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Evaluating Methods for Research in Physical Weed Control and Farm Asset Tracking

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EVALUATING METHODS FOR RESEARCH IN PHYSICAL WEED CONTROL AND FARM ASSET TRACKING

By

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By Johnny J. Sanchez

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An Abstract of the Thesis Presented
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Effective weed control has long been recognized as critical for agricultural production, yet weeds remain a major constraint to production and economic return in many agroecosystems. Moreover, improvements in physical weed control are necessary to address increasing problems of herbicide resistance in weeds of grain and fiber crops and the high cost of hand weeding in vegetables. From tractor-mounted cultivation tools to autonomous weeders, weeding implements are affected by weeds, crops, soil conditions, and actuator effectiveness. In order to address these complex and often interacting factors concerning weed control, new and innovative tools must be designed and evaluated.

Chapter one addresses a series of experiments designed to determine the functionality and efficacy of Franklin Robotics' Tertill™ and to explore its place in the growing field of robotic weeding. The Tertill™ demonstrated high weed control efficacy, supporting its utility as a tool for home gardeners. However, in its current form, the Tertill™ would require modification to be viable for farm-scale use. Yet, its simple and effective design may offer insights to inform future development of farm-scale weeding robots.

Chapter two addresses an analysis of the early growth characteristics of wild radish (*Raphanus raphanistrum* L.) and four related Brassica species commonly used as surrogate weeds in physical weed control research. Plants of each species were grown in a greenhouse, destructively harvested at three distinct growth stages, and analyzed for anchorage force and root architecture. Wild radish and the selected Brassica surrogate weeds were comparable in biomass and root architecture. However, differences in anchorage force necessitates caution and field validation.

Chapter three builds upon the previous chapter by making the explicit comparisons between surrogate weeds and their weedy counterparts that have hitherto been absent from the literature. Additionally, the viability of golf tees as artificial weeds was assessed. Field experiments were conducted in 2019 and 2020 using six flex-tine harrows to compare the reactions to cultivation of wild radish, two Brassica surrogate weeds, and golf tee artificial weeds. Rates of efficacy for both surrogate weed species were comparable to those of wild radish, indicating that these species are useful surrogates for this weed species. However, golf tees failed to accurately simulate weed seedling response to cultivation, and their response was highly variable.

Chapter four addresses the challenges and inefficiencies apparent in diversified organic farming by evaluating the potential of inexpensive, wearable GPS watches to monitor farm labor. Labor data acquired with GPS watches was correlated with a reference system. However, elevated rates of error associated with commercially available GPS devices potentially limits their viability in tracking labor on small farms where error may result in significant inaccuracies.

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LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
C	Celsius
cm	Centimeter
DPI	Dots Per Inch
FMIS	Farm Management Information System
GALILEO	European Global Satellite Navigation System
GLONASS	Global Navigation Satellite System
GPS	Global Positioning System
GNSS	Global Navigation Satellite System
h	Hour
ha	hectare
HSD	Honestly Significant Difference
kg	kilogram
kph	kilometers per hour
m	meter
MARS	Mobile Agricultural Robot Swarms
mg	milligram
min	minute
ml	milliliter
mm	millimeter
PWC	Physical Weed Control
N	Newton

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CHAPTER 1

FUNCTIONALITY AND EFFICACY OF FRANKLIN ROBOTICS' TERTILL™ ROBOTIC WEEDER

INTRODUCTION

Effective weed control has long been recognized as critical for agricultural production (Utstumo et al. 2018), yet weeds remain a major constraint to production and economic return in many agroecosystems (Gallandt and Weiner 2007; Jackson et al. 2004). While herbicides are the primary form of weed control in global cropping systems, herbicide-resistant weeds and the failure to commercialize any new herbicide modes of action over the last 30 years has led some to conclude that herbicides may have a limited future (Davis and Frisvold 2017; Duke 2012). In specialty crops (i.e., fruit, herbs, and vegetables), a lack of effective herbicides and labor shortages have prompted increasing interest in the development of autonomous robotic weeders for both conventional and organic systems (Fennimore and Cutulle 2019; Fennimore et al. 2016; Yunez-Naude et al. 2012).

At present, state-of-the-art physical weeding technologies have focused on tractor mounted implements, using global positioning system (GPS)- or camera-guidance to improve precision (i.e., closeness to crop rows) and working rates, as well as tools designed for intra-row weeding in crops that are widely spaced within rows (e.g., cabbage, head lettuce). Rasmussen et al. (2012) described tools that used sensors or mapping to selectively target intra-row weeds as "intelligent weeders." Presently, commercially available intelligent weeders, such as the Robovator (F. Poulsen Engineering ApS, Hvalsø, Denmark) or the Robocrop (Tillett and Hague Technology Ltd, England), are tractor-mounted implements that utilize "machine detection" to locate weeds and a metal hoeing device or "actuator" to kill the weeds (Fennimore and Cutulle 2019). Machine detection techniques may involve processing images taken while the tractor is in motion, pre-recording sown crop positions with GPS, or the interruption of a light beam directed over the crop row (Tillet et al. 2007).

Lati et al. (2016) found that the Robovator improved weed control 18 to 41% compared to a standard cultivator, while Fennimore (2014) found that the Robocrop reduced weed densities in transplanted crops by 85%. These two tractor-mounted, weeding machines rely on cameras to detect crop plants and precise measurement of forward speed to time movement of weeding tools in and out of crop rows, avoiding damage to the widely spaced crop plants. While several intelligent weeding systems, such as those listed here, are commercially available, the cost associated with camera- and GPS-guided detection systems can be prohibitive for smaller farms (Grimstad et al. 2015; Peruzzi et al. 2017). In field experiments with the Robovator, Melander et al. (2015) found that the investment cost for an intelligent weeder can be as much as 13 times that of widely available non-intelligent intra-row weeders, e.g., torsion- or finger-weeders. During the early years of intelligent and autonomous weeding systems, investment costs will most likely be high due to the technologies used for plant detection (Fennimore et al. 2016) and possibly elevated rates of crop damage in direct seeded crops (Fennimore et al. 2014).

Future weeding machines will surely be fully autonomous—true robots—but this remains a challenging goal. Merfield (2016) suggested that "every mechanical weeding job is different, requiring different weeders and different adjustments of the machinery." Furthermore, Merfield (2016) suggested that a "genuine weeding robot" should be able to monitor both crops and weeds to determine optimal management implementation as well as make real-time adjustments to tool settings and perform basic tool maintenance. The Dino (Naïo Technologies, France) is an example of an autonomous weeding robot commercially available today that employs GPS-guided systems to cultivate as close to crops as possible (Pérez-Ruiz et al. 2012). However, like the Robocrop and Robovator, its complex design currently comes at a potentially prohibitive capital cost (Melander et al. 2015). Autonomous weeding robot subscription services are a possible answer to the potentially prohibitive capital costs associated with purchasing and operating expensive autonomous weeders (Naïo Technologies 2020).

Franklin Robotics' (Bellerica, MA, USA) recently commercialized Tertill™, an autonomous solar-powered weeding robot for home gardeners that demonstrates parsimony of design. Instead of complex, heavy and energy-consuming camera- or GPS- guided detection systems, the Tertill™ operates much like a Roomba® home vacuum cleaner, using capacitive sensors on its sides to detect and avoid obstacles such as large crops and walls; Tertill™ has an additional capacitive sensor on its bottom that detects small weeds and activates a weed whacking mechanism (Figure 1.1). Control of small seedlings is achieved both by this sensor and temporally random activation of the weed whacker. Designed to independently traverse an enclosed area, the Tertill™ is programmed with a random walk function, moving on four cambered wheels or "grousers," suitable for moderately rough terrain. Following a successful crowdsource funding campaign, the Tertill™ was shipped to home gardening enthusiasts in September 2018 and was subsequently made commercially available.

