuce and eight in processing tomatoes were conducted in 2016-2018. Eight trials were done using physical labels (Figure 2.9) next to the plants and six others using a topical marker on the plants (Figure 2.11, Table 2.1).

Marking system descriptions.

Biodegradable beverage straws made from polylactic acid (PLA) or "corn plastic" were used as the physical plant labels in this study (Item Code: EP-ST910. Eco-Products. 4755 Walnut Street, Boulder, CO, 80301 www.ecoproductsstore.com/9_50_inch_clear_unwrapped_straws.html). The straws were 24 cm long with an 8 mm diameter and clear in color. Since the straws were clear, they were painted with green or orange fluorescent water-based paint (PRECSN line marking paint, product number 203032 and 203036. RUST-OLEUM. 11 E Hawthorn Pkwy, Vernon Hills, IL. https://www.zoro.com/rust-oleum-line-marking-paint-17-oz-fl-green-203032/i/G3270617/#description). The painted straws were then placed next to tomato seedlings in the planting trays.

Figure 2.9. Plant labels in tray of tomato seedlings.

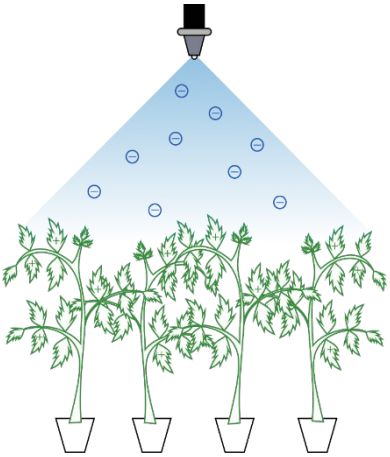

Figure 2.10. Spray applicator for topical marker.

The topical marker used was green or orange fluorescent water-based paint (Wildfire Visible Luminescent Paint, Wildfire Inc., Venice, California, USA), diluted with water to 45-50% concentration.

A foliar spray system (Figure 2.10) was used to apply the topical marker to lettuce and tomato seedlings prior to planting, while they were in trays. Figure 2.11b shows the minimum size targets for the painted area of a tomato seedling (10cm /4 inches minimum) and the unpainted gap (5cm /2 inches) while Figure 2.11a shows the topical marker on lettuce leaves.

Figure 2.11a. Topical marker on lettuce plant.

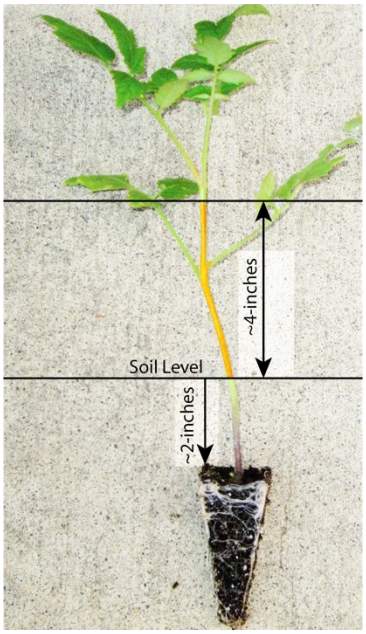

Figure 2.11b. Minimum size targets for the painted area on a tomato seedling

An alternative method was also used in which a spray system was mounted to the transplanter to spray tomato seedlings during transplanting (Figures 2.12 and 2.13). The two spray systems were not differentiated in the statistical analysis.

Figure 2.11a. Topical marker on lettuce plant.

Figure 2.12. Topical marker spray applicator mounted on back of tomato transplanter.

Figure 2.13. Topical marker being sprayed on tomato transplant by applicator mounted the transplanter.

Table 2.3. Location, year, crop, crop marker, and planting, with cultivation, hand-weeding, and harvest dates for tomato and romaine lettuce automated cultivator trials conducted at USDA research station and commercial field(*) in Salinas, CA and Davis, CA.

Trial	Location	Year	Crop	Crop Marker	Seeding	Transplanting /Thinning	Pre-counts taken	Cultivation	Post-counts taken	Hand Weeding	Harvest
1	UC Davis	2016	Tomato	Plant label							-
2	Salinas	2016	Lettuce	Plant label	June 27	-	July 22	July 23	July 25	July 25	-
3	Salinas	2016	Lettuce	Topical marker	-	Sept. 14	Sept. 21	Sept. 23	Sept. 27	Sept. 27	-
4	UC Davis	2017	Tomato	Topical marker	March 1	~ April 28	May 26	May 26	May 27	May 30	-
5	UC Davis	2017	Tomato	Plant label	~ March 1	~ May 5	June 1	June 2	June 4	June 6	Sept. 6
6	UC Davis	2017	Tomato	Topical marker	~ March 1	~ May 12	June 8	June 9	June 12	June 15	-
7	UC Davis	2017	Tomato	Topical marker	~ March 1	~ May 12	June 8	June 9	June 12	June 15	-
8	UC Davis	2017	Tomato	Plant label	~July 1	~Aug. 1	Aug. 17	Aug. 18	Aug. 24	Aug. 24	-
10	Salinas	2017	Lettuce	Plant label	June 5	June 21	July 7	July 7	July 10	July 10	Aug. 18
11	Salinas	2017	Lettuce	Plant label	June 12	July 11	July 19	July 20	July 21	July 24	Aug. 25
12	Salinas	2017	Lettuce	Plant label	June 27	July 18	July 26	July 27	July 28	July 28	Sept. 8
13	UC Davis	2018	Tomato	Topical marker	March 1	April 25	May 15	May 18	May 19	May 21	-
14	UC Davis	2018	Tomato	Topical marker	March 7	May 2	May 23	May 24	May 25	May 28	-
15	Salinas*	2018	Lettuce	Plant label	May 3	May 29	June 7	June 8	June 8	June 8	-

Tomato Field Trials.

Field trials on processing type tomatoes, (cv. 'Halley 3155'), took place on the UC Davis vegetable field crops research plots outside of Davis, CA (38°31'59.0"N 121°46'18.9"W). The soil is silt loam. The second trial in 2018, Trial 14, used variety HM 3887 in addition to Halley 3155.

The tomatoes were seeded in trays with Pro-Mix HP media and kept in a greenhouse about 45 days until they were 20-25 cm (8-10 inches) tall. Tomatoes were transplanted into 60-inch beds at 38-46 cm (15-18-inch) spacing in a single center row using a New Holland Transplanter with butterfly transfer fingers (Figure 2.14).

Figure 2.14. New Holland Transplanter with butterfly transfer fingers used for transplanting tomatoes. Shown here transplanting tomatoes with physical markers.

One field trial with processing tomatoes was conducted in 2016. Four trials of processing tomatoes were mechanically transplanted at Davis, CA a week apart in April 2017. A fifth trial was transplanted in August 2017. A representative plot map is shown in Figure 2.15; all plot maps are included in Appendix A. The plots were furrow irrigated.

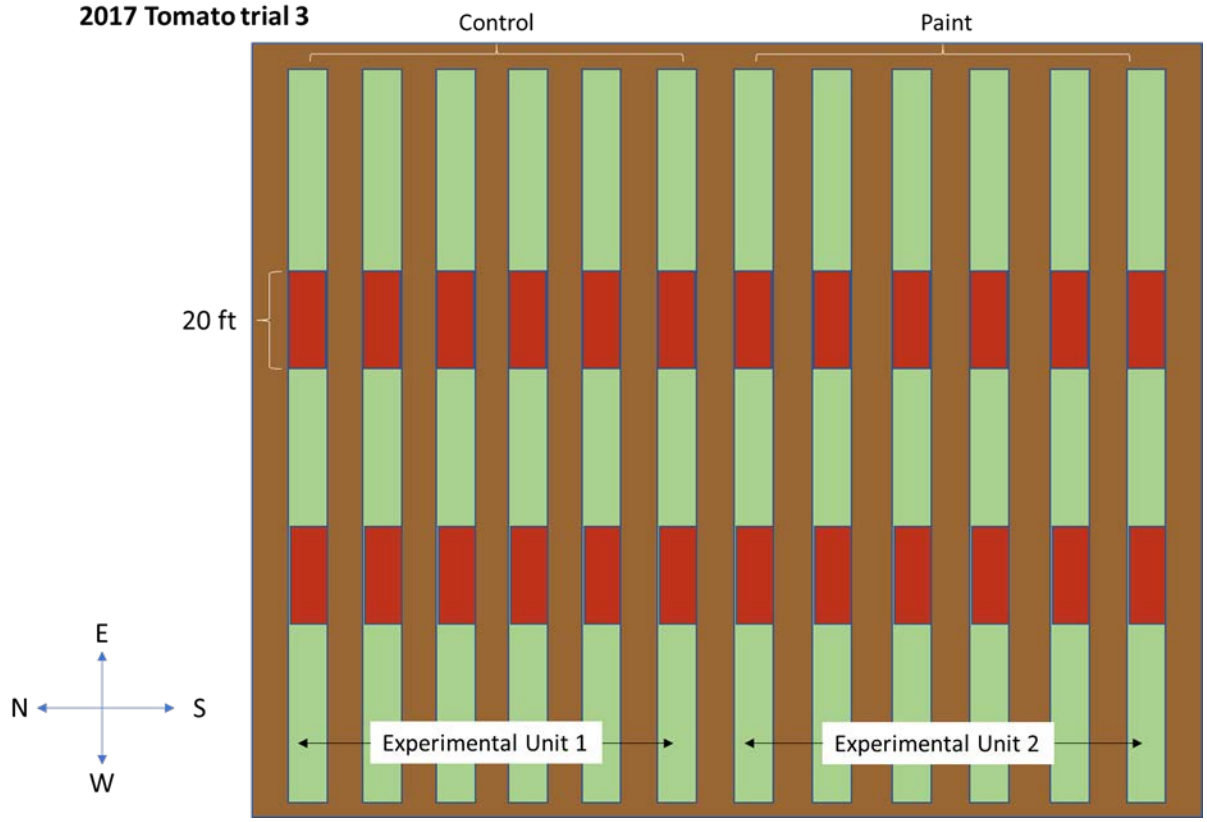

Figure 1.15. 2017 tomato trial 3 field map

Plant labels were added to seedling trays prior to transplanting (see Figure 2.9) or the topical marker was applied to trays of tomato seedlings as described above in *Marking system descriptions*. At transplanting, standard growing practices were followed; the top of the tomato plugs were placed 5-6 cm (2 to 2.5 inches) below the soil surface to maximize soil contact and minimize dehydration. Figure 2.16b shows a painted transplant in the field after planting, with the 10 cm (4-inch) painted stem above the soil level.

Figure 2.16a. Tomato seedling in soil with topical marker that was applied before transplanting

Figure 2.16b. Tomato seedlings in soil with topical marker applied during transplanting

Six weeks after seeding, or about three weeks after transplanting, the whole plot was cultivated with a standard mechanical cultivator, labeled the control in Figure 2.15. The standard cultivator used a tractor-mounted frame with angled top knives and squirrel cage rollers on the outside of the single plant row, coulters and curved sweep knives set on the bed shoulders, and cultivator sweeps set in the furrows (Figure 2.17).

The standard cultivator left a 15 cm (6-inch) non-cultivated band around the seed line in order to protect the crop. The experimental rows were additionally cultivated with the automated weeding machine. The automated weeding machine reaches in-between the plants in the seed line as explained in the introduction. The plant spacing was set to 30 cm.

Figure 2.17. Standard cultivator setup for tomatoes

Weed species densities were counted in four ten-row-feet samples randomly taken throughout the field in which the tomato trials were planted. Pre-cultivation weed counts were taken the day before cultivation and post-cultivation weed counts were taken the day after cultivation. Weed counts were taken in a 18 cm (seven-inch) band (centered on the seed line) in each of two 6 m (20-foot) sample sections except for the first trial in which weed counts were done for 55 m (180-feet) of the 60 m (200-foot) long rows. Weeds that were uprooted or had roots exposed were considered dead. Any crop plants killed during cultivation were noted.

The whole plot was then hand-weeded by a farm worker with a hand hoe who cleaned the field to the standard a commercial grower would expect. The time taken to hand weed was

recorded. Pre and post cultivation weed counts, as well as time of hand weeding, were recorded for the 20 ft sample areas.

The August 2017 tomato trial (trial 8) was maintained until harvest so that marketable yield data could be collected (tomato yield).

Lettuce Field Trials.

Field trials using Romaine lettuce (cv. 'Solid King') were conducted at the United States Department of Agriculture – Agricultural Research Service/University of California Cooperative Extension research station in Salinas, CA (36°40'12.3"N 121°36'16.5"W). The soil at the site is a sandy loam.

Two field trials were conducted in July and September of 2016. The July trial used plant labels and the September trial used plant markers.

Figure 2.18. Stanhay planter used for direct seeding lettuce

Figure 2.19. Single seed line of lettuce on 1 m (40-inch) beds. Control rows shown so no crop signal visible.

Three field trials were conducted in June-August of 2017. All three trials used plant markers. The three trials of Romaine lettuce were direct-seeded at two-week intervals during June and July 2017 in one seedline on standard 1 m (40-inch) beds (Figure 2.19). Direct seeding was done with a tractor mounted Stanhay planter (Figure 2.18). The Stanhay's ribbed belt was used with hole size 13. The base was a S-2 base. The wheel was standard with the choke in the A position. The pulley was set in the C position to give a 5.7cm (2.25 inch) in-line seed spacing. Each shoe had one slot set at a depth of six grooves (seed depth of ~ 1cm / 3/8-inch). The seeding density was determined to be 172,222 seeds ha^{-1} (69,696 seeds $acre^{-1}$). The plots were fertilized during listing with 6-20-20 fertilizer at a rate of 336 kg ha^{-1} (300 lbs $acre^{-1}$) and were side dressed with ammonium sulfate fertilizer 21-0-0-24 (S) at 336 kg ha^{-1} (300 lbs $acre^{-1}$).

The plots were sprinkler irrigated so the soil stayed moist until germination and then were watered about twice a week until harvest. Two weeks after emergence the plots were sprayed with Select, a grass herbicide, at a rate of 658ml ha^{-1} (9 oz. $acre^{-1}$) due to a high density of volunteer cereal coming up from a previous covercrop in the field. Weed density in the field was high as shown in Figure 2.20.

Figure 2.20. 2017 lettuce trial A prior to cultivation

Two weeks after emergence the plots were thinned with a hoe to an 20-25 cm (eight to ten-inch) spacing.

For the lettuce trials with physical makers, the markers were manually placed in the ground within 2.5 cm (one-inch) of the base of the plant (Figure 2.21) prior to cultivation.

Figure 2.21. Physical labels in lettuce row

Six weeks after seeding, the whole experiment was cultivated with a standard mechanical cultivator, called the control in Figure 2.15. The standard cultivator used a tractor-mounted diamond tool bar with angled top knives and squirrel cage roller set between plant rows, coulters and curved sweep knives set on the bed shoulders, and cultivator sweeps set in the furrows (Figures 2.22 and 2.23).

Figure 2.22. Standard cultivator setup for lettuce

Figure 2.23. Detail of standard cultivator setup for lettuce

The standard cultivator left a 15 cm (6-inch) uncultivated band around the seed line to protect the crop from cultivator damage. The test rows, labeled “straws” in Figure 2.15, were cultivated with the automated weeding machine. The automated weeding machine weeds in-between the crop plants in the seed line as explained in the introduction. The plant spacing was set to 13 cm. Pre-cultivation weed counts were measured the day before cultivation and post-cultivation weed counts were taken the day after cultivation.

Weed density was determined in a 15 cm (six-inch) band (8 cm / three inches on each side of the seed line) in each of two 6 m (20-foot) samples in the field. A third sample area was added in the second and third trials. Weeds were considered dead that were uprooted or had roots exposed. Any crop plants killed during cultivation were noted.

Hand-weeding was done after mechanical cultivation to provide weed control at the level expected in a commercial field. The time spent, by a laborer with a hoe, to hand-weed the same sample plots in which the weed density counts were taken, was recorded.

The 2017 lettuce trials were maintained until commercial maturity and harvested so that marketable yield data could be collected (number of marketable heads and weight of marketable heads).

The 2018 trial was conducted at a commercial lettuce field just south of Salinas, CA (36°37'50.2"N 121°35'25.8"W) with direct-seeded iceberg lettuce (cv. 'Oso Flaco'). The soil at the site is a silty clay. The lettuce was grown as described above for the 2017 field trials. The sample plots were 38.1 m (125 feet) long because the weed density was very low.