Our aim was to investigate the performance of the Tertill™ in a controlled environment using broadleaf and grass surrogate weeds. Observation of our early trials suggested that the grousers as well as the weed whacker were controlling weed seedlings, prompting an additional series of experiments examining this serendipitous weeding mechanism. The objectives of this study were to investigate the ability of the Tertill™ to control broadleaf and grass weeds, with and without its sting-trimmer-like weeding implement, and to evaluate grass weed control over time. We hypothesized that, given a sufficiently sized area and daily use, the Tertill™ would more effectively control broadleaf weeds than grass weeds, due to the lower placement of a grass's meristem.

Figure 1.1 Underside of the Tertill^{TM}, showing four grousers, weed whacking mechanism, capacitive sensors, and solar panel. Source: Franklin Robotics.

METHODS AND MATERIALS

An experimental arena (6.7 x 1.5 m) was constructed in the University of Maine Roger Clapp Greenhouse in Orono, Maine. The arena was lined with black woven landscape fabric and filled with a 7 cm layer of vermiculite beneath a 10 cm layer of field soil, a Pushaw silt loam that was collected from the University of Maine Rogers Farm (44.93°N, 68.70°W).

Weed control efficacy was determined by the percentage of weeds killed by the Tertill™ in permanent quadrats (Evans et al. 2012). Condiment mustard was used as a surrogate weed (Rasmussen 1991) to simulate a stand of broadleaf weeds; pearl millet was used instead for later experiments to determine efficacy with a monocot species. Prior to seeding, the experimental arena was scuffle hoed and flattened with a bed-shaping rake to remove any surviving surrogate or ambient weeds. For each iteration of the study, surrogate weeds were hand broadcast at 2,800 seeds m^{-2} and raked into the soil with a bed-shaping rake (Brown and Gallandt 2018; Olsen et al. 2005). The resulting average surrogate weed density was 256 plants m^{-2} quadrat across experiments. Due to the presence of weed seed in the field soil, ambient weeds were counted along with the surrogates. However, the population was small and declining over time (Sanchez and Gallandt, unpublished data). We did not expect it to affect the performance of the Tertill™ and therefore it is not included in analysis presented in this paper.

During our methods development, observation of the working Tertill™ indicated that the grousers (wheels) caused considerable shallow soil disturbance, possibly resulting in the uprooting or burial of weed seedlings (Figure 1.2). Thus, our first series of experiments were designed to examine the proportion of weed mortality caused by the weed whacker relative to the soil disturbance caused by the grousers. The arena was divided into 1.5 x 1.6 m sections, in which the robot was released for a duration of 30 min. The duration 30 min was arbitrarily chosen to ensure that the Tertill™ adequately demonstrated its weed controlling ability while also ensuring that a sufficient number of surrogate weeds would remain for subsequent counting (Vanhala et al. 2004). Because the Tertill™ operates using a random walk, rather than a programmed path, we did not account for spatially repeated weed control. Robots were tested with and without the standard weed whacker attachment. Weed control efficacy was measured in five randomly placed 0.125 m^{-2} quadrats. Quadrat placement was marked using golf tees that were pushed level with the soil to ensure no interference with the robots. Within these quadrats, pre- and post-treatment counts of surrogate weeds were conducted to assess efficacy, which was calculated using the following equation:

$$\text{Efficacy (\%)} = ((D_b - D_a) / D_b) \qquad [1]$$

Where D_b was the pre-treatment density of surrogate weeds in each quadrat and D_a was the post-treatment density of surrogate weeds in each quadrat. Experiments were replicated over time. The grouser efficacy experiments were replicated 3 times using mustard and 5 times using pearl millet.

Figure 1.2 Soil disturbance caused by grousers.

A subsequent series of experiments were designed to better understand the effect of the robot in monocot weed species, such as pearl millet, that were expected to regrow after mowing due to the location of the plant's intercalary meristem. Franklin Robotics recommends that gardeners place a Tertill™ in a freshly weeded, enclosed garden. The 6.7 x 1.5 m arena was divided into five designated blocks to mitigate effects of an observed ambient soil moisture gradient. Ten permanent quadrats were randomly placed across the arena with two quadrats per block. The arena was seeded with pearl millet, and the robot was released daily, starting immediately after seeding. In the first experiment, the robot ran for 53 min before shutting down to recharge via solar panel. This duration was used for all subsequent iterations of the experiment. Because sunlight was not always adequate given the northern latitude and time of year, the robot was charged overnight rather than relying on its built-in solar panel. Post-treatment counts were conducted 24 h after each daily use for one week. Evaluation of daily deployment aimed to mimic continuous weeding with Tertill™ as experienced after release in a weed-free garden; this experiment was replicated three times with pearl millet.

Statistical analyses were conducted in JMP 14 (SAS Institute Inc., Cary, NC, USA). To evaluate the grousers, treatment efficacy means, averaged over replicate quadrats ($n = 4$), were compared using Wilcoxon signed rank tests due to non-normality of the data. To avoid confounding effects due to regrowth between treatment and post-treatment weed counts, efficacy was also calculated the second day after treatment. Another Wilcoxon signed rank test was conducted to compare efficacy from both one and two days after the treatment.

To evaluate the effects of daily use, means for day were averaged over replicate quadrats ($n = 10$) and plotted across the five days during which the robot was assessed. A regression analysis was used to examine the relationship between time and efficacy.

RESULTS AND DISCUSSION

Weed Control Contribution of Grousers. In trials using condiment mustard, efficacy ranged from 60 to 72% with the weed whacker but was reduced to 4 to 39% without the weed whacker. In pearl millet trials, efficacy similarly ranged from 54 to 75% and 16 to 29% with and without the weed whacker, respectively. Rates of efficacy with the weed whacker are similar to those found by Gallandt (2010) and Gallandt et al. (2018), who noted a mean efficacy of 70% with colinear hoes and an overall mean efficacy of 66% for tractor-mounted implements, respectively. While efficacy was greatest with the combined action of the grousers and weed whacking implement, the grousers alone contributed 16 and 22% efficacy in mustard and pearl millet trials, respectively (Figure 1.3). Operation of the weed whacker improved weed control efficacy for both mustard and pearl millet ($P = 0.0006$ and $P = 0.0001$, respectively). Additionally, there was no difference in efficacy between mustard and pearl millet when surrogate counts were conducted 24 h after weeding (P = 0.6221), suggesting that the Tertill™ was as effective in both grass and broadleaf species tested here. Also, there were no differences between counts conducted one and two days after the treatment (P = 0.7289; data not shown).

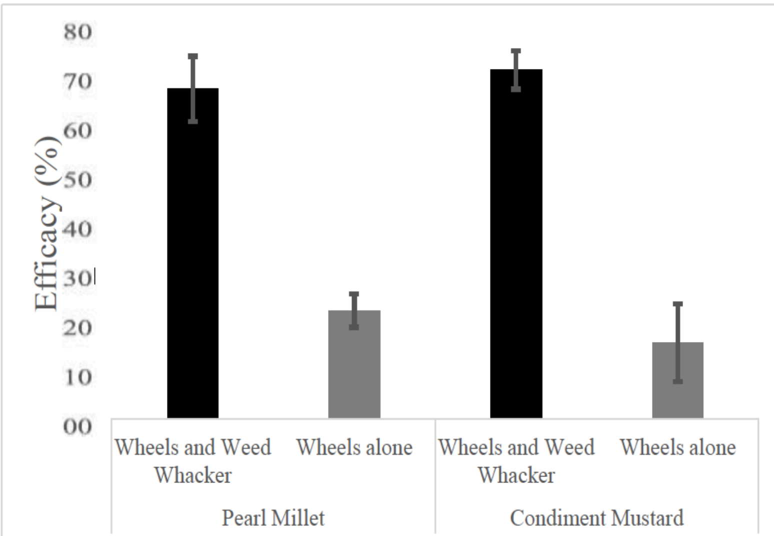


Figure 1.3 Weed control efficacy when Tertill™ was equipped with weed whacking implement and without. Means from three replicate experiments using condiment mustard and five replicate experiments using pearl millet as surrogates. Error bars show the standard error of the mean.