Statistical Analysis.

The weed density and hand-weeding time data were normalized to account for different sizes of sample areas. The variable Experimental Unit accounts for different amounts of randomness in different trials (see Appendix A Plot Maps). For example, the 2017 tomato trials (Trials 4-8) had all the rows of each treatment next to each other instead of randomly arranged, thus the individual rows could not be considered replicates but only subsamples. The treatment, row arrangement, and resulting Experimental Units are shown on all the plot maps in Appendix A.

Statistical analysis was performed using RStudio Version 1.1.383 (RStudio Inc., Boston, MA). See Appendix B for the complete R code used for the analysis.

The difference between pre-cultivation weed counts and post-cultivation weed counts were used to determine weed removal effectiveness. The most efficacious treatment removed the greatest proportion of weeds.

1. The difference in weed densities between pre and post cultivation was analyzed using analysis of covariance, to measure the effect of cultivator type on weed density. The

pre-cultivation weed count was the covariate. The assumptions of normality and homogeneity of variances were not met by the tomato data, based on the Shapiro-Wilk test and Levene's test, so a natural log transformation was applied to the response variable based on model fit. The assumptions of normality and homogeneity of variances were not met by the lettuce data, based on the Shapiro-Wilk test and Levene's test, so a square root transformation was applied to the covariate and the response (post-cultivation weed count) based on model fit.

The model used was: Post-cultivation weed count = Cultivation_method x Trial_number + Cultivation_method+Trial_number + Cultivation_method x Pre-cultivation weed count + Cultivation_method+Pre-cultivation weed count + RANDOM EFFECT(experimental_unit) + RANDOM EFFECT(row_number)

Equation 2.1. Weed density model in R syntax

```
letmod_sqrt <- lmer(sqrtPostcount ~  Cultivation*Trial+ Cultivation*sqrtPrecount  + (1|Experimental.Unit) +
(1|Row.number), data=lettuce)
```

2. Analysis of variance (ANOVA) was performed on the hand-weeding time data to measure the effect of the cultivators. The assumption of homogeneity of variances was not met with the lettuce hand-weeding time data, based on Levene's test, so a natural log transformation was applied to the result (hand-weeding time). No transformation was applied to the tomato hand-weeding time data because the assumption of homogeneity of variances was met according to Levene's test.

The model used was: Hand-weed time = Cultivation_method x Trial_number + Cultivation_method+Trial_number + RANDOM EFFECT(experimental_unit) + RANDOM EFECT(row_number)

Equation 2.2. Hand-weed time model in R syntax

```
lettuce_time_mod_ln <- lmer(lntime ~  Cultivation*Trial + (1|Experimental.Unit) + (1|Row.number), data=lettuce)
```

3. Analysis of variance (ANOVA) was conducted on the lettuce yield data (number of heads and weight of marketable yield) to determine if there was a significant effect of cultivator on lettuce yield. The assumption of homogeneity of variances was not met by the lettuce data, based on Levene's test, so a natural log transformation was applied to the results (number of heads per hectare and kg marketable yield per hectare). Transformation of the tomato data was not necessary. The number of heads per hectare model only applies to the lettuce trials.

The models used were:

Number of heads per hectare = Cultivation_method x Trial_number + Cultivation_method+Trial_number + RANDOM EFFECT(experimental_unit) + RANDOM EFFECT(row_number)

Kg marketable per hectare = Cultivation_method x Trial_number + Cultivation_method+Trial_number + RANDOM EFFECT(experimental_unit) + RANDOM EFFECT(row_number)

Equation 2.3. Yield models in R syntax

```
lettuce_heads_mod_ln <- lmer(lnheads ~  Cultivation*Trial + (1|Experimental.Unit) + (1|Row.number), data=lettuce0)
lettuce_kg_mod_ln <- lmer(lnkg ~  Cultivation*Trial + (1|Experimental.Unit) + (1|Row.number), data=lettuce0)
```

The EMMEANS package was used to calculation the least-square means (LS Means). Once analysis was complete, the results were back-transformed for presentation in the originals units.

Results.

Tomato Field Trials.

Weed species densities in 2017 tomato trials are shown in Table 2.2.

The treatment by trial term in the weed reduction model (Equation 2.1) was not significant so the trials were pooled i.e. the results were averaged over all the trials. Significantly more weeds (90%, with a 95% level of confidence) were removed by the automated cultivator compared with the standard cultivator (Table 2 .3 and Figure 2.24).

Table 2.2. Weed species densities and proportion of total weed densities in the 2017 tomato trials.

Weed species	Density	Proportion
	m^2	%
Prostrate pigweed	29.7	50
Yellow nutsedge	11.3	14
Common purslane	5.5	9
Common lambsquarters	4.8	8
Black nightshade	4.5	6
Barnyardgrass	1.3	2
Foxtail	0.6	1
Field bindweed	0.3	1
Sow thistle	0.3	1

The treatment by trial term in the hand-weed time model (Equation 2.2) was not significant so the trials were pooled. Nearly 50% (at a 95% level of confidence) less time was spent hand-weeding the rows weeded with the automated cultivator than the rows weeded with the standard cultivator (Table 2.4 and Figure 2.25).

Table 4.3. Effect of cultivator type on in-row weed densities in tomatoes.

Tomato Trial	Cultivator type	Weeds remaining after cultivation[b]	Lower confidence interval	Upper confidence interval	P value	% weed reduction
		----------No. m^{-2} ----------				
Overall[a]	Automated	11.2 a	8.3	15.2	0.0010	90.1
Overall[a]	Standard	113.2 b	79.8	160.7	<0.0001	

[a] All tomato trials for 2016-2018. Trials 1, 4-8, and 13-14 in Table 2.1.
[b] Values in the same column with different letters are significantly different at the 5% level of probability according to the least-square means method with Tukey's adjustment.

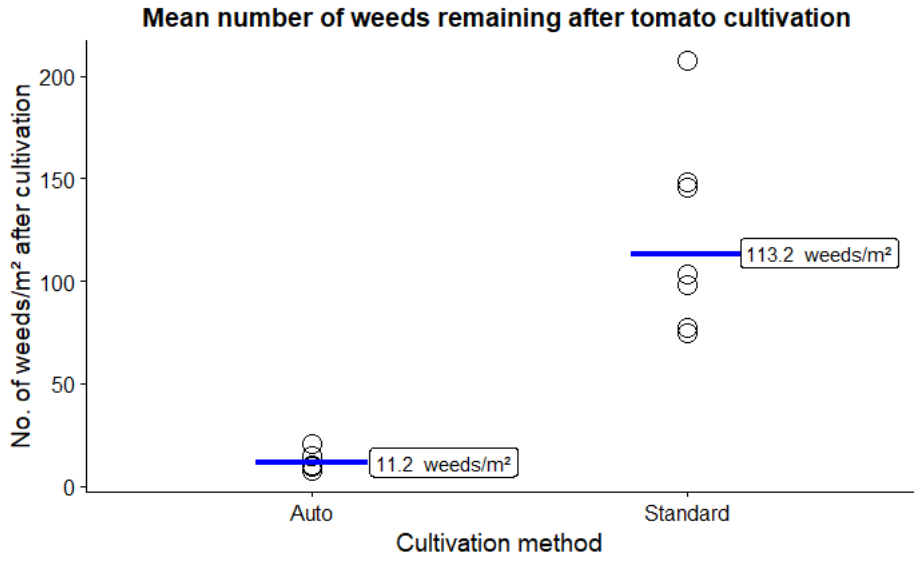

Figure 2.24. Plot of weed densities in tomato trials following automated and standard cultivation. The center line represents the LS Means of the eight tomato trials with the circles representing the mean from each trial so that the variation around the mean is visible.

Table 2.4. Effect of cultivator type on hand-weeding time following cultivation in tomatoes, and the percentage reduction in time from the automated cultivator compared to the standard cultivator.

Tomato Trial	Cultivator type	Time spent hand-weeding after cultivation[b]	Lower confidence interval	Upper confidence interval	P value	% time reduction
		----------hr ha^{-1}----------				
Overall[a]	Automated	19.2 a	8.7	29.6	0.0022	47.9
Overall[a]	Standard	36.8 b	29.1	44.4	<0.0001	

[a] All tomato trials for 2016-2018. Trials 1, 4-8, and 13-14 in Table 1.
[b] Values in the same column with different letters are significantly different at the 5% level of probability according to the least-square means method with Tukey's adjustment.

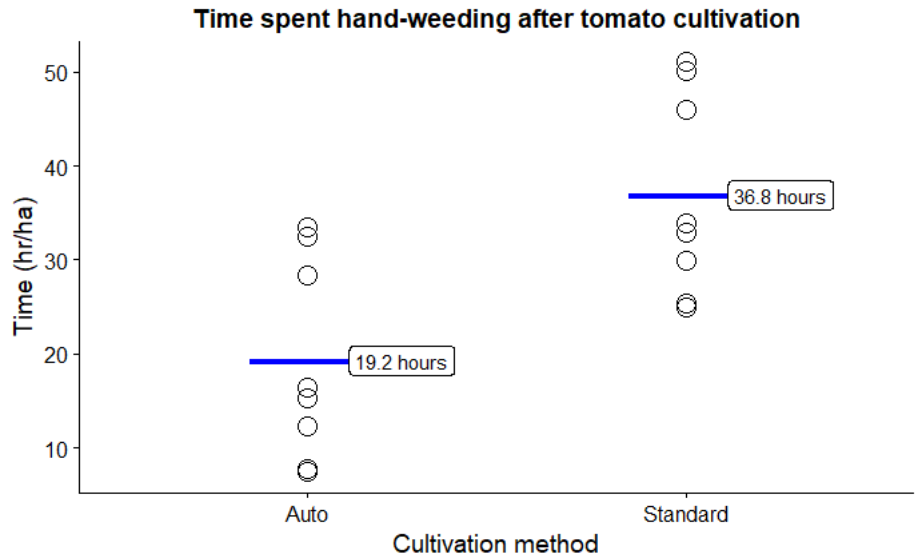

Figure 2.25. Plot of hand-weeding time in tomato trials following automated and standard cultivation. The center line represents the LS Means of the eight tomato trials with the circles representing the mean from each trial so that the variation around the mean is visible.

The treatment by trial term in the yield model (Equation 2.3) was not significant so the trials were pooled. Tomato fruit yield from rows cultivated with the automated cultivator and rows cultivated with the standard cultivator were not different at a 95% level of confidence (Table 2.5).

Table 2.5. Effect of cultivator type on yield following cultivation in tomatoes.

Tomato Trial	Cultivator type	Marketable yield[b]	Lower confidence interval	Upper confidence interval	P value
		----------kg ha^{-1}----------			
Overall[a]	Automated	49450.6 a	40331.3	58569.9	<.0001
Overall[a]	Standard	56379.7 a	45589.6	67169.8	<.0001

[a] All tomato trials taken to yield for 2016-2017. Trials 1 and 4-8 in Table 1.
[b] Values in the same column with different letters are significantly different at the 5% level of probability according to the least-square means method with Tukey's adjustment.

Lettuce Field Trials.

Weed species densities were estimated throughout the field in which the lettuce trials were conducted in 2016 (Table 2.6).

Table 2.6. Weed species proportions in 2016 lettuce trials

Weed species	Percent
Burning Nettle	95%
Hairy Nightshade	2%
Little Mallow	2%
Other	1%

The treatment by trial term in the weed reduction model (Equation 2.4) was not significant ($p < 0.001$) so the trials were pooled. Significantly more weeds (66%, at a 95% level of confidence) were weeds removed by the automated cultivator compared with the standard cultivator (Table 2.7 and Figure 2.26).

Table 2.7. Effect of cultivator type on in-row weed densities in lettuce.

Lettuce Trial	Cultivator type	Weeds remaining after cultivation[b]	Lower confidence interval	Upper confidence interval	P value	% weed reduction
		----------No. m^{-2} ----------				
Overall[a]	Automated	18.0 a	15.8	20.4	<.0001	65.9
Overall[a]	Standard	52.8 b	48.5	57.2	<.0001	

[a] All lettuce trials for 2016-2018. Trials 2-3, 10-12, and 15 in Table 1.
[b] Values in the same column with different letters are significantly different at the 5% level of probability according to the least-square means method with Tukey's adjustment.

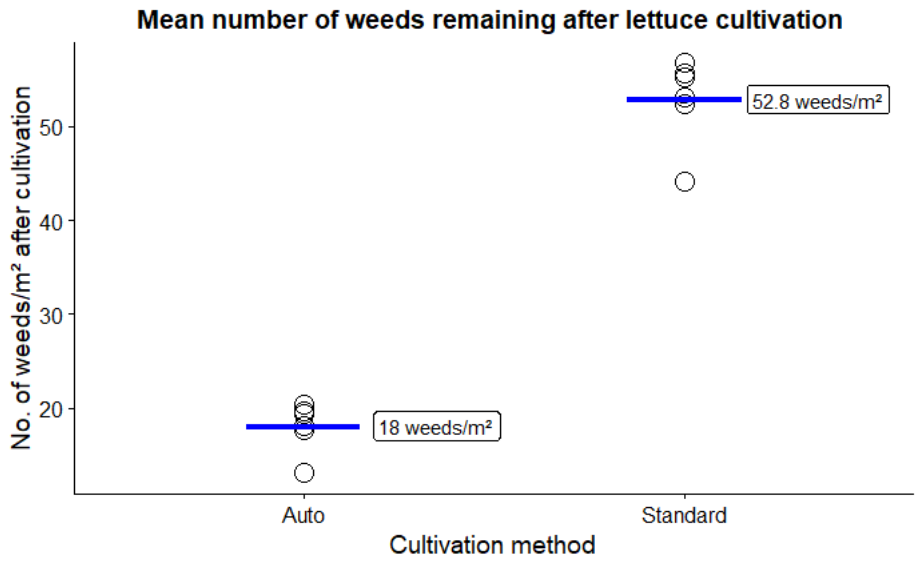

Figure 2.26. Plot of weed densities in lettuce trials following automated and standard cultivation. The center line represents the LS Means of the six lettuce trials with the circles representing the mean from each trial so that the variation around the mean is visible.

The treatment by trial term in the hand-weed time model (Equation 2.2) was not significant so the data were pooled (Table 2.8 and Figure 2.27). Significantly less time (45%, at a 95% level of confidence) was spent hand-weeding the rows weeded with the automated cultivator than the rows weeded with the standard cultivator.

Table 2.8. Effect of cultivator type on hand-weeding time following cultivation in lettuce, and the percentage reduction in time from the automated cultivator compared to the standard cultivator.

Lettuce Trial	Cultivator type	Time spent hand-weeding after cultivation[a]	Lower confidence interval	Upper confidence interval	P value	% time reduction
		----------hr ha^{-1}----------				
Overall[a]	Automated	39.6 a	32.7	47.8	<.0001	45.0
Overall[a]	Standard	72.0 b	58.7	88.3	<.0001	

[a] All lettuce trials for 2016-2018. Trials 2-3, 10-12, and 15 in Table 1.
[b] Values in the same column with different letters are significantly different at the 5% level of probability according to the least-square means method with Tukey's adjustment.

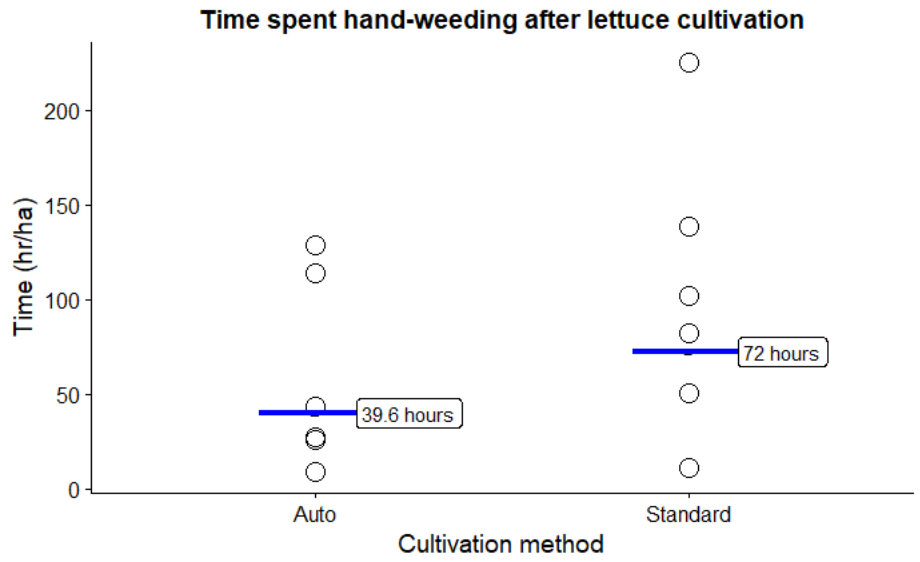

Figure 2.27. Plot of hand-weeding time in lettuce trials following automated and standard cultivation. The center line represents the LS Means of the eight tomato trials with the circles representing the mean from each trial so that the variation around the mean is visible.