Effect of Daily Use on Weed Pressure. Density of the pearl millet increased rapidly, before declining at a slower rate (data not shown). This was likely due to the meristem of seedlings being too low for the weed whacker to kill initially. Linear regression analysis of efficacy over time indicated a negative trend (Figure 1.4), reflecting the ability of the Tertill™ to decrease the density of pearl millet within the arena over time (R2 = 0.9617).

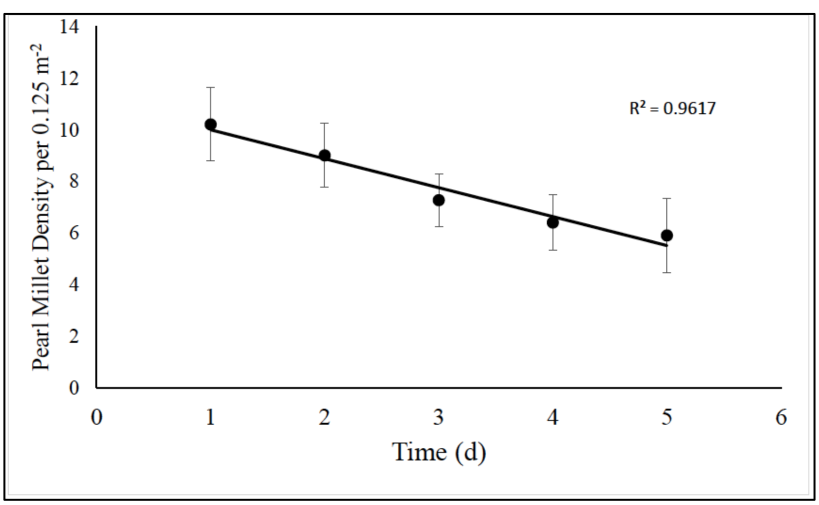


Figure 1.4 Pearl millet density recorded daily and plotted across five days. Error bars show the standard error of the mean. Best fit line equation: $y = -1.12x + 11.113$. $R^2 = 0.9617$

Implications for Future Research. Autonomous weeding robots represent a possible solution to the stagnation of herbicide development and labor shortages in high-value fruit and vegetable crops, and perhaps also a way to address intractable problems with herbicide resistant weeds. The Tertill™ is a viable form of weed control for a small home gardener, with high rates of efficacy in both annual grass and broadleaf surrogate weeds. We found that the Tertill™ was effective when used daily in a garden, as recommended by its manufacturers. While the robot was more effective when it was utilizing its weed whacker, the serendipitous discovery of the weed controlling potential of its grousers is an opportunity for future design enhancements to improve this mechanism.

In its current form, the Tertill™ would require modification to be viable for farm-scale use. In a commercial agricultural setting, a farm-scale autonomous weeding robot would need to overcome several shortcomings apparent with the Tertill™. While its modest design allows the Tertill™ to be lightweight, inexpensive, and simple to use, a farmer will demand greater efficacy, increased working rates, and perhaps the ability to work in conjunction with additional robots. Additionally, while the Tertill™ is designed to work in widely-spaced crops, farm-scale autonomous robots will need to control weeds between and within rows of crops of many spatial arrangements. These improvements will likely come at the cost of simplicity and may result in increased capital costs.

Given the working rates we observed, it would take one Tertill™ approximately 353 hours to cover an acre; 40 units could cover an acre in approximately 8 h. For comparison, based on working rates determined in a field study by Gallandt (2010), it would take approximately 19 hours to weed an acre by hand using a stirrup hoe. While using multiple units would increase working rates, it would require a system of path planning and communication among the robots to minimize overlap in coverage. Improvements such as the ability to communicate as part of a swarm would require a system for communication between robots, path planning, optimization, and supervision. This is the approach of the Mobile Agricultural Robot Swarms (MARS) system for autonomous farming operations (Blender et al. 2016). McAllister et al. (2019) found that as the number of robot units in a field increases, information sharing strongly improves overall system performance.

Beyond the technological complexities associated with developing autonomous weeding robots, there are several real-world considerations with which new robots should be evaluated. Successful robotic weeding systems will be designed to perform in the context of variable weed (i) density (seedbanks), and (ii) diversity; and these factors will vary over (iii) time and (iv) space. The density of weeds varies widely. While seedbank densities on conventional farms may be relatively low and predictable, densities on organic farms vary widely. Jabbour et al. (2014) found germinable seed densities raged from 2,775 m^{-2} to 24,678 m^{-2} on 23 New England farms. Species abundance and richness of weed communities also vary across farms (Crowder and Jabbour 2014). Weed communities vary in time and space. Seasonal emergence periodicity results in a dynamic community with changing species, size, and density (Gallandt et al. 2018). Emergence periodicity has long been important in designing weed control strategies (Egley and Williams 1991; Stoller and Wax 1973). The spatial heterogeneity of weeds results in populations dispersed in patches that may range in size from fractions of a hectare to many hectares (Cardina et al. 1997), further complicating field research but representing an important consideration for the development of any physical weed controlling implement (Lindquist et al. 1998). Soil conditions such as moisture content, organic matter, textural class, residues, and heterogeneity across fields can affect the action of traditional physical weeding tools (Kurstjens et al. 2004;

Mohler 2001). Weeding robots may offer a solution to the problem of constantly changing weed conditions, but these changes in species and density must be considered in their design. As complex plant sensing technologies become more democratized, it is imperative that future research regarding autonomous weeding is contextualized in real world scenarios.

Additionally, there must also be greater focus placed on actuator components. In a review of 55 mechanical cultivation studies, Gallandt et al. (2018) found that efficacy of mechanical cultivation tools is low and highly variable. Autonomous weeding robots would benefit from increased actuator response times, which would increase working rates (Fennimore and Cutulle 2019). Improving actuator components should be a goal to ensure efficient use of robotic technologies.

As weeds remain a challenge in agricultural production systems globally, technologies to reduce weeding labor and overcome challenges associated with herbicide resistance are a pressing need. Autonomous weeding machines represent an emerging solution. We found the simple design of Franklin Robotics' Tertill™ to be effective for use at home garden scales, and though we do not recommend its deployment at the farm scale at this time, believe this tool offers insights to inform development of future farm-scale weeding robots. Further, we believe that the development of future intelligent and autonomous weeders should be contextualized by real-world considerations.