The treatment by trial term in the yield models (Equation 2.3) was not significant so the data were pooled. No significant differences were found among the yields (with a 95% level of confidence) from plots cultivated with the intelligent cultivator and plots cultivated with the standard cultivator (Tables 2.9 and 2.10). Yield data were analyzed both as the number of marketable heads per hectare and kilos of marketable lettuce (based on head weight) per hectare.

Table 2.9. Effect of cultivator type on yield following cultivation in lettuce.

Lettuce Trial	Cultivator	Marketable yield[b]	Lower confidence interval	Upper confidence interval	P value
		----------No. heads ha^{-1}----------			
Overall[a]	Automated	39193.5 a	28997.0	52975.4	<.0001
Overall[a]	Standard	36964.5 a	26707.3	26707.3	<.0001

[a] All lettuce trials taken to yield, Trials 10-12 in Table 1.
[b] Values in the same column with the same letters are not significantly different at the 5% level of probability according to the least-square means method with Tukey's adjustment.

Table 2.10. Effect of cultivator type on yield following cultivation in lettuce.

Lettuce Trial	Cultivator	Marketable yield[b]	Lower confidence interval	Upper confidence interval	P value
		----------kg ha^{-1}----------			
Overall[a]	Automated	45840.8 a	32255.8	65147.3	<.0001
Overall[a]	Standard	38045.8 a	26038.4	55590.2	<.0001

[a] All lettuce trials taken to yield, Trials 10-12 in Table 1.
[b] Values in the same column with the same letters are not significantly different at the 5% level of probability according to the least-square means method with Tukey's adjustment.

Discussion.

No differences in yields between rows cultivated with the automated or standard cultivator were found in lettuce or tomato. This suggests that both cultivators were safe to the crop. Thus, the two cultivation methods can be compared based on the reduction in weed density, reduction in time spent hand-weeding, and the purchase cost of the equipment.

Significantly fewer weeds remained after the automated cultivator went through the fields than after the standard cultivator. In the tomato trials, 11.2 weeds per m^2 remained after automated cultivation while 113.2 weeds per m^2 remained after standard cultivation which is a 90% reduction in the number of weeds remaining after cultivation. In the lettuce trials, 18.0 weeds per m^2 remained after automated cultivation while 52.8 weeds per m^2 remained after standard cultivation which is a 66% reduction in the number of weeds remaining after cultivation.

The automated cultivator also significantly reduced the time spent hand-weeding the weeds remaining after mechanical cultivation. In the tomato trials, 19.2 hours ha^{-1} were spent hand-weeding the remaining weeds after automated cultivation while 36.8 hours ha^{-1} were spent after standard cultivation. This is a 48% reduction in the time spent hand-weeding the weeds remaining after cultivation, a notably smaller percentage reduction than in weed densities. This is

because the intelligent cultivator removes the easy weeds; the remaining weeds, at the base of crop plants, take more time for the field crew to remove than weeds further from the crop plant.

In lettuce, 39.6 hours ha^{-1} were spent hoeing the rows after weeding with the automated cultivator while 72.0 hours ha^{-1} were spent hand-weeding the rows weeded with the standard cultivator. This was a 45% reduction in time spent hand-weeding after cultivation, again a notably smaller percentage reduction than in the weed densities. Trial 10 likely contributed to the wide variation around the pooled mean due to an inexperienced farm worker doing the hand-weeding. Trial 15 likely also contributed to the wide variation because it was conducted in a commercial lettuce field where weed densities were low instead of on the research station where weed densities were high.

It is possible that the significance of the results is larger in these trials than would be seen in commercial fields because most of the trials were conducted on research station fields, which were very weedy compared to commercial conventional fields. Additionally, no herbicides were used, which would have greatly reduced weed densities. However, weed densities tested here would be similar to the problems common in commercial organic fields.

The automated cultivator did not remove all the weeds it passed over. Weed control in close proximity (less than 2.5 cm / 1 inch) to crop plants will still require some manual labor. But, significant reductions in manual labor can be achieved while maintaining effective weed control.

Substantial improvements in weed control attained and reduction in time spent hand-weeding are seen in these results. Thus, the remaining question is “what is the minimum production area needed for the reduction in hand-weeding costs to offset the higher capital cost of the intelligent cultivator?”.

Chapter 3: Economic Analysis of Automated Cultivator

Introduction.

Increasing weed control costs threaten vegetable crop profitability due to labor shortages, rising labor expense, as well as lack of registered herbicides and loss of old herbicides. Weed control costs in head lettuce production in California have been estimated at between $632 and $788 per hectare ($242 - $319 acre^{-1}) in cost studies conducted by the University of California extension service (Tourte et al. 2015, 2017) with weed control costs in organic leaf lettuce reaching $1208 per hectare ($498 acre^{-1}) (Tourte et al. 2009a updated with current labor rates). This is seven to eleven percent of total production costs (Tourte et al. 2015, 2017). In processing tomatoes, weed control costs are about $556 per hectare ($225 acre^{-1}) which is nearly twelve percent of total production costs (Miyao et al. 2017).

As labor rates increase in California, the cost of weed control will continue to rise. Labor rates will increase 150%, from the 2016 minimum wage of $10.00 per hour, to $15.00 per hour in in 2022. California's minimum wage law are projected to increase weed management costs 124-132%, see Table 3.1 (California Department of Industrial Relations 2016). Some producers already pay above minimum wage so they would be affected differently. Additionally, labor shortages are a concern due to fewer people wanting to work in agriculture, new limits on overtime, and increasing overtime wages per hour due to the increase in the minimum wage (Tourte et al. 2017). If farmers cannot find enough people willing to hand-weed at the critical time for their crop, yield and quality of labor-dependent speciality crops could be increasingly affected by weeds.

Table 3.1. Current weed management practices and costs.

Practice	Iceberg[a]	Romaine Hearts[b]	Organic leaf lettuce[c]	Processing Tomatoes[d]
	----------$ ha^{-1}----------			
Herbicide application	227	106	0	230
Mechanical cultivation	163	148	84	35
Hand weeding	398	378	941	297
Total weed mgt cost	788	632	1025	562
% of total production costs	11	9	22	9
% of production costs in 2022	16	17	23	16

[a] Costs taken from (Tourte et al. 2017)
[b] Costs taken from (Tourte et al. 2015)
[c] Costs taken from (Tourte et al. 2009a)
[d] Costs taken from (Miyao et al. 2017)

Hand weeding need reduced by intelligent mechanical cultivator.

Traditional inter-row mechanical cultivation is not sufficient, as it does not remove weeds within the seed line during the critical period of weed removal. Thus, intra-row hand weeding is necessary, but increasingly expensive. An automated weed control systems has the potential to reduce weed control costs.

Intelligent intra-row cultivators (IC) can remove weeds within the crop row while avoiding the crop plants, thus reducing the uncultivated area remaining in the field. Intelligent intra-row cultivators can have a smaller plant safety zone, the unweeded area left around a crop plant to avoid injuring it, due to precise control mechanisms which detect the crop plants and guide the weed removal tool. Intelligent intra-row cultivators can reduce the need for hand-weeding by removing a greater proportion of the weed load than standard mechanical cultivators.

While weed control costs are a substantial part of production costs, the monetary costs of a new piece of farm equipment, such as an intelligent mechanical cultivator, are not the only

factors a farmer considers (Bisschoff et al. 1994). The amount of land, compatibility of crops to cultivation, availability and reliability of hand-weeding labor, availability of skilled labor to use and repair the new equipment, and reliability and efficacy of the equipment are also factors which must be considered (Bisschoff et al. 1994, Gandonou et al. 2006).

Table 3.2. Weed reduction costs in lettuce by different weed management strategies.

Standard cultivator weed management strategy	Cost[a]	Weeds[b]	Intelligent mechanical cultivator weed management strategy	Cost[a]	Weeds[b]
	$ ha^{-1}	no. ha^{-1}		$ ha^{-1}	no. ha^{-1}
Initial weed load		448,002	Initial weed load		448,002
Herbicide application	227	↓ 296,526	Herbicide application	227	↓ 296,526
Cultivate: Lilliston and sled cultivator	163	↓ 98,842	Cultivate: Lilliston and intelligent cultivator	261[c]	↓ 34,595
Hand weed	398	↓ 0	Hand weed	227	↓ 0
Total cost	788		Total cost	716	

[a] Costs taken from (Tourte et al. 2017)
[b] Weed density estimates taken from (Fennimore 2013).
[c] Cost of intelligent cultivator use was estimated to be twice that of a standard sled cultivator.

Materials and Methods.

Partial Budget Analysis.

Potential changes in income and costs between traditional mechanical cultivation and intelligent cultivation were evaluated using a partial budget analysis. A partial budget analysis

includes only items that are under consideration to change, such as the effects of a new piece of equipment (Tigner, 2006).

The cultural practices used in the partial budget analysis are based on production procedures considered typical for the crop and area. Production costs are based on many factors, including soil type, pest pressures, location, grower opinions, and thus vary considerably in reality. Sample costs for labor, materials, equipment, and custom services are based on current figures from University of California Cooperative Extension Cost and Return studies avilable at https://coststudies.ucdavis.edu (Miyao et al. 2017, Tourte et al. 2009b, 2015, 2017, Tourte and Buchanan 2003).

Costs are given for one growing cycle. In short-season crops like lettuce it is common practice to grow multiple crops per year, while on the other hand, tomatoes are a long-season crop with only one cycle per year. Thus, the per-hectare hand-weeding costs found for lettuce can be multiplied by the number of growing cycles per calendar year in order to obtain annual values. These values can then be compared to the annual cost of the cultivators to obtain the net effect on costs.

Current weed control practice in processing tomatoes includes the following: glyphosate (Roundup UltraMax) in combination with oxyfluorfen (Goal 2XL) is sprayed on the fallow beds in late winter to control emerged weeds and repeated in early spring with glyphosate only. Before planting, the beds are cultivated to control weeds and to prepare a seedbed. As a preplant herbicide treatment in the spring, trifluralin (Triflurex HFP) is tank-mixed with S-metolachlor (Dual II Magnum) as a broadcast and incorporated with a power mulcher across the bed. Post-transplant, rimsulfuron (Matrix SG) is applied to a narrow strip over the plant row to control weeds. Post-transplant at layby, a power incorporator is used to re-shape beds but without

additional herbicides. The crop is mechanically cultivated with a sled-mounted cultivator once during the season. Finally, contract labor crews hand-removes remaining weeds during the season (Miyao et al. 2017).

Current weed control practice in romaine lettuce includes the following: Kerb (pronamide) herbicide is applied to a narrow strip over the plant row immediately after planting. The crop is cultivated as it is mechanically thinned and again about two weeks later with a standard cultivator. The beds are hand weeded and closely spaced lettuce plants are removed approximately three weeks after the initial thinning (Tourte et al. 2015).

Current weed control practice in iceberg lettuce includes the following: Kerb (pronamide) herbicide is applied to a narrow strip over the plant row immediately after planting. The crop is cultivated as it is mechanically thinned. A second cultivation with a standard cultivator occurs roughly two weeks after thinning. The beds are hand weeded and closely spaced lettuce plants are removed approximately three weeks after thinning (Tourte et al. 2017).

An interest rate of 5% was used to calculate interest on on operating capital (Tourte et al. 2017). The annual installation, operation, and maintenance costs include repairs, fuel, taxes, insurance, and purchase price. The prices and labor rates were taken from *Sample Costs to Produce Processing Tomatoes* (Miyao et al. 2017) and *Sample Costs to Product and Harvest Iceberg Lettuce* (Tourte et al. 2017). The price of the intelligent cultivator is estimated to be $125,000. The price of a standard cultivator for lettuce is estimated to be $9,500 and $13,054 for a tomato cultivator (Miyao et al. 2017, Tourte et al. 2017).

Use of the intelligent cultivator would replace a traditional mechanical cultivator in tomatoes and lettuce. Operation costs for the intelligent cultivator are estimated at twice the operation costs of a standard cultivator because higher maintenance costs are associated with

more complex machinery. While labor needed for hand-weeding will be reduced with the use of the intelligent cultivator, it is not eleminated.

Net Returns.

A simple analysis of net returns allows for comparing the economic benefit of using an intelligent cultivator instead of the standard mechanical cultivator (Ndakidemi et al. 2006). Net returns were calculated for the three lettuce and one tomato field trials which were taken to harvest (Trial 5, 10-12 in Table 2.1). The prices and labor rates were taken from *Sample Costs to Produce Processing Tomatoes* (Miyao et al. 2017) and *Sample Costs to Produce and Harvest Iceberg Lettuce* (Tourte et al. 2017). The yield and hand weeding times were collected during the field trials. Because no significant difference was found in the yields between the standard cultivation and cultivation with the intelligent cultivator, the average yield from the two treatments was used in the net return equation (Equation 3.3).

The hand weeding times used in Equation 3.3 are the outputs from the ANOVA on the hand-weeding time model (Equation 2.2) found in Table 2.4 and 2.8. In the analysis of Equation 2.2, the data were normalized to account for different sizes of sample areas. The variable Experimental Unit accounts for different amounts of randomness in different trials (see Appendix A Plot Maps). The assumption of homogeneity of variances was not met with the lettuce hand-weeding time data, so a natural log transformation was applied to the result (hand-weeding time). No transformation was applied to the tomato hand-weeding time data because the assumption of homogeneity of variances was met. The back-transformed results were used in Equation 3.3.

Statistical analysis of the hand-weeding time data was performed using RStudio Version 1.1.383 (RStudio Inc., Boston, MA). See Appendix B for the complete R code used for the analysis. The trials were pooled when the treatment by trial interactions were not significant. The EMMEANS package was used to calculate the least-square means (LS Means).

The model used to calculate net returns is:

Equation 3.3. Net return equation

Net Return = Price x Yield + Hand-weeding cost – Cultivator cost

$$\text{Net Return}_{IC} - \text{Net Return}_{SC} = -(\text{Hand-weeding cost}_{IC} - \text{Hand-weeding cost}_{SC}) - (\text{Cultivator cost}_{IC} - \text{Cultivator cost}_{SC})$$

Breakeven Analysis.

A break-even analysis provides a useful benchmark for aiding in the decision to adopt a new method or piece of equipment (Gandonou et al. 2006). If a grower does not have sufficient farm land to approach the break-even point, the farmer could rent the equipment (if available) or hire a custom service to perform the operation (Gandonou et al. 2006, Ibendahl and Halich 2010).

The model used to calculate the one-year breakeven point is:

Equation 3.1. Breakeven equation.

IC cost + Hand-weeding cost after IC x A = SC cost + Hand-weeding cost after SC x A

where SC is standard mechanical cultivation, LA is labor rate, and A is land area.

The amount of land needed to breakeven, A, is calculated by:

Equation 3.2. Minimum area needed for intelligent cultivator to increase profits equation.

A = (IC cost – SC cost) / (Hand-weeding cost after SC – Hand-weeding cost after IC)

Results.

Partial Budget Analysis.

Table 3.3 reports the annual capital costs, annual operating costs, and annual cost of equipment for both types of cultivators used in processing tomatoes. The higher purchase price and annual cost of equipment of the intelligent cultivator is offset by the reduced hand-weeding costs incured when using the intelligent cultivator. Labor costs are reduced because the time spent hand-weeding is reduced by 48% (averaged time reduction from Table 2.4).