CHAPTER TWO

A COMPARISON OF BRASSICA SURROGATE WEEDS AND WILD RADISH (*RAPHANUS RAPHANISTRUM*): I. EARLY GROWTH AND DEVELOPMENT

INTRODUCTION

Improving physical weed control (PWC) would help farmers address increasing problems of herbicide resistance in weeds of grain and fiber crops (Gaines et al. 2020), and the high cost of hand weeding in vegetables (Lee and Thierfelder 2017; Thierfelder et al. 2018). Organic farmers also rely heavily on PWC to reduce weed density, and thus crop yield and quality losses (Gallandt et al. 2018). Unfortunately, research related to PWC has lagged well behind efforts to develop and optimize herbicides, and as a consequence, PWC efficacy and selectivity are comparatively low and variable. Weeds, crops, soil conditions, and tools all affect efficacy and selectivity. Moreover, weed presence is highly variable in time and space, due to seasonal emergence periodicity and spatial heterogeneity (Cardina et al. 1997; Egley and Williams 1991; Gallandt et al. 2018). Given these multiple, perhaps interacting factors, researchers often aim to simplify the system by using domesticated "surrogate" weeds in addition to, or instead of, real weeds (Appendix A. Supplemental Table 1).

Surrogate weeds are usually crop species that are related to wild weed species of interest (Rasmussen 1991). Surrogate weeds have been widely used in PWC research, providing a genetically uniform, even-aged cohort, and assuring uniform spatial distribution and densities (McCollough et al. 2020; Merfield et al. 2017; Page et al. 2012). Most common are Brassica species: Condiment mustards (*Brassica juncea* L.*, Guillenia flavescens* Hook.*, Sinapis alba* L.)

and rapeseed (*Brassica napus* L.), which have been used as surrogate weeds in PWC studies in organic grains and vegetable systems (Brainard et al. 2013; Kolb et al. 2010).

Surrogate weeds are easy to work with and reliable, improving the efficiency of experimental research. In contrast to weedy species that often exhibit low and unreliable germination rates (Tricault et al. 2018) and high rates of seed dormancy (Cheam 1986), domesticated surrogates exhibit high viability, rapid and uniform germination and reliable establishment (Smith et al. 2015). They are often easier to differentiate from ambient weed species that naturally occur in the research area (Giambalvo et al. 2010), and can obviate possible confounding factors of real weeds, such as varying heights within a stand (Smith et al. 2014). Furthermore, real weed species can be difficult and time-consuming to acquire whereas surrogates have a more readily available seed supply (Myers et al. 2005).

Despite the relatively common use of surrogate weeds, explicit comparisons to real weeds have not been done (Melander and McCollough 2020). Dormancy and seed shattering are known to be lost during plant domestication (McGinty et al. 2021; Rodríguez et al. 2017), but other traits, such as growth rate and biomass allocation are likely to differ between domesticates and their weedy relatives. A more thorough understanding of these and other early development characteristics, such as anchorage force (i.e., the force required to vertically pull a plant out of the soil) and root architecture (i.e., the explicit geometric allocation of root axes and branches (Lynch 1995)) could inform the use of surrogate weeds in PWC studies, expanding inference from these studies.

The objective of this study was to evaluate four Brassica crop species for their suitability as surrogates for PWC research focused on improved control of wild radish (*Raphanus* *raphanistrum* L.), a common weed in small grains. We hypothesized that early growth of the candidate surrogate weeds would not differ significantly from that of *R. raphanistrum*, making all four species viable options for use in the field. Additionally, we hypothesized that the larger-seeded surrogates would most closely reflect the early growth of *R. raphanistrum*.

METHODS AND MATERIALS

Early growth experiments were conducted May through June 2019 and November through December 2020 in the University of Maine Roger Clapp Greenhouse in Orono, ME. Using a factorial randomized block design with six replications, this study involved the destructive harvest of four surrogate weed species and one real weed species, all at three distinct growth stages (one, two, and three true leaves) (Hess 1997; Meier 2001). A blocked design was chosen to account for an observed environmental gradient in the greenhouse.

Plant Material. Wild radish (*Raphanus raphanistrum* L.) seeds were collected in 2017 in Parkman, ME (45.1° N, -69.4° W). To improve germination, *R. raphanistrum* seeds were separated from the siliques by hand prior to sieving (Mekenian and Willemsen 1975). Condiment mustards (*Guillenia flavescens* L.), (*Brassica juncea* L.), (*Sinapis alba* L.), and canola (*Brassica napus* L.) were sourced from Johnny's Selected Seeds (Winslow, ME) and selected based on previous uses as surrogate weeds in field studies (Brown and Gallandt 2018; Kolb et al. 2012; Melander et al. 2003; Melander and McCollough 2020). Real and surrogate weed 100-seed mass ranged from 264 to 532 mg (Table 2.1). *G. flavescens*, *B. napus*, and *S. alba* were considered large-seeded surrogates while *B. juncea* was designated as small-seeded, due to the relative similarity in 100-seed mass of the first three and dissimilarity of the latter.

Table 2.1. The 100 seed mass (mg) of *R. raphanistrum* and Brassica surrogate weed seed lots[1], used in comparative early growth and anchorage force assays.

Species	100 Seed Mass	Size Classification
	mg	
Raphanus raphanistrum (L.)	629	n/a
Guillenia flavescens (Hook.)	532	Large-seeded
Sinapis alba (L.)	518	Large-seeded
Brassica napus (L.)	503	Large-seeded
Brassica juncea (L.)	264	Small-seeded

[1] *Raphanus raphanistrum* (L.) seeds were removed from their siliques by hand and, along with seed lots of all other species, were sieved to ensure uniform size within species. Germination assays were performed on all seed lots to ensure viability.

Seed Preparation. Seeds were sieved to ensure seed size uniformity within each species (Kaufmann and Guitard 1967; Westoby et al. 1996). Anticipating the unreliable germination of weed species, all seeds were germinated prior to planting (Fang et al. 2019). Seeds were placed in petri dishes (8.5 cm) on blotter paper (Ahlstrom-Munkjö, Helsinki, Finland) and wetted with 4 ml of water before being placed into an incubator at 20° C (Baskin and Baskin 2014). Upon radicle protrusion of 3 mm, germinated seeds were planted in 720 ml conically shaped plastic containers (Stuewe and Sons Inc., Tangent, Oregon). The 25 cm by 7 cm containers allowed for adequate space in which plant roots could grow unimpeded (Poorter et al. 2012). Each plastic container was filled with coarse pool filter sand (Quikrete©) which was found to be a suitable substrate for producing realistic and easily cleaned roots (Parks, unpublished data 2019). Germinated seeds were planted in the sand at a depth of 1 cm. Plants were irrigated to field capacity three times daily and fertilized with 20-20-20 fertilizer (ICL Specialty Fertilizers, Summerville, SC, USA) three times per week. To avoid the possibly confounding effect of turgidity, plants were irrigated and fertilized a set amount of time before harvest. Temperature and relative humidity were measured in 2020 using a HOBO Onset (Bourne, MA) data logger. Temperature ranged from 16.1 to 26.1° C while the relative humidity ranged from 24 to 74%.

Anchorage Force. Anchorage force was measured at each developmental stage using a stationary FMI-B50 force gauge (Alluris GmbH & Co., Germany). A metal clip, blunted with rubber so as not to damage the stem, was affixed to each plant at the soil level (Figure 2.1). Plants were pulled vertically at a constant velocity until fully uprooted. To ensure uniform sand moisture and plant turgidity, plants were always harvested one hour after irrigation. The force gauge recorded the amount of force being exerted upon each plant at one second intervals, from which the maximum force was selected (Toukura et al. 2006).

Figure 2.1. A *Guillenia flavescens* seedling, at one true leaf after being uprooted with an Alluris force gauge.