Table 3.3. Costs of changing from traditional to intelligent mechanical cultivator in tomatoes

	Standard cultivator[a]	Intelligent cultivator
Purchase price	13,0540.00	125,000.00
Years of use	5	10
Salvage value	4,252.00	0.00
Annual capital cost[b]	2,339.00	1,153.75
Annual operating cost $ ha^{-1}	29.65	59.31
Annual cost of equipment	697.80	13,653.75
Hand-weeding hours ha^{-1}	36.8	19.2
Hand-weeding $ ha^{-1}	621.24	323.92

[a] (Miyao et al. 2017)
[b] Capital recovery factor used, 0.01846

Table 3.4 reports the annual capital costs, annual operating costs, and annual cost of equipment for both types of cultivators used in iceberg lettuce production. The higher purchase price and annual cost of equipment of the intelligent cultivator is offset by the reduced hand-weeding costs incured when using the intelligent cultivator. Labor costs are reduced because the time spent hand-weeding is reduced by 45% (averaged time reduction from Table 2.8).

Table 3.4. Costs of changing from traditional to intelligent mechanical cultivator in iceberg lettuce

	Standard cultivator[a]	Intelligent cultivator
Purchase price	9,500.00	125,000.00
Years of use	10	10
Salvage value	1,680.00	0.00
Annual capital cost[b]	1,157.00	1,153.75
Annual operating cost $ ha^{-1}	98.84	197.68
Annual cost of equipment	427.00	13,653.75
Hand-weeding hours ha^{-1}	72.0	39.6
Hand-weeding $ ha^{-1}	1,216.47	668.47

[a] (Tourte et al. 2017)
[b] Capital recovery factor used, 0.01846

Net Returns per hectare.

Table 3.5 reports weeding costs per hectaure for the two types of cultivators. Weed costs are reducted by amost 50% for each crop if the intelligent cultivator is used. In order to identify when adopting the intelligent cultivator would be profitable for a grower, the higher capital cost per hectare must by compared to the lower hand-weeding costs.

Table 3.5. Hand-weeding costs per hectare by crop.

Crop	Wage rate[a]	Hand-weeding cost after SC	Hand-weeding cost after IC
	$ hr^{-1}	$ ha^{-1}	$ ha^{-1}
Lettuce[b]	16.90	1,216.47	668.47
Tomato[c]	16.31	621.24	323.92

[a] Wage rate in iceberg lettuce production from (Tourte et al. 2017) and wage rate in processing tomatoes from (Miyao et al. 2017).
[b] Lettuce hand-weeding costs based on six trials (Table. 2.1).
[c] Tomato hand-weeding costs based on eight trials (Table 2.1).

Breakeven Analysis.

Table 3.6 reports the number of hectares required for adoption of the intelligent cultivator to increase profits. The breakeven analysis hectares only assumed one crop cycle per year and in short season crops such as broccoli, cauliflower and lettuce, multiple crop cycles are grown within a calendar year (Table 3.5). For multiple crop cycles, one can multiply hand-weeding costs by the annual number of cycles and compute the number of hectares necessary for the reduction in hand-weeding costs to offset the higher capital cost of the intelligent cultivator. The minimum number of hectares will decrease proportionately.

Table 3.6. Minimum hectares needed for intelligent cultivator to increase profits.

Crop	Annual SC cost[a]	Annual IC cost	Wage rate[a]	Hand-weeding cost after SC	Hand-weeding cost after IC	Minimum hectares for IC to increase profits
	$	$	$ hr^{-1}	$ ha^{-1}	$ ha^{-1}	ha
Lettuce[b]	427.00	13,653.75	16.90	1,216.47	668.47	24
Tomato[c]	697.80	26,153.75	16.31	621.24	323.92	86

[a] (Miyao et al. 2017, Tourte et al. 2017)
[b] Lettuce hand-weeding costs based on six trials (Table. 2.1).
[c] Tomato hand-weeding costs based on eight trials (Table 2.1).

Discussion.

The partial budget analysis shows an almost 50% reduction in hand-weeding costs per hectare per crop cycle that uses the intelligent cultivator. This suggests that switching from a standard inter-row cultivator to an intelligent intra-row cultivator would have a positive economic impact for farmers due to lower labor costs. The positive effects would be increased by using the intelligent cultivator for multiple crop cycles annually on a field. The intellgient cultivator could also provide more flexibility in timing of cultivation because it can be used on

larger plants than the standard cultivator since the plant safety zone is adjustable. Also due to labor shortages timely operations with a field crew is not always possible. In contrast to a field crew, the intelligent cultivator may permit more timely weeding operations.

The minimum production area required for the adoption of the intelligent cultivator to increase profits is a modest 24 hectares for lettuce and 86 hectares for tomatoes. Since the breakeven analysis assumed one crop cycle per year and in short season crops such as lettuce, multiple crop cycles are grown within a year, so the number of hectares needed to breakeven can be divided by the number of crop cycles in a year. Thus only 12 hectares of lettuce would be needed at two crop cycles per year. Alternatively, a farmer could rent the intelligent cultivator or custom hire the service. While the cost to rent the intelligent cultivator may be greater than the operating costs, there could still be a positive impact on net returns due to the decrease in labor needed for hand-weeding.

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Conclusion

Weeds can compete with desired plants for water and nutrients reducing yields and causing economic loss. They can also be host to insects and pathogens which can infest crops (Fennimore et al. 2014b, Lati et al. 2016, Lechenet et al. 2017, Slaughter et al. 2008b). Increasing weed control costs threaten vegetable crop profitability due to labor shortages, rising labor expense, as well as a lack of registered herbicides and loss of old herbicides. A farmer has some control of the weed seed bank but no control of herbicide availability and efficacy or labor shortages. Traditional inter-row mechanical cultivation has limited reach because it does not remove weeds within the seed line during early growth periods when competition for nutrients, water and light is critical. Thus, intra-row hand weeding has been necessary to remove the remaining weeds left by a standard cultivator. Automated weed control systems can help manage weed control costs by making intra-row cultivation feasible, reducing the amount of labor needed to hand-weed.

The main technical challenge which must be overcome, for automated intra-row cultivation, is the computer's ability to differentiate between crop and weeds (Slaughter et al. 2008a, 2008b). The complexity of field conditions, including variable lighting and visual occlusion, continue to challenge machine learning (Rasmussen et al. 2012, Slaughter et al. 2008a).

A novel "plant signaling" approach to weed and crop differentiation was tried in lettuce and processing tomatoes. Results from field trials in 2016-2018 showed no significant difference in yield between plots cultivated with the intelligent or standard cultivator. This suggests that the automated cultivator was just as safe to the crop as was the standard cultivator. Thus, the

intelligent cultivator can be compared to traditional cultivation methods based on the level of weed control attained, reduction in time spent hand-weeding, and net costs.

Substantial improvements in weed control attained and reduction in time spent hand-weeding were seen in the 2016-2018 field trials. The automated cultivator did not remove all the weeds it passed over. But, significant reductions in manual labor were achieved while maintaining weed control efficacy.

The remaining question, “what is the minimum production area needed for the reduction in hand-weeding costs to offset the higher capital cost of the intelligent cultivator?”, was addressed by a breakeven analysis. The minimum production area required for the adoption of the intelligent cultivator to increase profits is a modest 12 hectares for lettuce and 86 hectares for tomatoes. This assumes two lettuce cycles and one tomato cycle annually.

Given the almost 50% reduction in hand-weeding costs per hectare per crop cycle and thus the relatively small production area needed for the intelligent cultivator to increase profits, switching from a standard inter-row cultivator to an intelligent intra-row cultivator would have a positive economic impact for vegetable producers in California.

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Appendix A: Plot maps for each field trial.

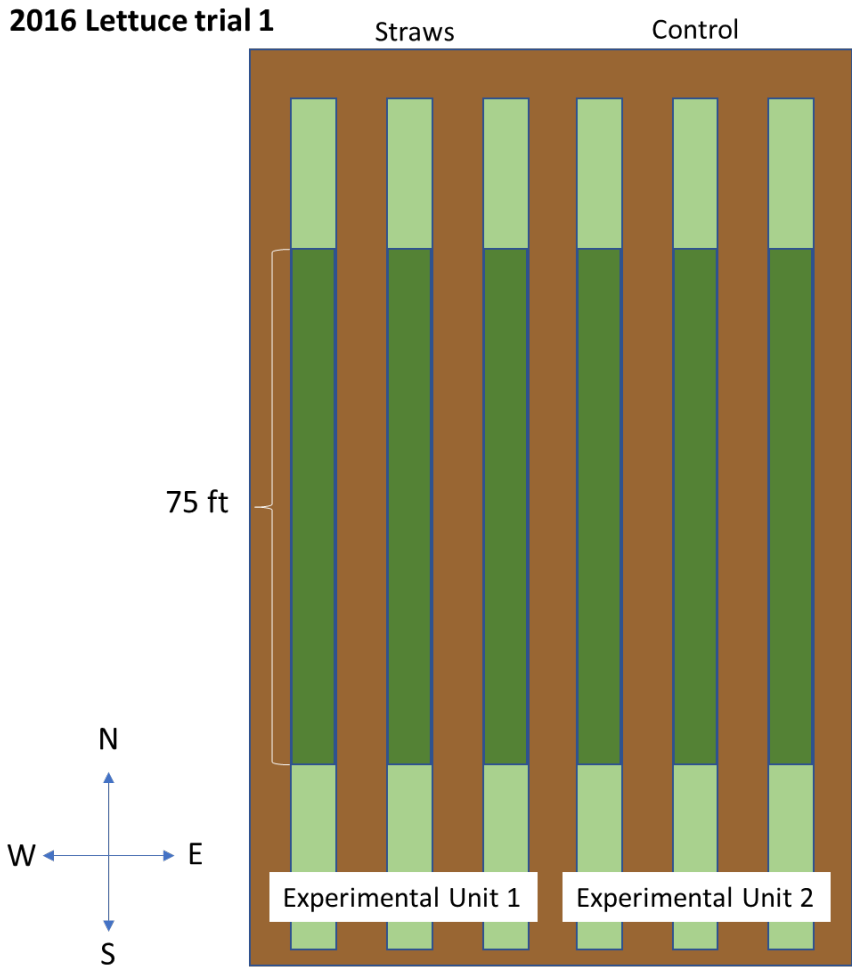

Figure A.1 First romaine lettuce, cultivar Solid King, trial in 2016, conducted in Salinas, CA. Treatment: straws used as plant label with intelligent cultivator. Trial 2 in Table 2.1

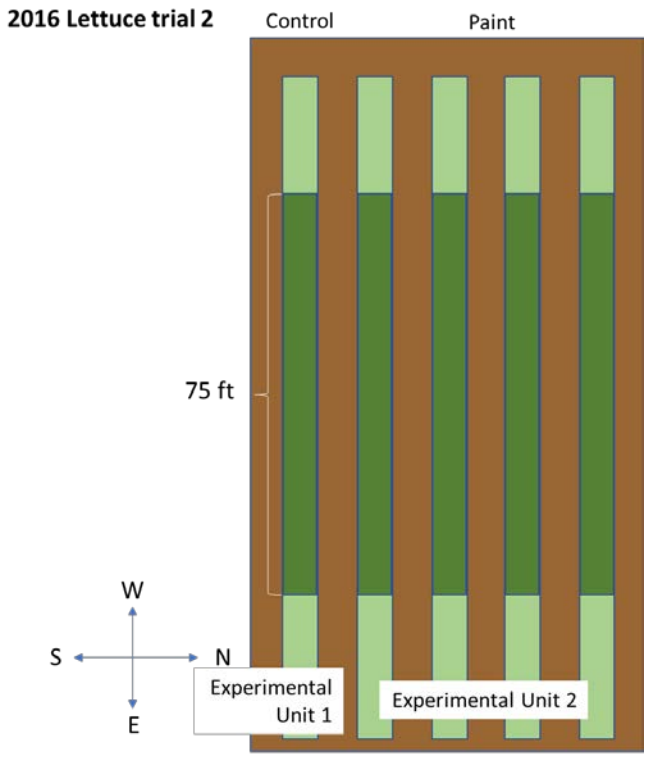

Figure A.2 Second romaine lettuce, cultivar Solid King, trial in 2016, conducted in Salinas, CA. Treatment: paint used as topical marker with intelligent cultivator. Trial 3 in Table 2.1

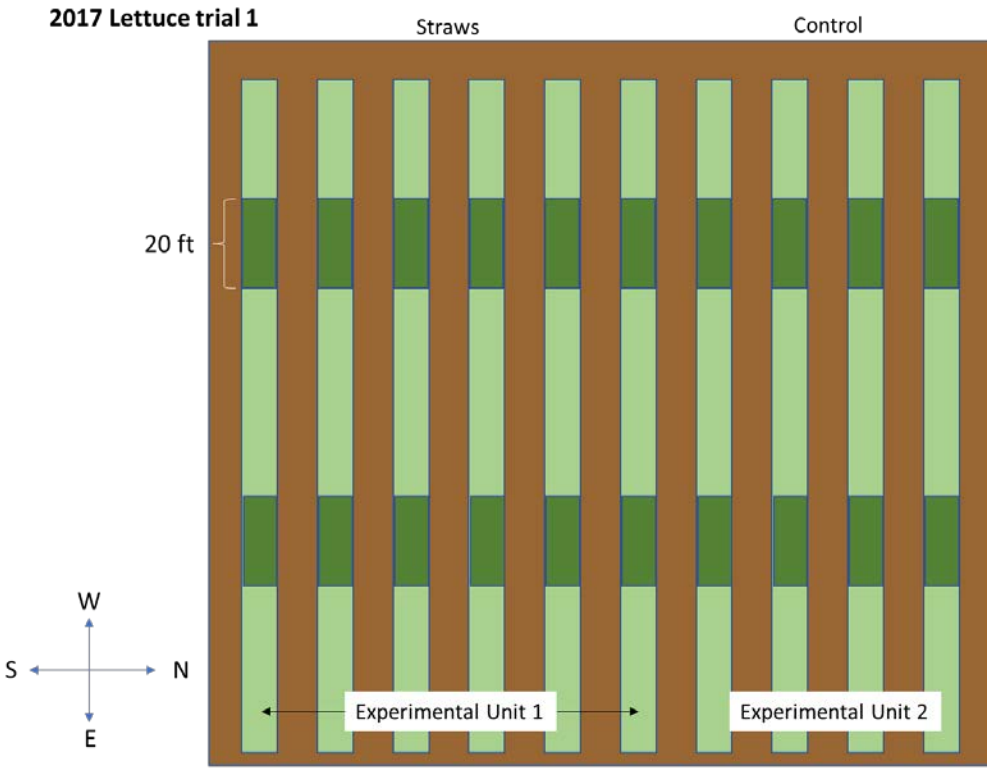

Figure A.3 First romaine lettuce, cultivar Solid King, trial in 2017, conducted in Salinas, CA. Treatment: straws used as plant label with intelligent cultivator. Trial 10 in Table 2.1

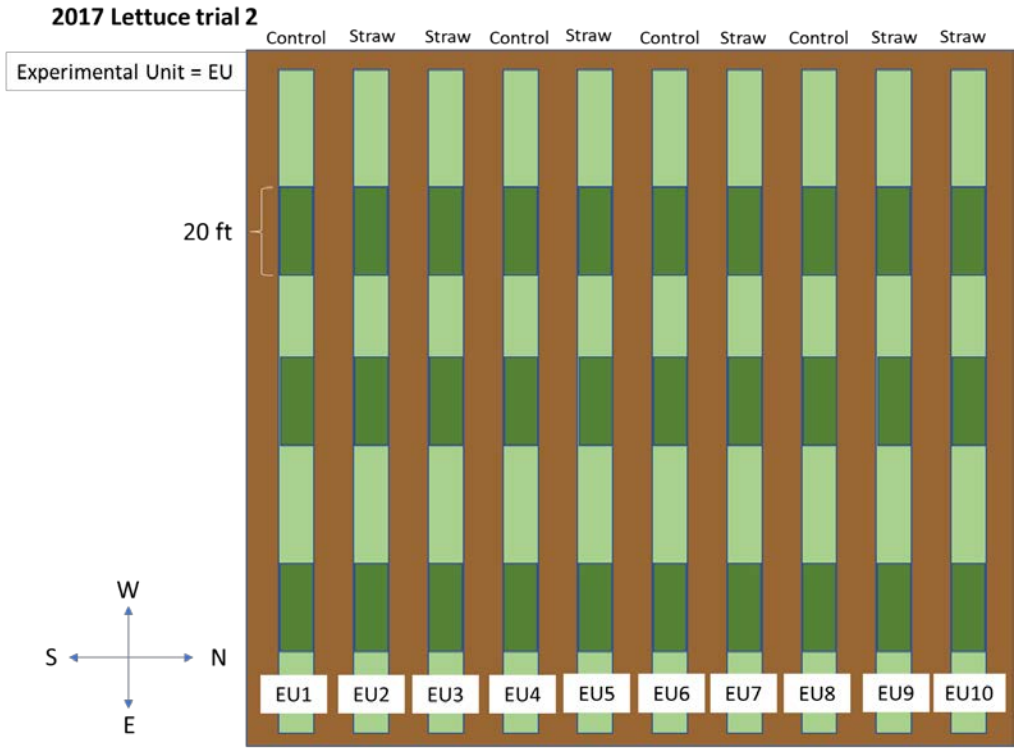

Figure A.4 Second romaine lettuce, cultivar Solid King, trial in 2017, conducted in Salinas, CA. Treatment: straws used as plant label with intelligent cultivator. Trial 11 in Table 2.1

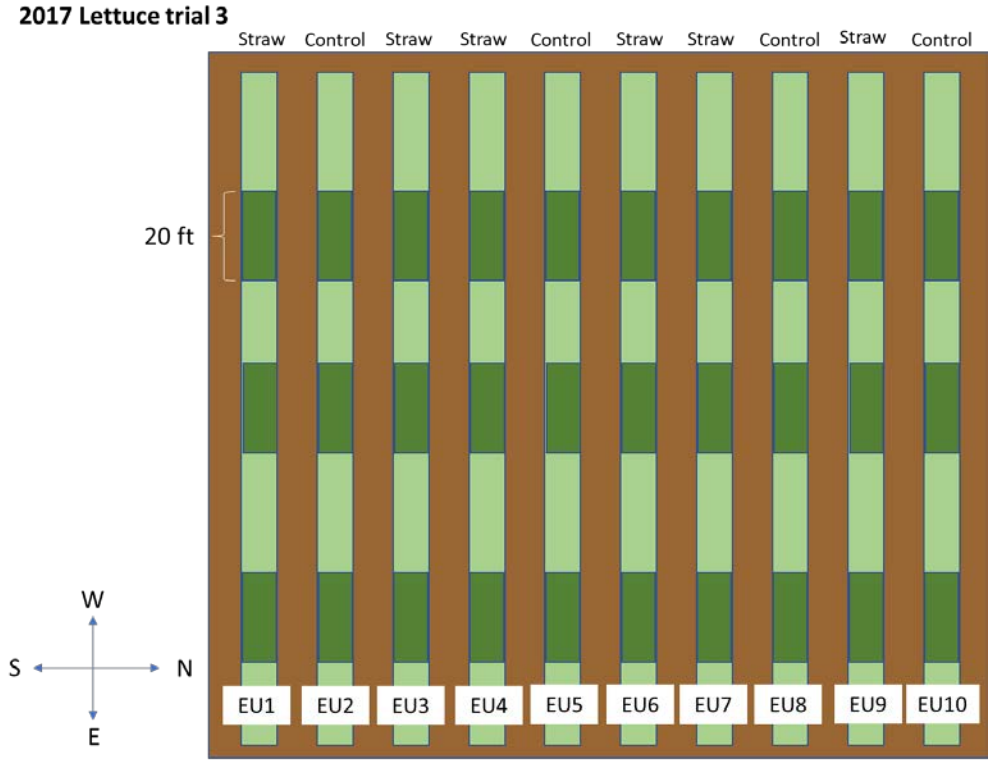

Figure A.5 Third romaine lettuce, cultivar Solid King, trial in 2017, conducted in Salinas, CA. Treatment: straws used as plant label with intelligent cultivator. Trial 12 in Table 2.1

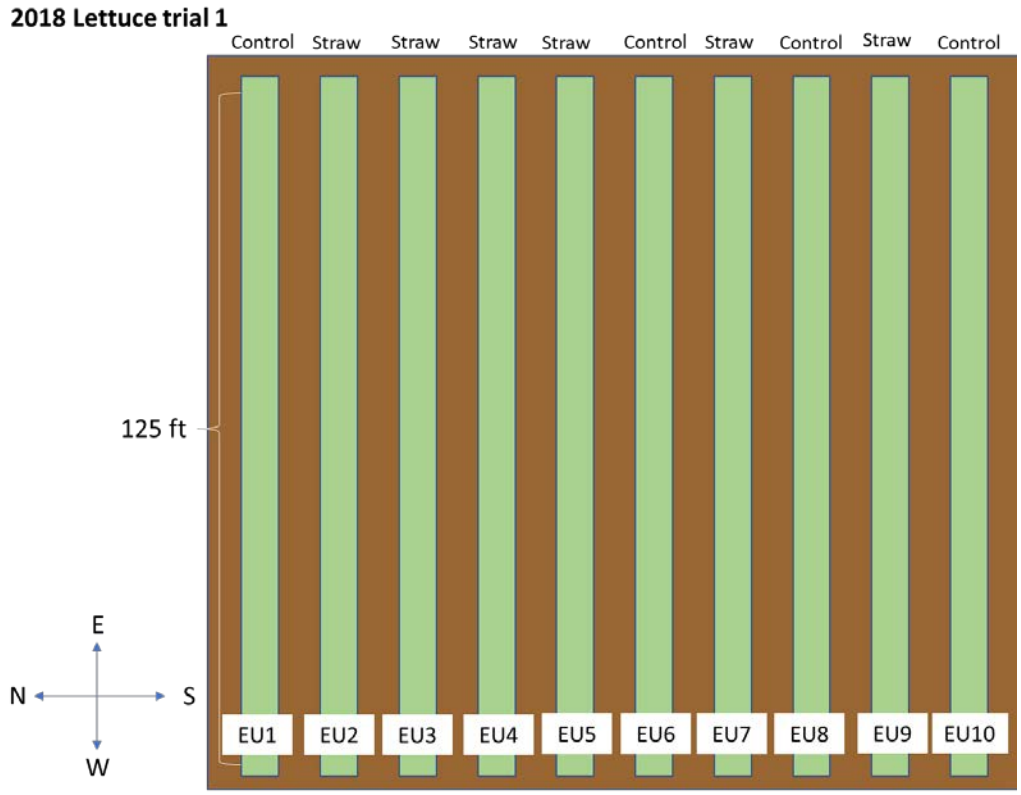

Figure A.6 First romaine lettuce, cultivar Solid King, trial in 2018, conducted in Salinas, CA. Treatment: straws used as plant label with intelligent cultivator. Trial 15 in Table 2.1

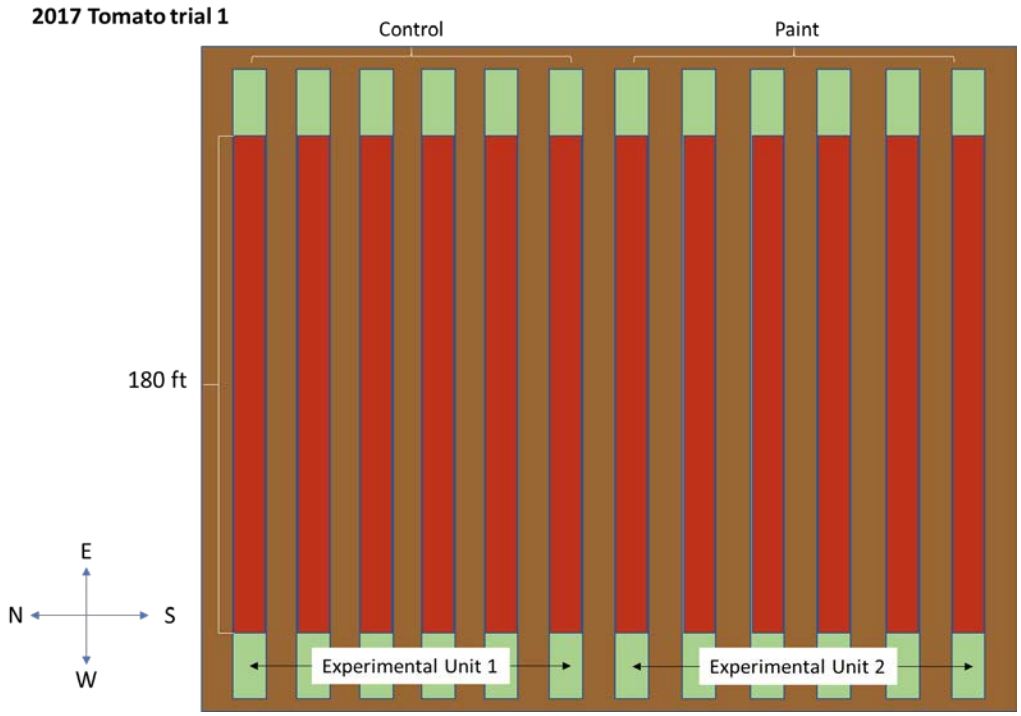

Figure A.7 First processing tomato, cultivar Halley 3155, trial in 2017, conducted in Davis, CA. Treatment: paint used as topical marker with intelligent cultivator. Trial 4 in Table 2.1

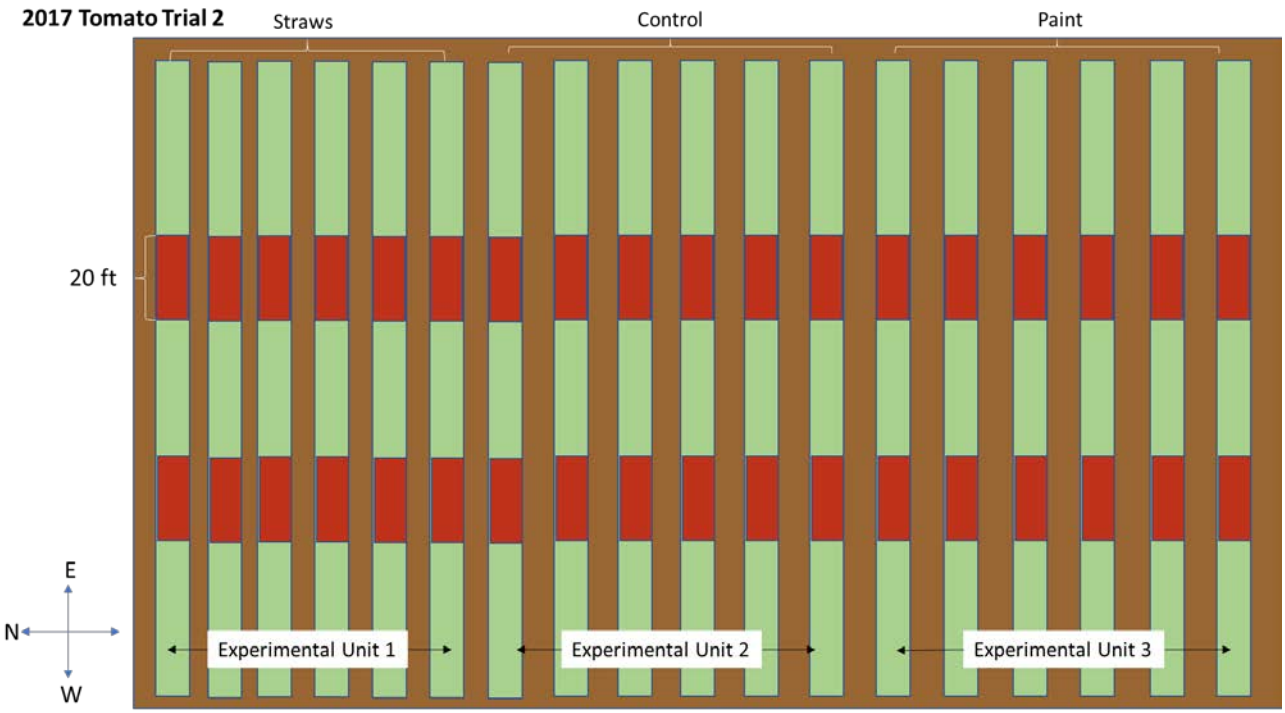

Figure A.8 Second processing tomato, cultivar Halley 3155, trial in 2017, conducted in Davis, CA. Treatment: straws used as plant labels and paint used as topical marker with intelligent cultivator. Trial 5 in Table 2.1

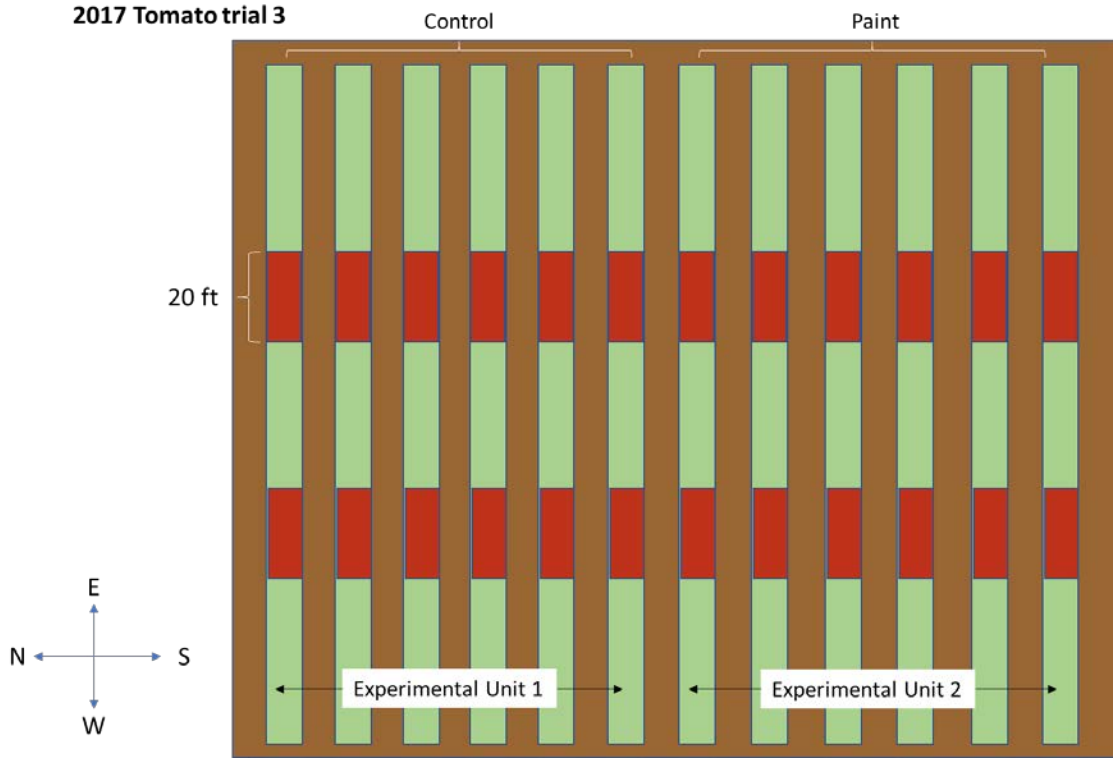

Figure A.9 Third processing tomato, cultivar Halley 3155, trial in 2017, conducted in Davis, CA. Treatment: paint used as topical marker with intelligent cultivator. Trial 6 in Table 2.1