Biomass Allocation. Four parameters of root architecture, in addition to shoot surface area, were measured using a WinRhizo flatbed scanning system (Version 2003b, Regent Instrument, Quebec, Canada) (Bouma et al. 2000). Parameters included root length, root surface area, average root diameter, and number of root tips. Plants were gently removed from the cones, before being washed with water. Roots were separated from shoots, spread out with rubber tweezers to minimize root overlap, and placed in a 30 cm by 40 cm Plexiglas tray containing a 4 to 6 mm deep layer of water. Roots were then scanned using a large-format scanner (Epson

Expression 12,000 XL) (Fang et al. 2019). A 600 DPI grayscale image was obtained for each plant root. To quantify the shoot surface area of each plant, grayscale images were also generated for each corresponding plant shoot with leaves removed from the stem and pressed flat against the glass. Roots and shoots were subsequently placed in a drying oven at 60° C for three days before being weighed; root-to-shoot ratios were calculated using these dry weights.

Statistical Analyses. Data were analyzed using JMP 15 Pro statistical software (SAS Institute Inc., Cary, NC, USA). Data were checked for normality, constant variance, and independence using Shapiro-Wilk's test, Levene's tests, and q-q plots before being subjected to Analysis of Variance (ANOVA) (Quinn and Keough 2014). Means were compared using orthogonal contrasts and Tukey's HSD, where appropriate. Data that did not meet the assumptions of ANOVA were subjected to Box-Cox, square root, and natural log transformations as necessary (Box-Cox 1964). Untransformed summary statistics are presented. An alpha level of 0.07 was used throughout.

RESULTS AND DISCUSSION

Biomass Allocation. Both total dry biomass and shoot surface area differed between the two study years ($P = 0.062$; $P = 0.001$). In 2019, plants were on average 0.05 g or approximately 71% larger than in 2020 (Figure 2.2). This difference in biomass may have been related to the time of the year during which the experiments were conducted. Maine experienced an average of 14.5 daylight hours from May to June when the experiment was conducted in 2019, but only an average of 8.9 daylight hours from November to December, when the experiment was conducted in 2020. Not surprisingly, Adams and Langton (2004) found that increased exposure to sunlight can increase rates of photosynthesis, resulting in greater accumulation of dry biomass. This has also been observed in members of the Brassica family (Chen et al. 2021). As both *R.*

raphanistrum and the selected Brassica species included in this study are considered long-day plants (D'Aloia et al. 2009; King and Kondra 1986; Simard and Légère 2017), the two study years were analyzed and will be discussed separately due to the possibly confounding effects of heterogenous growth patterns caused by different day length exposure.

While total dry biomass did not vary between species in 2019 (Table 2.2), in 2020, the species did vary in total dry biomass (Table 2.3). However, differences in total biomass observed in 2020 were only between surrogate species, with the total biomass of *R. raphanistrum* not varying significantly from that of the surrogate species. The root-to-shoot ratio of *R. raphanistrum* tended to be smaller than those of the surrogate species at all leaf stages in 2019 (Table 2.4), however, in 2020, the root-to-shoot ratio of *R. raphanistrum* differed from surrogates only at the second and third leaf stages (Table 2.5). Similarly, in both years, shoot surface area differed between *R. raphanistrum* and the Brassica surrogates only at the second and third true leaf stage (Tables 2.6 and 2.7).

Table 2.2. 2019 ANOVA for biomass, root architecture, and anchorage force dependent variables. Bold font indicates statistically significant P-values.

Source	df	Biomass			Root Architecture				Anchorage Force
		Total Biomass	*Shoot Surface Area*	*Root-to-shoot Ratio*	*Root Length*	*Root Surface Area*	*Average Root Diameter*	*Number of Root Tips*	*Maximum Anchorage Force*
Block	5	0.108	0.704	0.648	0.773	0.656	0.981	0.151	0.439
Species	4	0.755	**< 0.001**	0.573	**< 0.001**	**< 0.001**	0.135	**< 0.001**	**< 0.001**
Leaf Stage	2	0.301	**0.001**	**0.016**	**< 0.001**	**< 0.001**	**< 0.001**	**0.003**	**0.001**
Species*Leaf Stage	8	0.789	**0.059**	0.241	**< 0.001**	**< 0.001**	0.816	0.148	0.598

Table 2.3. 2020 ANOVA for biomass, root architecture, and anchorage force dependent variables. Bold font indicates statistically significant P-values.

Source	df	Biomass			Root Architecture				Anchorage Force
		Total Biomass	*Shoot Surface Area*	*Root-to-shoot Ratio*	*Root Length*	*Root Surface Area*	*Average Root Diameter*	*Number of Root Tips*	*Maximum Anchorage Force*
Block	5	0.704	0.482	0.316	0.753	0.767	0.271	0.692	0.728
Species	4	**0.050**	**< 0.001**	**0.017**	**0.001**	**0.001**	**0.010**	**0.006**	**< 0.001**
Leaf Stage	2	**< 0.001**	**< 0.001**	**0.001**	**< 0.001**	**< 0.001**	**< 0.001**	**< 0.001**	**< 0.001**
Species*Leaf Stage	8	**0.066**	**0.001**	**0.001**	0.079	0.139	0.275	0.715	**0.029**

Table 2.4. 2019 main effect means for biomass, root architecture, and anchorage force dependent variables. Data were square-root transformed to meet the assumptions of ANOVA. Back-transformed mean values are shown. Means not connected by the same letter are signficantly different. No connecting letters represents a nonsignficant effect.

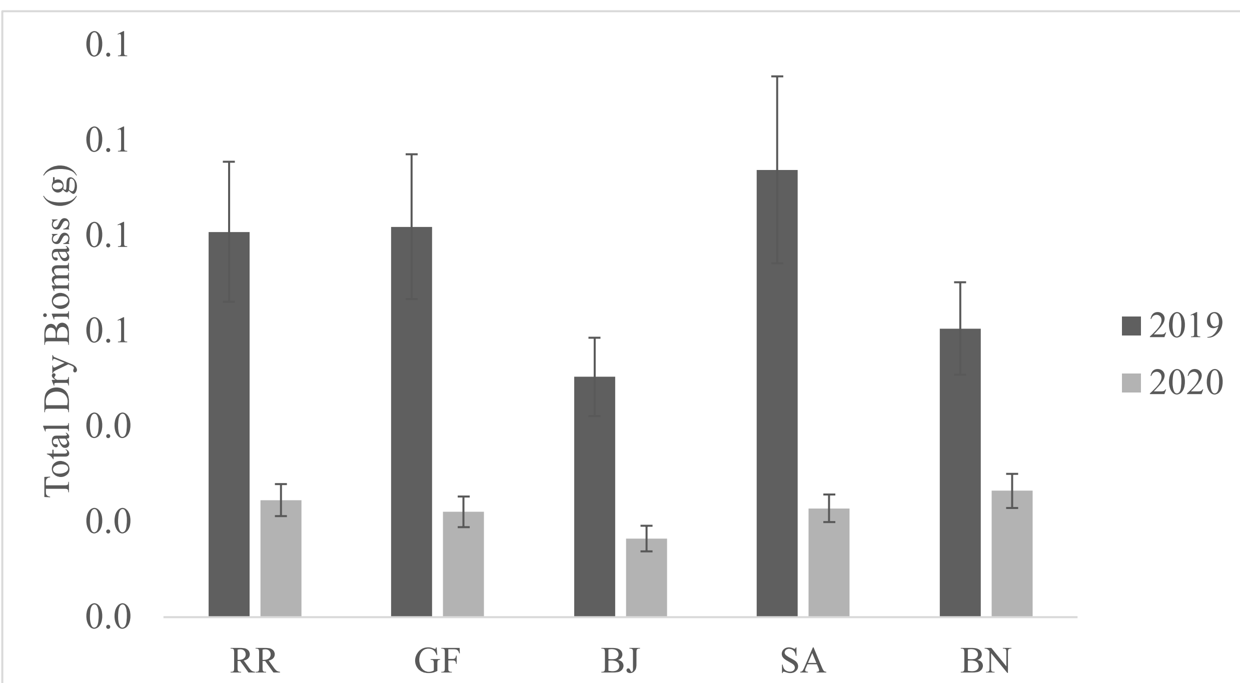
Main Effects	Total Biomass	Shoot Surface Area	Root-to-shoot ratio	Root length	Root Surface Area	Average Root Diameter	Number of Root Tips	Maximum Anchorage Force
	--- *g* ---	-- *cm*^{2} --	--- *g/g* ---	-- *cm* --	-- *cm*^{2} --	--- *mm* ---	-- *no.* --	---- *N* ----
Species								
RR	0.08	29.4$_{a}$	0.96$_{b}$	103$_{b}$	10.0$_{c}$	0.31$_{c}$	154$_{b}$	0.77$_{ab}$
GF	0.10	12.3$_{bc}$	1.71$_{ab}$	108$_{b}$	15.4$_{b}$	0.45$_{a}$	241$_{a}$	0.65$_{b}$
SA	0.08	15.7$_{bc}$	1.37$_{ab}$	128$_{b}$	16.1$_{bc}$	0.40$_{b}$	308$_{a}$	0.60$_{b}$
BN	0.06	21.8$_{ab}$	1.13$_{ab}$	250$_{a}$	24.6$_{a}$	0.34$_{c}$	421$_{a}$	0.89$_{a}$
BJ	0.05	12.2$_{c}$	1.79$_{a}$	99$_{b}$	11.9$_{bc}$	0.39$_{b}$	246$_{ab}$	0.54$_{b}$
Leaf Stage								
One	0.07	9.2$_{b}$	1.28	73$_{b}$	8.4$_{b}$	0.38	142$_{b}$	0.49$_{c}$
Two	0.08	16.1$_{b}$	1.43	96$_{b}$	11.6$_{b}$	0.39	188$_{b}$	0.66$_{b}$
Three	0.08	31.2$_{a}$	1.49	258$_{a}$	27.7$_{a}$	0.36	509$_{a}$	0.91$_{a}$