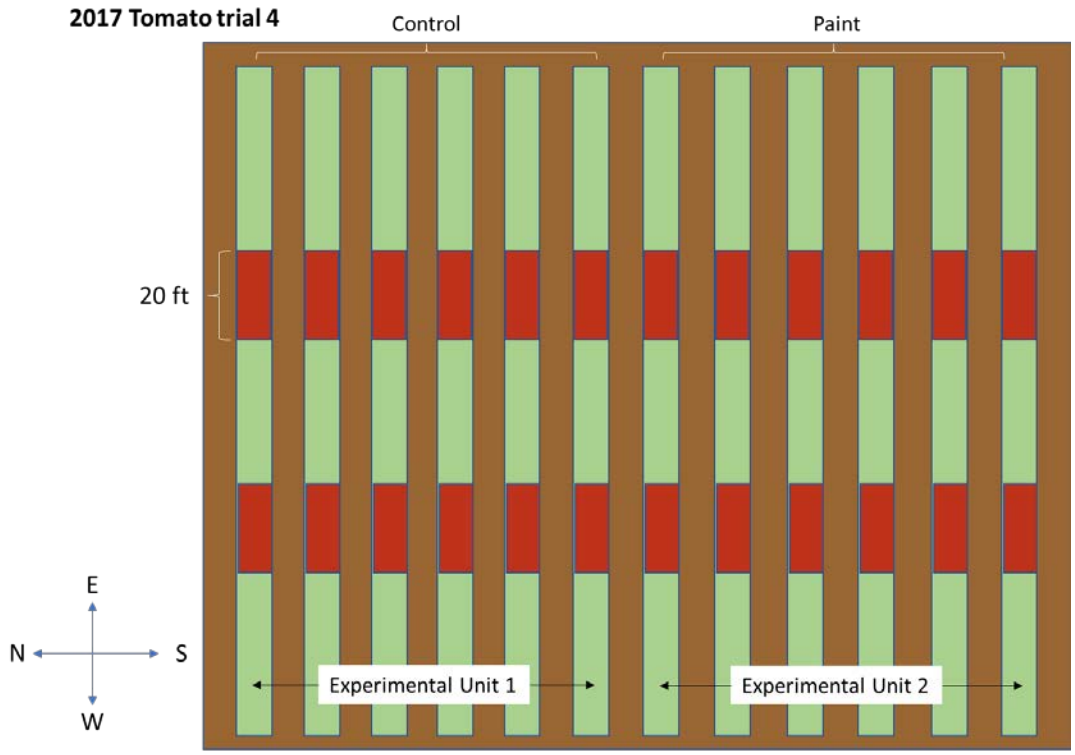

Figure A.10 Fourth processing tomato, cultivar Halley 3155, trial in 2017, conducted in Davis, CA. Treatment: paint used as topical marker with intelligent cultivator. Trial 7 in Table 2.1

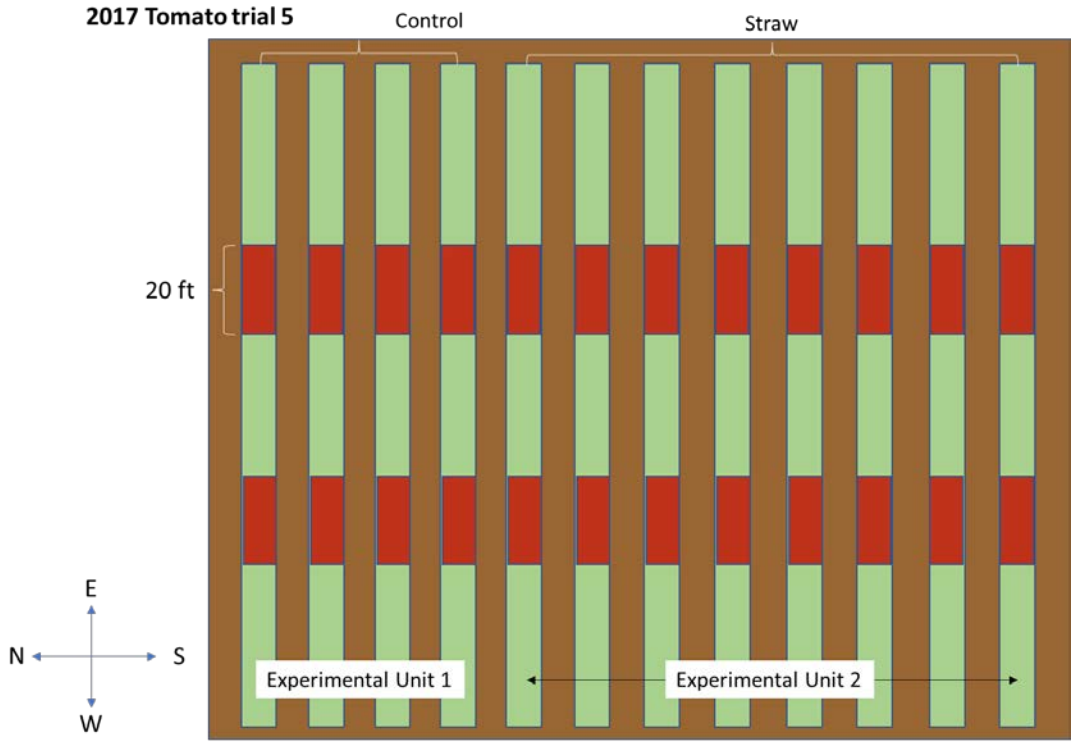

Figure A.11 Fifth processing tomato, cultivar Halley 3155, trial in 2017, conducted in Davis, CA. Treatment: straws used as plant label with intelligent cultivator. Trial 8 in Table 2.1

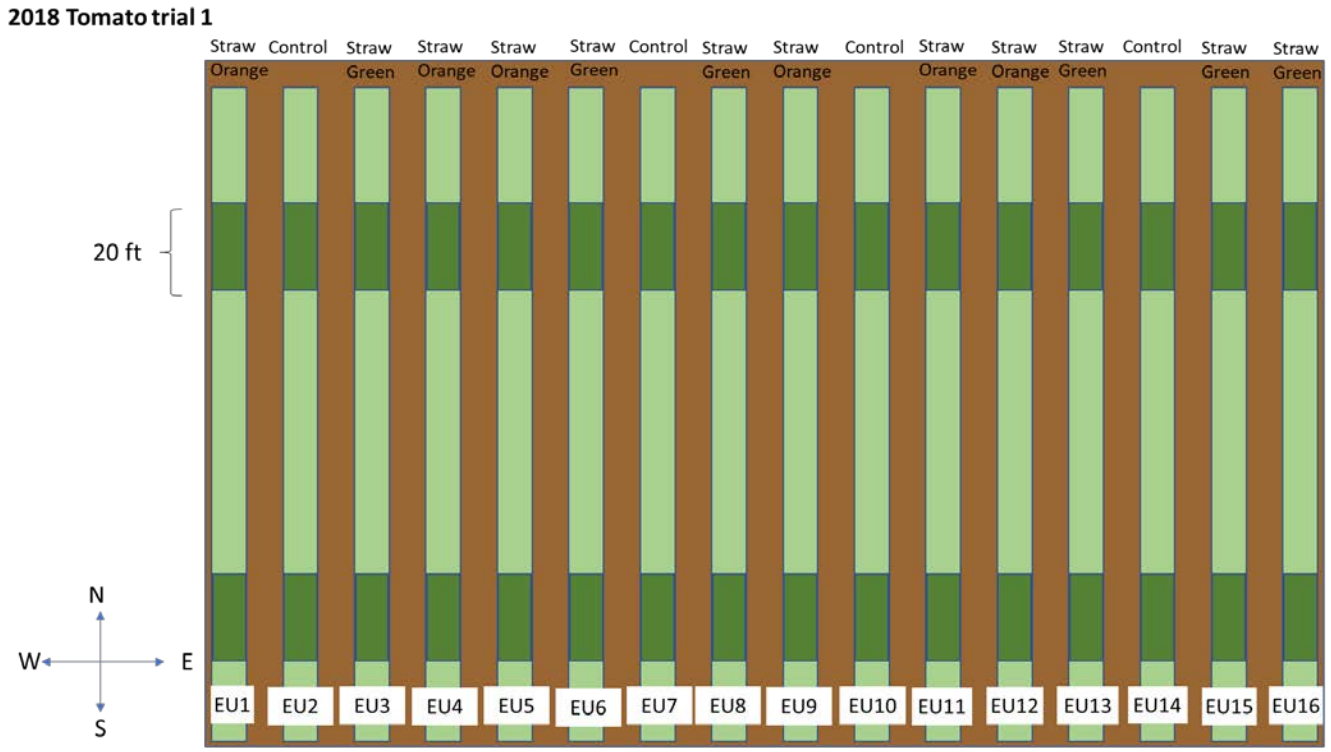

Figure A.12 First processing tomato, cultivar Halley 3155, trial in 2018, conducted in Davis, CA. Treatment: straws used as plant label with intelligent cultivator. Trial 13 in Table 2.1

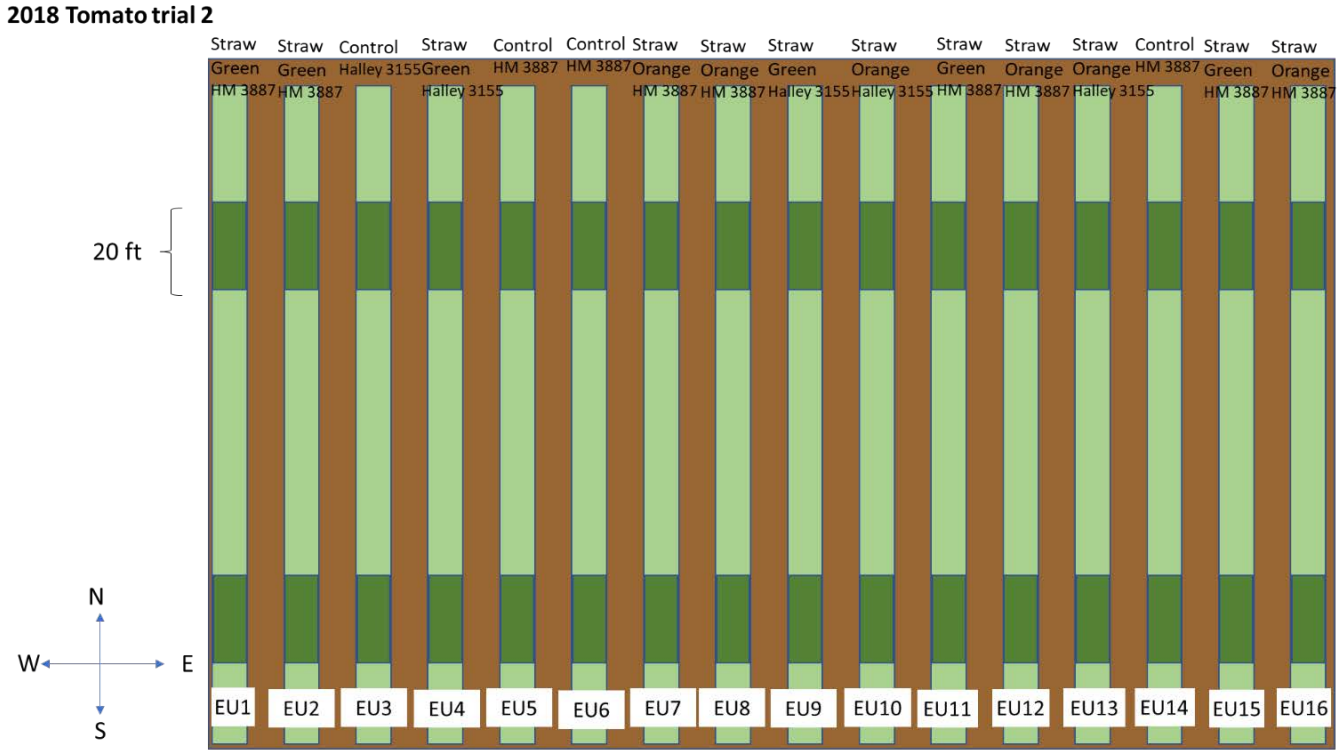

Figure A.13 Second processing tomato, cultivar Halley 3155, trial in 2018, conducted in Davis, CA. Treatment: straws used as plant label with intelligent cultivator. Trial 14 in Table 2.1

Appendix B: R code used for statistical analysis.

R code for lettuce weed density

libraries
```{r}
library(lme4)
library(lmerTest)
library(ggplot2)
library(cowplot)
library(emmeans)
library(pbkrtest)
library(car)
```

```{r}
datapath <- "C:/Users/hj/Documents/HJ documents/grad school/weed science research/lettuce field trials"
lettuce <- read.csv(file.path(datapath, "all lettuce Data formatted 6-2018.csv"), header = TRUE)

lettuce$Trial <- as.factor(lettuce$Trial)
lettuce$Row.number <- as.factor(lettuce$Row.number)
lettuce$Replicate <- as.factor(lettuce$Replicate)
lettuce$Sample.number <- as.factor(lettuce$Sample.number)
```

Fit the model
```{r}
#model terms ordered according to PLS 205 best practice
letmod10 <- lmer(Post.count..weeds.m2.  ~  Pre.count..weeds.m2. + Trial + Cultivation + Pre.count..weeds.m2.:Cultivation + Trial:Cultivation  +  (1|Experimental.Unit) + (1|Row.number), data=lettuce)

anova(letmod10, ddf='Kenward-Roger')
```

#test covariate assumptions
```{r}
#assumption 1. The covariate is independent of the treatment.
cov_model <- lm(Pre.count..weeds.m2. ~ Trial + Cultivation, lettuce)
anova(cov_model)

#assumption 2. The covariate is linearly correlated with the response, with the same slope across treatments (and blocks) ## The best way to verify that the Covariate is linearly related to the Response is to make a scatter-plot of the data.
ggplot(lettuce,aes(x=Pre.count..weeds.m2.,y=Post.count..weeds.m2. )) + geom_point()
```

#We also want to evaluate whether the Response~Covariate relationship varies among treatments. We can do this visually by coloring the points by Trt, and fitting lines separately to each group
ggplot(lettuce,aes(x=Pre.count..weeds.m2.,y=Post.count..weeds.m2.)) + geom_point(aes(color = Cultivation)) + geom_smooth(aes(color = Cultivation),se=F,method='lm')

#The slopes look slightly different. The differences among TRTs appears to be smaller when there is little Organic Matter than when there is a lot. This indicates that might might need to report the effect of Trt differences **as a Function of COVARIATE**. This certainly complicates the analysis!
However, is this change in treatment differences large enough to matter?
#We can use our full model to evaluate this using an ANOVA

anova(letmod10, ddf='Kenward-Roger')

#trial:Cultivation interaction is not significant so drop it
reduced_letmod10 <- lmer(Post.count..weeds.m2. ~ Pre.count..weeds.m2. + Trial + Cultivation + Pre.count..weeds.m2.:Cultivation + (1|Experimental.Unit) + (1|Row.number), data=lettuce)
anova(reduced_letmod10, ddf='Kenward-Roger')
```

### Run diagnostic plots
```{r}
#test for normality
#qqplot
qqPlot(residuals(reduced_letmod10))

#Shaperio wilks test for normality
shapiro.test(residuals(reduced_letmod10))

#test for homogenaity of variances
## approximate S/L plot
fitted_values = fitted(reduced_letmod10)
abs_sqrt_resids = sqrt(abs(resid(reduced_letmod10,scaled=T)))
plot(abs_sqrt_resids~fitted_values)
lines(sort(fitted_values),predict(loess(abs_sqrt_resids~fitted_values),sort(fitted_values)))

##residuls vs fitted values plot
fitted_values = fitted(reduced_letmod10)
resids = (resid(reduced_letmod10,scaled=T))
plot(resids~fitted_values)
lines(sort(fitted_values),predict(loess(resids~fitted_values),sort(fitted_values)))
```

#normality isn't met and variances don't seem normal so try transformations
```{r}
#sqrt transformation of response variable pre-counts
lettuce$sqrtPrecount <- sqrt(lettuce$Pre.count..weeds.m2.)
#sqrt transformation of response variable post-counts

```
lettuce$sqrtPostcount <- sqrt(lettuce$Post.count..weeds.m2.)

#refit model
letmod_sqrt <- lmer(sqrtPostcount ~ sqrtPrecount + Trial + Cultivation + sqrtPrecount:Cultivation +
(1|Experimental.Unit) + (1|Row.number), data=lettuce)

#qqplot
qqPlot(residuals(letmod_sqrt))#

#Shaperio wilks test for normality
shapiro.test(residuals(letmod_sqrt))

#test for homogenaity of variances
approximate S/L plot
fitted_values = fitted(letmod_sqrt)
abs_sqrt_resids = sqrt(abs(resid(letmod_sqrt,scaled=T)))
plot(abs_sqrt_resids~fitted_values)
lines(sort(fitted_values),predict(loess(abs_sqrt_resids~fitted_values),sort(fitted_values)))

##residuls vs fitted values plot
fitted_values = fitted(letmod_sqrt)
resids = (resid(letmod_sqrt,scaled=T))
plot(resids~fitted_values)
lines(sort(fitted_values),predict(loess(resids~fitted_values),sort(fitted_values)))

#qqplot for random terms
ranef(letmod_sqrt)
qqPlot(ranef(letmod_sqrt)$`Experimental.Unit`[,1])
```
```
anova(letmod_sqrt, ddf='Kenward-Roger')
#TRT:Block term is not significant so can report means averaged over Trial.
```