Table 2.5. 2020 main effect means for biomass, root architecture, and anchorage force dependent variables. Data were square-root transformed to meet the assumptions of ANOVA. Back-transformed mean values are shown. Means not connected by the same letter are signficantly different. No connecting letters represents a nonsignficant effect.

Main Effects	Total Biomass	Shoot Surface Area	Root-to-shoot ratio	Root length	Root Surface Area	Average Root Diameter	Number of Root Tips	Maximum Anchorage Force
	----- *g* ------	-- *cm*^{2} ---	-- *g/g* ---	-- *cm* --	-- *cm*^{2} ---	--- *mm* ---	-- *no.* ---	---- *N* -----
Species								
RR	0.025$_{ab}$	13.0$_{ab}$	1.77$_{ab}$	79$_{b}$	8.8$_{bc}$	0.37$_{ab}$	345$_{b}$	0.94$_{a}$
GF	0.022$_{ab}$	9.7$_{bc}$	1.90$_{ab}$	118$_{ab}$	13.1$_{abc}$	0.37$_{ab}$	703$_{a}$	0.66$_{bc}$
SA	0.021$_{ab}$	10.7$_{bc}$	1.58$_{b}$	130$_{ab}$	15.0$_{ab}$	0.39$_{a}$	745$_{a}$	0.69$_{bc}$
BN	0.027$_{a}$	18.1$_{a}$	1.58$_{b}$	155$_{a}$	15.6$_{a}$	0.34$_{b}$	708$_{a}$	0.72$_{ab}$
BJ	0.016$_{b}$	5.8$_{c}$	2.81$_{a}$	75$_{b}$	8.2$_{c}$	0.35$_{ab}$	474$_{ab}$	0.46$_{c}$
Leaf Stage								
One	0.016$_{b}$	6.4$_{c}$	2.42$_{a}$	61$_{b}$	7.3$_{b}$	0.39$_{a}$	373$_{b}$	0.46$_{c}$
Two	0.019$_{b}$	10.3$_{b}$	1.74$_{ab}$	89$_{b}$	10.2$_{b}$	0.37$_{a}$	549$_{b}$	0.63$_{b}$
Three	0.030$_{a}$	19.1$_{a}$	1.59$_{b}$	187$_{a}$	19.2$_{a}$	0.34$_{b}$	883$_{a}$	1.01$_{a}$

As larger weeds have been shown to be more difficult to control across a range of PWC tools (Baerveldt and Ascard 1999; Lundkvist 2009; Pullen and Cowell 1997), differences in total biomass are potentially critical restrictions to the ability of a surrogate weed to reflect the reaction to cultivation of real a weed. Likewise, differences in biomass allocation, as reflected in root-to-shoot ratios, have been linked to susceptibility to mechanical uprooting (Ennos 2000). The similarities between *R. raphanistrum* and surrogate weeds in biomass and biomass allocation support our hypothesis that these Brassica species are viable surrogates. Additionally, similarities in root-to-shoot ratios at the first leaf stage are potentially more important than dissimilarities at later leaf stages (Table 2.4) as PWC studies generally focus on cultivation while weeds are in the cotyledon to first true leaf stages (Brown and Gallandt 2018), due to the importance of maintaining a size advantage for crops (Gallandt and Weiner 2015).

Figure 2.2. Total plant biomass of *Raphanus raphanistrum* and Brassica surrogate weed species. Means from two experiments in two different years, each with six replicates. Error bars show the standard error of the mean.



Root System Architecture. While *R. raphanistrum* had shorter roots than *S. alba* and *B. napus* in 2020 at all leaf stages (Table 2.7), in 2019 *R. raphanistrum* did not differ from the surrogates at the first leaf stage (Table 2.6). As expected, root length, across all species, increased with growth stage (Tables 2.4 and 2.5). Similarly, in 2020, *R. raphanistrum* had smaller root surface areas than *S. alba* and *B. napus* at all leaf stages (Table 2.7) but did not differ from any surrogate in 2019 at the first leaf stage (Table 2.6). Across all species, plants in 2020 had more root tips, but in both years, *R. raphanistrum* had significantly fewer root tips than all surrogate species at all leaf stages (Tables 2.6 and 2.7). *R. raphanistrum* had smaller average root diameters than *G. flavescens*, *S. alba, and B juncea* at all three leaf stages in 2019 and *S. alba* in 2020 (Tables 2.8 and 2.9). Additionally, at all leaf stages, *R. raphanistrum* and surrogate roots were primarily composed of roots 0.55 mm, or smaller, in diameter (Figure 2.3).

Root length and root tensile strength are generally correlated to the uprooting resistance of plants (Bailey et al. 2002; Edmaier et al. 2014; Ennos 1989; Dupuy et al. 2005). Also, root tensile strength was positively correlated to root diameter (Pollen and Simon 2005; Pohl et al. 2011). Our results demonstrating similarities in root length and root surface area of *R. raphanistrum* and surrogates at earlier leaf stages support the use of these surrogate species for PWC research. Differences at later growth stages are less concerning as PWC studies are typically conducted while weeds are small and therefore characteristics at the third leaf stage might be of less consequence in this context.

Table 2.6. Interacting effects of species and plant growth stage on the shoot surface area, root length, and root surface area of *Raphanus raphanistrum* and Brassica surrogate weeds in 2019. Data were square-root transformed to meet the assumptions of ANOVA. Back-transformed mean values are shown. Bold font indicates significant P-values.