Generate model summaries and tests
```{r}
#means averaged over Trial b/c Trial:Cultivation term was not significant
means_lettuce <- emmeans(letmod_sqrt, pairwise ~ Cultivation,mode='k')
summary(means_lettuce,level = 0.95,infer=T)
(cld_avg <- cld(means_lettuce$emmeans, Letters=letters))
```

#back transformation of means and CI
```{r}
transformed_estimates = as.data.frame(summary(emmeans(letmod_sqrt, ~ Cultivation,mode='k' )))
transformed_estimates$De_trans_estimate = (transformed_estimates$emmean)^2
transformed_estimates$De_trans_SE = (transformed_estimates$SE)^2
transformed_estimates$De_trans_lower.CL = (transformed_estimates$lower.CL)^2
transformed_estimates$De_trans_upper.CL = (transformed_estimates$upper.CL)^2
```

```
transformed_estimates[,c('De_trans_estimate', 'De_trans_SE',
'De_trans_lower.CL','De_trans_upper.CL')]

transformed_estimates_trial = as.data.frame(summary(emmeans(letmod_sqrt, ~
Cultivation|Trial,mode='k' )))
transformed_estimates_trial$De_trans_estimate = (transformed_estimates_trial$emmean)^2
transformed_estimates_trial$De_trans_lower.CL = (transformed_estimates_trial$lower.CL)^2
transformed_estimates_trial$De_trans_upper.CL = (transformed_estimates_trial$upper.CL)^2
transformed_estimates_trial[,c('De_trans_estimate','De_trans_lower.CL','De_trans_upper.CL')]
```

```{r}
originalunits <- aggregate(Pre.count..weeds.m2. ~ Cultivation + Trial, lettuce, mean)
originalunits
transformed_estimates2 <- cbind(transformed_estimates_trial, originalunits[,3])
transformed_estimates2
str(transformed_estimates2)

# plot
 ggplot(transformed_estimates2,aes(x=Cultivation,y=De_trans_estimate)) +
    geom_point(shape=1, size=5) +
  geom_point(data=transformed_estimates,aes(x=Cultivation,y=De_trans_estimate), shape="-", size=5
)+ geom_segment(data=transformed_estimates, aes(x = (as.numeric(Cultivation)-.15), y =
De_trans_estimate, xend=(as.numeric(Cultivation)+.15), yend=De_trans_estimate),   size = 1.5,
color="blue") +
  ggtitle("Mean number of weeds remaining after lettuce cultivation ") +
  xlab("Cultivation method") +
  ylab("No. of weeds/m² after cultivation") +
geom_label(data=transformed_estimates,aes(x=(as.numeric(Cultivation)+.35),y=(as.numeric(De_trans_
estimate)+.1), label=paste0(round(De_trans_estimate, digits=1), " weeds/m²")))
```

R code for lettuce hand weeding time

libraries
```{r}
library(lme4)
library(lmerTest)
library(ggplot2)
library(cowplot)
library(emmeans)
library(car)
```

```
library(pbkrtest)
```
```{r}
datapath <- "C:/Users/hj/Documents/HJ documents/grad school/weed science research/lettuce field trials"
lettuce <- read.csv(file.path(datapath, "all lettuce Data formatted 6-2018.csv"), header = TRUE)

lettuce$Trial <- as.factor(lettuce$Trial)
lettuce$Row.number <- as.factor(lettuce$Row.number)
lettuce$Replicate <- as.factor(lettuce$Replicate)
lettuce$Sample.number <- as.factor(lettuce$Sample.number)
lettuce$time.ha <- lettuce$time..hr.ac./0.404686
```

Fit the model
```{r}
lettuce_time_mod <- lmer(time.ha ~  Cultivation*Trial + (1|Experimental.Unit) + (1|Row.number), data=lettuce)

anova(lettuce_time_mod , ddf='Kenward-Roger')
```

Run diagnostic plots
```{r}
#test for normality
#qqplot
qqPlot(residuals(lettuce_time_mod ))

#Shaperio wilks test for normality
shapiro.test(residuals(lettuce_time_mod ))

#test for homogenaity of variances
plot(lettuce_time_mod )

leveneTest(lm(time.ha ~  Cultivation*Trial, data=lettuce))

#test for homogenaity of variances
## approximate S/L plot
fitted_values = fitted(lettuce_time_mod)
abs_sqrt_resids = sqrt(abs(resid(lettuce_time_mod,scaled=T)))
plot(abs_sqrt_resids~fitted_values)
lines(sort(fitted_values),predict(loess(abs_sqrt_resids~fitted_values),sort(fitted_values)))

##residuls vs fitted values plot
fitted_values = fitted(lettuce_time_mod)
resids = (resid(lettuce_time_mod,scaled=T))
plot(resids~fitted_values)
lines(sort(fitted_values),predict(loess(resids~fitted_values),sort(fitted_values)))
```

```

#variances don't seem normal so try transformations
ln transformation
https://onlinecourses.science.psu.edu/stat501/node/322
```{r}
#ln transformation of response variable time
lettuce$lntime <- log(lettuce$time.ha)

#refit model
lettuce_time_mod_ln <- lmer(lntime ~  Cultivation*Trial + (1|Experimental.Unit) + (1|Row.number),
data=lettuce)

#qqplot
qqPlot(residuals(lettuce_time_mod_ln ))

#Shaperio wilks test for normality
shapiro.test(residuals(lettuce_time_mod_ln))

#diagnostic plots
plot(lettuce_time_mod_ln)

leveneTest(lm(lntime ~  Cultivation*Trial, data=lettuce))

#test for homogenaity of variances
## approximate S/L plot
fitted_values = fitted(lettuce_time_mod_ln)
abs_sqrt_resids = sqrt(abs(resid(lettuce_time_mod_ln,scaled=T)))
plot(abs_sqrt_resids~fitted_values)
lines(sort(fitted_values),predict(loess(abs_sqrt_resids~fitted_values),sort(fitted_values)))

##residuls vs fitted values plot
fitted_values = fitted(lettuce_time_mod_ln)
resids = (resid(lettuce_time_mod_ln,scaled=T))
plot(resids~fitted_values)
lines(sort(fitted_values),predict(loess(resids~fitted_values),sort(fitted_values)))
```

Generate model summaries and tests
```{r}
anova(lettuce_time_mod_ln, ddf='Kenward-Roger')

###interaction term is NOT significant because small errorSS and ##residuls vs fitted values plot is ok
##so CAN report results averaged over Trials
means_lettucetime <- emmeans(lettuce_time_mod_ln, pairwise ~ Cultivation )
summary(means_lettucetime,level = 0.95,infer=T)
(cld_time_avg <- cld(means_lettucetime$emmeans, Letters=letters))
```
```

```
means_lettucetime2 <- emmeans(lettuce_time_mod_ln, pairwise ~ Cultivation|Trial ,mode='k')    # the |
gives the results "by" trial i.e. the differences
summary(means_lettucetime2,level = 0.95,infer=T)
(cld_time_trial <- cld(means_lettucetime2$emmeans, Letters=letters))
```

#back transformation of means and CI

```{r}
# extract the treatment means and confidence intervals # make into a data.frame #back transform
as.data.frame(summary(means_lettucetime))
transformed_estimates_time_pool <- as.data.frame(summary(means_lettucetime))
transformed_estimates_time_pool$De_trans_estimate =
exp(transformed_estimates_time_pool$emmeans.emmean)
transformed_estimates_time_pool$De_trans_SE =
exp(transformed_estimates_time_pool$emmeans.SE)
transformed_estimates_time_pool$De_trans_lower.CL =
exp(transformed_estimates_time_pool$emmeans.lower.CL)
transformed_estimates_time_pool$De_trans_upper.CL =
exp(transformed_estimates_time_pool$emmeans.upper.CL)
transformed_estimates_time_pool[,c( "emmeans.Cultivation", 'De_trans_estimate',
'De_trans_SE','De_trans_lower.CL','De_trans_upper.CL')]

as.data.frame(summary(means_lettucetime2))
transformed_estimates_time <- as.data.frame(summary(means_lettucetime2))
transformed_estimates_time$De_trans_estimate =
exp(transformed_estimates_time$emmeans.emmean)
transformed_estimates_time$De_trans_SE = exp(transformed_estimates_time$emmeans.SE)
transformed_estimates_time$De_trans_lower.CL =
exp(transformed_estimates_time$emmeans.lower.CL)
transformed_estimates_time$De_trans_upper.CL =
exp(transformed_estimates_time$emmeans.upper.CL)
transformed_estimates_time[,c("emmeans.Trial", "emmeans.Cultivation", 'De_trans_estimate',
'De_trans_SE','De_trans_lower.CL','De_trans_upper.CL')]
```

#plot

```{r}
ggplot(transformed_estimates_time,aes(x=emmeans.Cultivation,y=De_trans_estimate)) +
    geom_point(shape=1, size=5) +

geom_point(data=transformed_estimates_time_pool,aes(x=emmeans.Cultivation,y=De_trans_estimate)
, shape="-", size=5 )+
  geom_segment(data=transformed_estimates_time_pool, aes(x = (as.numeric(emmeans.Cultivation)-
.15), y = De_trans_estimate, xend=(as.numeric(emmeans.Cultivation)+.15), yend=De_trans_estimate),
size = 1.5, color="blue") +
   ggtitle("Time spent hand-weeding after lettuce cultivation") +
  xlab("Cultivation method") +
  ylab("Time (hr/ha)") +
```

```
geom_label(data=transformed_estimates_time_pool,aes(x=(as.numeric(emmeans.Cultivation)+.25),y=(a
s.numeric(De_trans_estimate)+.2), label=paste0(round(De_trans_estimate, digits=1), " hours")))
```

R code for lettuce yield data

libraries

```{r}
library(lme4)
library(lmerTest)
library(ggplot2)
library(cowplot)
library(emmeans)
library(car)
library(pbkrtest)
```

```{r}
datapath <- "C:/Users/hj/Documents/HJ documents/grad school/weed science research/lettuce field
trials"
lettuce <- read.csv(file.path(datapath, "all lettuce Data formatted 3-2018.csv"), header = TRUE)

lettuce$Trial <- as.factor(lettuce$Trial)
lettuce$Row.number <- as.factor(lettuce$Row.number)
lettuce$Replicate <- as.factor(lettuce$Replicate)
```

```
lettuce$Sample.number <- as.factor(lettuce$Sample.number)
lettuce$No..heads.marketable..Acre <- as.numeric(lettuce$No..heads.marketable..Acre)
lettuce$Kg.marketable..Acre <- as.numeric(lettuce$Kg.marketable..Acre)
lettuce$KLb.marketable..Acre    <- as.numeric(lettuce$Lb.marketable..Acre  )
lettuce$Kg.marketable.ha <- as.numeric(lettuce$Kg.marketable..Acre)/0.404686
lettuce$No..heads.marketable.ha <- as.numeric(lettuce$No..heads.marketable..Acre)/0.404686
```

Fit the model

```{r}
lettuce_heads_mod <- lmer(No..heads.marketable.ha ~  Cultivation*Trial + (1|Experimental.Unit) +
(1|Row.number), data=lettuce)
anova(lettuce_heads_mod , ddf='Kenward-Roger')

lettuce_lb_mod <- lmer(Kg.marketable.ha ~  Cultivation*Trial + (1|Experimental.Unit) +
(1|Row.number), data=lettuce)
anova(lettuce_lb_mod , ddf='Kenward-Roger')
```

Run diagnostic plots

```{r}
#test for normality

#qqplot
qqPlot(residuals(lettuce_heads_mod ))
qqPlot(residuals(lettuce_lb_mod ))
#Shaperio wilks test for normality
shapiro.test(residuals(lettuce_heads_mod ))
shapiro.test(residuals(lettuce_lb_mod ))

#test for homogenaity of variances
plot(lettuce_heads_mod )
plot(lettuce_lb_mod )

leveneTest(lm(No..heads.marketable.ha ~  Cultivation*Trial, data=lettuce))
leveneTest(lm(Kg.marketable.ha ~  Cultivation*Trial, data=lettuce))

#test for homogenaity of variances
## approximate S/L plot
fitted_values = fitted(lettuce_heads_mod)
abs_sqrt_resids = sqrt(abs(resid(lettuce_heads_mod,scaled=T)))
plot(abs_sqrt_resids~fitted_values)
lines(sort(fitted_values),predict(loess(abs_sqrt_resids~fitted_values),sort(fitted_values)))

##residuls vs fitted values plot
fitted_values = fitted(lettuce_heads_mod)
resids = (resid(lettuce_heads_mod,scaled=T))
plot(resids~fitted_values)
lines(sort(fitted_values),predict(loess(resids~fitted_values),sort(fitted_values)))
```

```
## approximate S/L plot
fitted_values = fitted(lettuce_lb_mod )
abs_sqrt_resids = sqrt(abs(resid(lettuce_lb_mod ,scaled=T)))
plot(abs_sqrt_resids~fitted_values)
lines(sort(fitted_values),predict(loess(abs_sqrt_resids~fitted_values),sort(fitted_values)))

##residuls vs fitted values plot
fitted_values = fitted(lettuce_lb_mod )
resids = (resid(lettuce_lb_mod ,scaled=T))
plot(resids~fitted_values)
lines(sort(fitted_values),predict(loess(resids~fitted_values),sort(fitted_values)))
```

#variances don't seem normal so try transformations
```{r}
#remove 0 value
lettuce0 <- lettuce[-c(56,59),]

#ln transformation of response variable yield
lettuce0$lnheads <- log((lettuce0$No..heads.marketable.ha))
lettuce0$lnlb <- log((lettuce0$Kg.marketable.ha))

#refit model
lettuce_heads_mod_ln <- lmer(lnheads ~  Cultivation*Trial + (1|Experimental.Unit) + (1|Row.number),
data=lettuce0)
lettuce_lb_mod_ln <- lmer(lnlb ~  Cultivation*Trial + (1|Experimental.Unit) + (1|Row.number),
data=lettuce0)

#qqplot
qqPlot(residuals(lettuce_heads_mod_ln ))
qqPlot(residuals(lettuce_lb_mod_ln ))

#Shaperio wilks test for normality
shapiro.test(residuals(lettuce_heads_mod_ln ))
shapiro.test(residuals(lettuce_lb_mod ))

#test for homogenaity of variances
plot(lettuce_heads_mod_ln )
plot(lettuce_lb_mod_ln )

leveneTest(lm(lnheads ~  Cultivation*Trial, data=lettuce0))
leveneTest(lm(lnlb ~  Cultivation*Trial, data=lettuce0))

#test for homogenaity of variances
## approximate S/L plot
fitted_values = fitted(lettuce_heads_mod_ln)
abs_sqrt_resids = sqrt(abs(resid(lettuce_heads_mod_ln,scaled=T)))
```

```
plot(abs_sqrt_resids~fitted_values)
lines(sort(fitted_values),predict(loess(abs_sqrt_resids~fitted_values),sort(fitted_values)))

##residuls vs fitted values plot
fitted_values = fitted(lettuce_heads_mod_ln)
resids = (resid(lettuce_heads_mod_ln,scaled=T))
plot(resids~fitted_values)
lines(sort(fitted_values),predict(loess(resids~fitted_values),sort(fitted_values)))

## approximate S/L plot
fitted_values = fitted(lettuce_lb_mod_ln)
abs_sqrt_resids = sqrt(abs(resid(lettuce_lb_mod_ln ,scaled=T)))
plot(abs_sqrt_resids~fitted_values)
lines(sort(fitted_values),predict(loess(abs_sqrt_resids~fitted_values),sort(fitted_values)))

##residuls vs fitted values plot
fitted_values = fitted(lettuce_lb_mod_ln )
resids = (resid(lettuce_lb_mod_ln,scaled=T))
plot(resids~fitted_values)
lines(sort(fitted_values),predict(loess(resids~fitted_values),sort(fitted_values)))
```

Generate model summaries and tests

```{r}
anova(lettuce_heads_mod_ln, ddf='Kenward-Roger')
anova(lettuce_lb_mod_ln, ddf='Kenward-Roger')

###interaction term is not significant so can report results averaged over Trials
means_lettucehead <- emmeans(lettuce_heads_mod_ln, pairwise ~ Cultivation ,mode='k')
summary(means_lettucehead,level = 0.95,infer=T)
(cld_heads_avg <- cld(means_lettucehead$emmeans, Letters=letters))

means_lettucelb <- emmeans(lettuce_lb_mod_ln, pairwise ~ Cultivation ,mode='k')
summary(means_lettucelb,level = 0.95,infer=T)
(cld_lb_avg <- cld(means_lettucelb$emmeans, Letters=letters))
```