	Shoot Surface Area			Root Length			Root Surface Area		
Species	One	Two	Three	One	Two	Three	One	Two	Three
	----------- *cm*------------			----------- *cm* -----------			------------ cm^2 ------------		
R. raphanistrum (RR)	11	31	47	63	105	143	7	10	14
G. flavescens (GF)	9	11	19	71	95	184	10	14	26
S. alba (SA)	9	14	24	84	98	203	10	13	26
B. napus (BN)	8	17	44	73	119	619	7	13	59
B. juncea (BJ)	9	9	18	70	67	157	9	9	18
Contrasts	-- P > F --								
RR vs GF	0.978	**0.008**	**0.001**	0.803	0.854	0.241	0.360	0.249	**0.004**
RR vs SA	0.715	**0.032**	**0.005**	0.501	0.856	0.114	0.348	0.545	**0.005**
RR vs BN	0.618	**0.068**	0.723	0.766	0.605	< **0.001**	0.810	0.394	< **0.001**
RR vs BJ	0.728	**0.003**	**0.001**	0.817	0.330	0.655	0.521	0.797	0.217

Table 2.7. Interacting effects of species and plant growth stage on the shoot surface area, root length, and root surface area of *Raphanus raphanistrum* and Brassica surrogate weeds in 2020. Data were square-root transformed to meet the assumptions of ANOVA. Back-transformed mean values are shown. Bold font indicates significant P-values.

	Total Biomass			Shoot Surface Area			Root-to-shoot ratio		
Species	One	Two	Three	One	Two	Three	One	Two	Three
	------------- *g* ------------			------------ *cm²* ------------			------------- *g/g* ------------		
R. raphanistrum (RR)	0.02	0.03	0.03	6.6	11.8	21.9	1.8	2.5	1.0
G. flavescens (GF)	0.01	0.02	0.03	6.8	7.2	16.3	1.6	2.1	2.0
S. alba (SA)	0.02	0.02	0.02	7.6	9.8	14.5	2.4	1.6	0.7
B. napus (BN)	0.19	0.02	0.04	6.9	16.3	31.1	3.0	1.2	0.5
B. juncea (BJ)	0.01	0.01	0.03	4.3	5.6	8.12	3.2	1.4	3.6
	--- P > F ---								
RR vs GF	0.619	0.124	0.467	0.937	0.118	0.077	0.750	0.327	**0.032**
RR vs SA	0.547	0.502	0.118	0.719	0.637	**0.019**	0.363	0.110	0.452
RR vs BN	0.625	0.167	0.111	0.914	0.145	**0.002**	0.095	**0.045**	0.265
RR vs BJ	0.638	**0.005**	0.446	0.436	**0.057**	< **0.001**	0.100	0.103	**0.001**

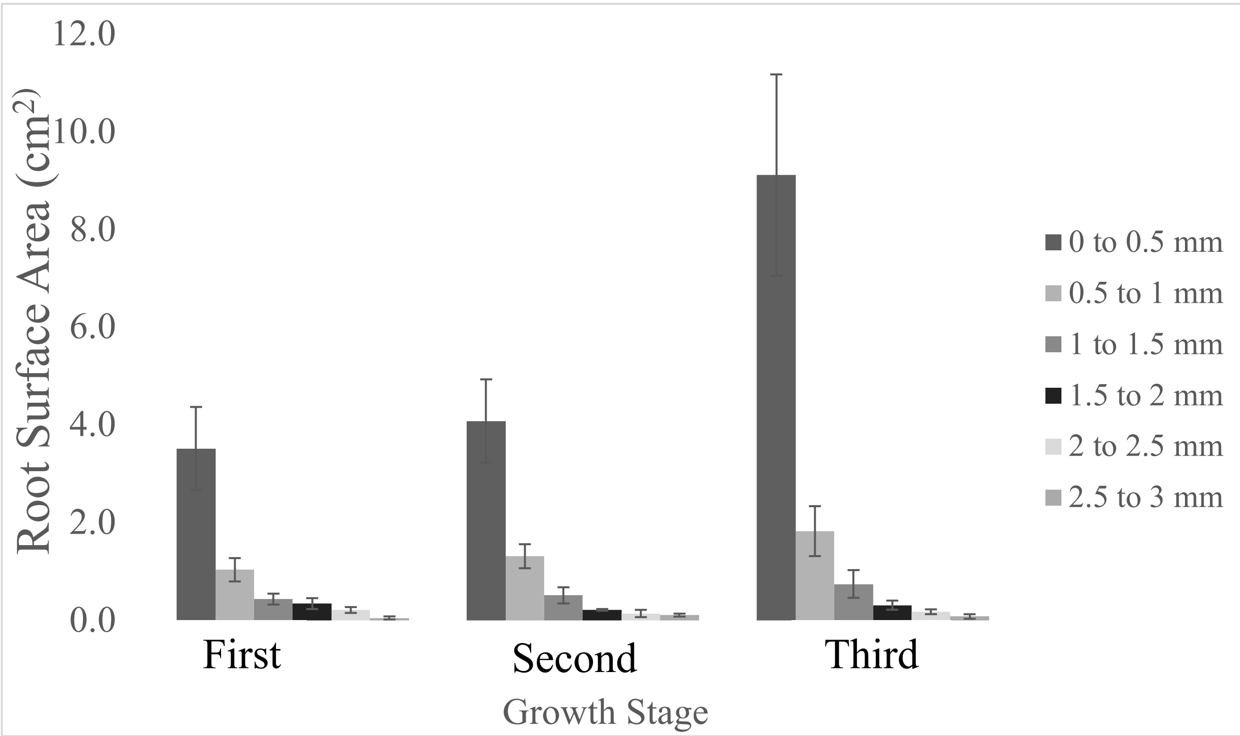
Table 2.8. The root-to-shoot ratios, average root diameters, number of root tips, and anchorage forces of *R. raphanistrum* and selected Brassica surrogate weeds in 2019. Data were square-root transformed to meet the assumptions of ANOVA. Back-transformed mean values are shown. Bold font indicates significant P-values.

Species	Root-to-shoot ratio	Average Root Diameter	Number of Root Tips
	------- *g/g* -------	------- *mm* -------	------- *no.* -------
R. raphanistrum (RR)	0.9	1.4	154
G. flavescens (GF)	1.1	1.6	241
S. alba (SA)	1.1	1.5	308
B. napus (BN)	1.0	1.4	421
B. juncea (BJ)	1.2	1.5	246
Contrasts	----------------------------	P > F	----------------------------
RR vs. GF	**0.012**	**< 0.001**	**0.005**
RR vs. SA	**0.061**	**< 0.001**	**0.002**
RR vs. BN	0.201	0.259	**0.001**
RR vs. BJ	**0.001**	**< 0.001**	**0.015**

Table 2.9. The root lengths, root surface areas, average root diameters, and numbers of root tips of *R. raphanistrum* and selected Brassica surrogate weeds in 2020. Data were square-root transformed to meet the assumptions of ANOVA. Back-transformed mean values are shown. Bold font indicates significant P-values.

Species	Root Length	Root Surface Area	Average Root Diameter	Number of Root Tips
	----- *cm* ------	----- *cm*^{2} ------	----- *mm* ------	------ *no.* -----
R. raphanistrum (RR)	79	8.8	0.34	345
G. flavescens (GF)	118	13.1	0.37	703
S. alba (SA)	130	15.0	0.39	745
B. napus (BN)	155	15.6	0.34	708
B. juncea (BJ)	75	8.2	0.35	474
Contrasts	---------------------------------	P > F	---------------------------------	
RR vs. GF	0.100	**0.068**	0.689	**0.005**
RR vs. SA	**0.034**	**0.010**	0.081	**0.002**
RR vs. BN	**0.001**	**0.004**	0.103	**0.004**
RR vs. BJ	0.724	0.708	0.372	0.333

Figure 2.3. *Raphanus raphanistrum* root surface area separated, into first, second, and third leaf stages, within six size classes. Means from one experiment, each with six replicates. Error bars shown the standard error of the mean.