#back transformation of means and CI

```{r}
transformed_estimates4 <- as.data.frame(summary(means_lettucehead))
transformed_estimates4$De_trans_estimate = exp(transformed_estimates4$emmeans.emmean)
transformed_estimates4$De_trans_SE = exp(transformed_estimates4$emmeans.SE)
transformed_estimates4$De_trans_lower.CL = exp(transformed_estimates4$emmeans.lower.CL)
transformed_estimates4$De_trans_upper.CL = exp(transformed_estimates4$emmeans.upper.CL)
transformed_estimates4[,c( "emmeans.Cultivation", 'De_trans_estimate','De_trans_SE',
'De_trans_lower.CL','De_trans_upper.CL')]
cld_heads_avg$back_transformed_mean <- exp(cld_heads_avg$emmean)
```

cld_heads_avg

transformed_estimates3 <- as.data.frame(summary(means_lettucelb))
transformed_estimates3$De_trans_estimate = exp(transformed_estimates3$emmeans.emmean)
transformed_estimates3$De_trans_SE = exp(transformed_estimates3$emmeans.SE)
transformed_estimates3$De_trans_lower.CL = exp(transformed_estimates3$emmeans.lower.CL)
transformed_estimates3$De_trans_upper.CL = exp(transformed_estimates3$emmeans.upper.CL)
transformed_estimates3[,c("emmeans.Cultivation", 'De_trans_estimate',
'De_trans_SE','De_trans_lower.CL','De_trans_upper.CL')]
cld_lb_avg $back_transformed_mean <- exp(cld_lb_avg $emmean)
cld_lb_avg
```

## R code for tomato weed density

libraries
```{r}
library(lme4)
library(lmerTest)
library(ggplot2)
library(cowplot)
library(emmeans)
library(pbkrtest)
library(car)
```

```{r}
datapath <- "C:/Users/hj/Documents/HJ documents/grad school/weed science research/tomato field
trials"
tomato <- read.csv(file.path(datapath, "all tomato Data formatted 6-2018.csv"), header = TRUE)

tomato$Trial <- as.factor(tomato$Trial)
tomato$Row.number <- as.factor(tomato$Row.number)
tomato$Replicate <- as.factor(tomato$Replicate)
tomato$Sample.number <- as.factor(tomato$Sample.number)
tomato$Post.count <- as.numeric(as.character(tomato$Post.count))
tomato$Post.count.normalized..weeds.ft. <-
as.numeric(as.character(tomato$Post.count.normalized..weeds.ft.))
tomato$Post.count..weeds.m.2. <- as.numeric(as.character(tomato$Post.count..weeds.m.2.))
```

Fit the model
```{r}
#model terms ordered according to PLS 205 best practice

```
tomatomod <- lmer(Post.count..weeds.m.2. ~  Pre.count..weeds.m.2. + Trial + Cultivation + Pre.count..weeds.m.2.:Cultivation + Trial:Cultivation  +  (1|Experimental.Unit) + (1|Row.number), data=tomato)

anova(tomatomod, ddf='Kenward-Roger')
```

#test covariate assumptions

```{r}
#assumption 1. The covariate is independent of the treatment.
cov_model <- lm(Pre.count..weeds.m.2. ~ Trial + Cultivation, tomato)
anova(cov_model)

#assumption 2. The covariate is linearly correlated with the response, with the same slope across treatments (and blocks) ## The best way to verify that the Covariate is linearly related to the Response is to make a scatter-plot of the data.
ggplot(tomato,aes(x=Pre.count..weeds.m.2.,y=Post.count..weeds.m.2.)) + geom_point()

#We also want to evaluate whether the Response~Covariate relationship varies among treatments. We can do this visually by coloring the points by Trt, and fitting lines separately to each group
ggplot(tomato,aes(x=Pre.count..weeds.m.2.,y=Post.count..weeds.m.2.)) + geom_point(aes(color = Cultivation)) + geom_smooth(aes(color = Cultivation),se=F,method='lm')


#The slopes look slightly different. The differences among TRTs appears to be smaller when there is little Organic Matter than when there is a lot. This indicates that might might need to report the effect of Trt differences **as a Function of COVARIATE**. This certainly complicates the analysis!
# However, is this change in treatment differences large enough to matter?
#We can use our full model to evaluate this using an ANOVA
anova(tomatomod, ddf='Kenward-Roger')

#trial:Cultivation interaction is not significant so drop it
reduced_tomatomod <- lmer(Post.count..weeds.m.2. ~  Pre.count..weeds.m.2. + Trial + Cultivation + Pre.count..weeds.m.2.:Cultivation +  (1|Experimental.Unit) + (1|Row.number), data=tomato)
anova(reduced_tomatomod, ddf='Kenward-Roger')
```

Run diagnostic plots

```{r}
#test for normality

#qqplot
qqPlot(residuals(reduced_tomatomod))

#Shaperio wilks test for normality
shapiro.test(residuals(reduced_tomatomod))

#test for homogenaity of variances
```

```
## approximate S/L plot
fitted_values = fitted(reduced_tomatomod)
abs_sqrt_resids = sqrt(abs(resid(reduced_tomatomod,scaled=T)))
plot(abs_sqrt_resids~fitted_values)
lines(sort(fitted_values),predict(loess(abs_sqrt_resids~fitted_values),sort(fitted_values)))

##residuls vs fitted values plot
fitted_values = fitted(reduced_tomatomod)
resids = (resid(reduced_tomatomod,scaled=T))
plot(resids~fitted_values)
lines(sort(fitted_values),predict(loess(resids~fitted_values),sort(fitted_values)))
```
#normality isn't met and variances don't seem normal so try transformations

```{r}
#remove NA's
tomatoNA <- tomato[-c(86:97,138,172:183 ),]
tomatoNA$sqrdPostcount <- log(tomatoNA$Post.count..weeds.m.2.)

#refit model
tomatomod_sqrd <- lmer(sqrdPostcount ~   Pre.count..weeds.m.2. + Trial + Cultivation +
Pre.count..weeds.m.2.:Cultivation +  (1|Experimental.Unit) + (1|Row.number), data=tomatoNA)

#qqplot
qqPlot(residuals(tomatomod_sqrd))#

#Shaperio wilks test for normality
shapiro.test(residuals(tomatomod_sqrd))

#test for homogenaity of variances
## approximate S/L plot
fitted_values = fitted(tomatomod_sqrd)
abs_sqrt_resids = sqrt(abs(resid(tomatomod_sqrd,scaled=T)))
plot(abs_sqrt_resids~fitted_values)
lines(sort(fitted_values),predict(loess(abs_sqrt_resids~fitted_values),sort(fitted_values)))

##residuls vs fitted values plot
fitted_values = fitted(tomatomod_sqrd)
resids = (resid(tomatomod_sqrd,scaled=T))
plot(resids~fitted_values)
lines(sort(fitted_values),predict(loess(resids~fitted_values),sort(fitted_values)))

#qqplot for random terms
ranef(tomatomod_sqrd)
qqPlot(ranef(tomatomod_sqrd)$`Experimental.Unit`[,1])
```

```{r}
```

```
anova(tomatomod_sqrd, ddf='Kenward-Roger')
```

Generate model summaries and tests
```{r}
#means averaged over Trial b/c Trial term was not significant
means_tomato <- emmeans(reduced_tomatomod, pairwise ~ Cultivation,mode='k')
summary(means_tomato,level = 0.95,infer=T)
(cld_avg <- cld(means_tomato$emmeans, Letters=letters))

##gives means for Treatment for each block (Trial)
means_tomato2 <- emmeans(reduced_tomatomod, pairwise~ Cultivation|Trial)
summary(means_tomato2,level = 0.95,infer=T)
(cld_trial <- cld(means_tomato2$emmeans, Letters=letters))
```

#back transformation of means and CI
```{r}
transformed_estimates = as.data.frame(summary(emmeans(tomatomod_sqrd, ~ Cultivation,mode='k'
)))
transformed_estimates$De_trans_estimate = exp(transformed_estimates$emmean)
transformed_estimates$De_trans_SE = exp(transformed_estimates$SE)
transformed_estimates$De_trans_lower.CL = exp(transformed_estimates$lower.CL)
transformed_estimates$De_trans_upper.CL = exp(transformed_estimates$upper.CL)
transformed_estimates[,c('De_trans_estimate', 'De_trans_SE',
'De_trans_lower.CL','De_trans_upper.CL')]

transformed_estimates_trial = as.data.frame(summary(emmeans(tomatomod_sqrd, ~
Cultivation|Trial,mode='k' )))
transformed_estimates_trial$De_trans_estimate = exp(transformed_estimates_trial$emmean)
transformed_estimates_trial$De_trans_lower.CL = exp(transformed_estimates_trial$lower.CL)
transformed_estimates_trial$De_trans_upper.CL = exp(transformed_estimates_trial$upper.CL)
transformed_estimates_trial[,c('De_trans_estimate','De_trans_lower.CL','De_trans_upper.CL')]
```

```{r}
# extract the treatment means and confidence intervals# make into a data.frame
pooled_trt_means_tomato <- as.data.frame(summary(means_tomato ,infer=T))
pooled_trt_means_tomato

trt_means_tomato <- as.data.frame(summary(means_tomato2 ,infer=T))
trt_means_tomato

originalunits <- aggregate(Pre.count..weeds.m.2. ~ Cultivation + Trial, tomato, mean)
originalunits
transformed_estimates2 <- cbind(transformed_estimates_trial, originalunits[,3])
transformed_estimates2
str(transformed_estimates2)
```

```
# plot
 ggplot(transformed_estimates2,aes(x=Cultivation,y=De_trans_estimate)) +
    geom_point(shape=1, size=5) +
  geom_point(data=transformed_estimates,aes(x=Cultivation,y=De_trans_estimate), shape="-", size=5
)+    geom_segment(data=transformed_estimates, aes(x = (as.numeric(Cultivation)-.15), y =
De_trans_estimate, xend=(as.numeric(Cultivation)+.15), yend=De_trans_estimate),   size = 1.5,
color="blue") +
  ggtitle("Mean number of weeds remaining after tomato cultivation ") +
  xlab("Cultivation method") +
  ylab("No. of weeds/m² after cultivation") +
   geom_label(data=transformed_estimates,
aes(x=(as.numeric(Cultivation)+.35),y=(as.numeric(De_trans_estimate)+.45), label=
paste(round(De_trans_estimate, digits=1)," weeds/m²")))
```

R code for tomato hand weeding time

libraries
```{r}
library(lme4)
library(lmerTest)
library(ggplot2)
library(cowplot)
library(emmeans)
library(car)
library(pbkrtest)
```

```{r}
datapath <- "C:/Users/hj/Documents/HJ documents/grad school/weed science research/tomato field trials"
tomato <- read.csv(file.path(datapath, "all tomato Data formatted 5-2018.csv"), header = TRUE)

tomato$Trial <- as.factor(tomato$Trial)
tomato$Row.number <- as.factor(tomato$Row.number)
tomato$Replicate <- as.factor(tomato$Replicate)
tomato$Sample.number <- as.factor(tomato$Sample.number)
tomato$time..hr.ac. <- as.numeric(as.character(tomato$time..hr.ac.))
tomato$time.ha <- as.numeric(as.character(tomato$time..hr.ac.))/0.404686
tomato <- tomato[1:143,]  #drop empty rows r brought in from excel
```

Fit the model
```{r}
tomato_time_mod <- lmer(time.ha ~  Trial*Cultivation + (1|Experimental.Unit) + (1|Row.number), data=tomato)
anova(tomato_time_mod , ddf='Kenward-Roger')

#trial:Cultivation interaction is not significant so drop it
reduced_tomato_time_mod <- lmer(time.ha ~  Trial + Cultivation + (1|Experimental.Unit) + (1|Row.number), data=tomato)
anova(reduced_tomato_time_mod , ddf='Kenward-Roger')
```

Run diagnostic plots
```{r}
#test for normality
#qqplot
qqPlot(residuals(tomato_time_mod ))

#Shaperio wilks test for normality
```

```
shapiro.test(residuals(tomato_time_mod ))

#test for homogenaity of variances
plot(tomato_time_mod )
leveneTest(lm(time.ha ~  Cultivation*Trial, data=tomato))

#test for homogenaity of variances
## approximate S/L plot
fitted_values = fitted(tomato_time_mod)
abs_sqrt_resids = sqrt(abs(resid(tomato_time_mod,scaled=T)))
plot(abs_sqrt_resids~fitted_values)
lines(sort(fitted_values),predict(loess(abs_sqrt_resids~fitted_values),sort(fitted_values)))

##residuls vs fitted values plot
fitted_values = fitted(tomato_time_mod)
resids = (resid(tomato_time_mod,scaled=T))
plot(resids~fitted_values)
lines(sort(fitted_values),predict(loess(resids~fitted_values),sort(fitted_values)))
```

Generate model summaries and tests

```{r}
anova(reduced_tomato_time_mod, ddf='Kenward-Roger')

##means averaged over Trial b/c Trial term was not significant
means_tomatotime <- emmeans(reduced_tomato_time_mod, pairwise ~ Cultivation,mode='k' )
summary(means_tomatotime,level = 0.95,infer=T)
(cld_time_avg <- cld(means_tomatotime$emmeans, Letters=letters))

means_tomatotime2 <- emmeans(reduced_tomato_time_mod, pairwise ~ Cultivation|Trial ,mode='k')
# the | gives the results "by" trial i.e. the differences
```

```{r}
# extract the treatment means and confidence intervals
pooled_trt_means <- as.data.frame(summary(means_tomatotime,infer=T))
pooled_trt_means
# make into a data.frame
trt_means <- as.data.frame(summary(means_tomatotime2,infer=T))

# plot
 ggplot(trt_means,aes(x=emmeans.Cultivation,y=emmeans.emmean)) +
    geom_point(shape=1, size=5) +
  geom_point(data=pooled_trt_means,aes(x=emmeans.Cultivation,y=emmeans.emmean), shape="-",
size=5 )+ geom_segment(data=pooled_trt_means, aes(x = (as.numeric(emmeans.Cultivation)-.15), y =
emmeans.emmean, xend=(as.numeric(emmeans.Cultivation)+.15), yend=emmeans.emmean),   size =
1.5, color="blue") +
   ggtitle("Time spent hand-weeding after tomato cultivation") +
```

```
  xlab("Cultivation method") +
  ylab("Time (hr/ha)") +

geom_label(data=pooled_trt_means,aes(x=(as.numeric(emmeans.Cultivation)+.25),y=(as.numeric(emm
eans.emmean)+ 0.1), label=paste0(round(emmeans.emmean, digits=1)," hours")))
```

R code for tomato yield data

libraries

```{r}
library(lme4)
```

```
library(lmerTest)
library(ggplot2)
library(cowplot)
library(emmeans)
library(car)
library(pbkrtest)
```

```{r}
datapath <- "C:/Users/hj/Documents/HJ documents/grad school/weed science research/tomato field trials"
tomato <- read.csv(file.path(datapath, "all tomato Data formatted 3-2018.csv"), header = TRUE)
tomato$Trial <- as.factor(tomato$Trial)
tomato$Row.number <- as.factor(tomato$Row.number)
tomato$Replicate <- as.factor(tomato$Replicate)
tomato$Sample.number <- as.factor(tomato$Sample.number)
tomato$kg.ha <- tomato$Lb.Acre*1.12085116
tomato <- tomato[1:143,]  #drop empty rows r brought in from excel
```

Fit the model
```{r}
#remove NA's
tomatoNA3 <- tomato[c(14,16,18,20, 22, 82, 84, 86, 88, 90, 92,94),]

tomato_lb_mod6 <- lm(kg.ha ~  Cultivation , data=tomatoNA3)
anova(tomato_lb_mod6)
```
Run diagnostic plots
```{r}
#diagnostic plots for fixed effect models
plot(tomato_lb_mod6,which=1:3)
```
Generate model summaries and tests
```{r}
anova(tomato_lb_mod6)

means_tomatolb <- emmeans(tomato_lb_mod6,  ~ Cultivation )
summary(means_tomatolb,level = 0.95,infer=T)
(cld_lb_avg <- cld(means_tomatolb, Letters=letters))`


```