Anchorage Force. *R. raphanistrum*, *G. flavescens*, and *S. alba*, had higher anchorage forces in 2020 than in 2019 (Table 2.10). Higher anchorage forces in 2020 may be related to shorter daylengths, which have been noted in previous studies to result in shorter roots with more fine, lateral root growth (Franco et al. 2011; Macdonald and Owens 2010) that can increase anchorage (Ennos 1993; Edmaier 2014). In 2019, *R. raphanistrum* had a higher anchorage force than *B. juncea* at the second leaf stage and *G. flavescens* and *S. alba* at the third leaf stage but similar to all surrogates at the first leaf stage (Table 2.10). In 2020, *R. raphanistrum* had a higher anchorage force than all of the surrogate species across growth stages (Table 2.10). For all species, anchorage force increased with each leaf stage (P = 0.0007), as expected and noted in previous studies (Bailey et al. 2002; Meyler and Rühling 1966) (Figure 2.4).

As with biomass and root architecture parameters, anchorage force was analyzed separately by year. Results for both years were within the range of previously recorded root anchorage forces in similar studies (Edmaier et al. 2014). As noted in other studies, anchorage force is affected by root tensile strength, soil composition, and root-soil adherence properties (Ennos 1989; Ennos 1990). We observed that at the beginning of the uprooting process, the force exerted on each plant increased linearly with time until reaching a maximum, while in the latter half of the curve the force dropped sharply a number of times, presumably due to root release from the sand and breakage of small secondary roots (Figure 2.5).

Several studies have investigated the relationship between anchorage force and the cultivation susceptibility of field weeds (Fogelberg and Dock Gustavsson 1998; Meyler and Ruhling 1966), and Kurstjens and Kropff (2000) developed a model for predicting the selective uprooting by flex-tine harrows based on plant anchorage forces. Comparable anchorage forces at the first leaf stage in 2019 are in accordance with previously stated similarities in root architecture at earlier leaf stages and suggest that *R. raphanistrum* and the surrogate weed species would theoretically react similarly to cultivation. However, the higher anchorage force of *R. raphanistrum* in 2020 is contrary to what one would expect given the observed root parameters (Table 2.3 and Table 2.5). Differences between the anchorage forces of real weeds and corresponding surrogate species, may decrease the viability of surrogate use in PWC studies, particularly while assaying tools for which uprooting is the primary mode of action.

Figure 2.4. Maximum anchorage force of *Raphanus raphanistrum* and Brassica surrogate weed species at one, two, and three true leaves. Means from two experiments, each with six replicates. Error bars show the standard error of the mean.

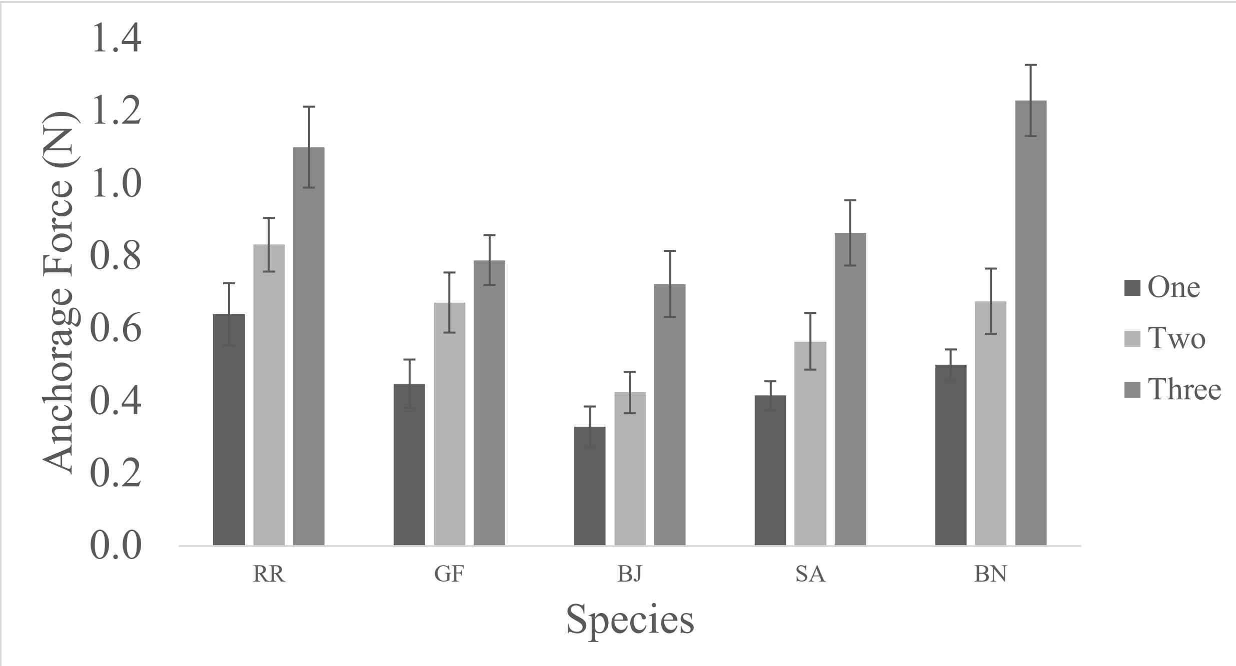
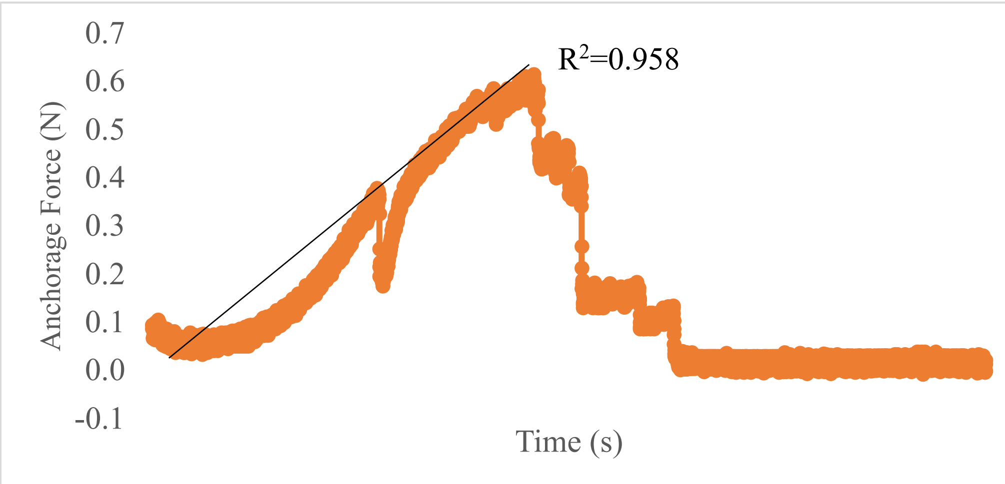


Table 2.10. The anchorage forces of Raphanus raphanistrum and Brassica surrogate weeds separated into the two study years and the three leaf stages. Data were square-root transformed to meet the assumptions of ANOVA. Back-transformed mean values are shown. Bold font indicates statistically significant P-values.

Species	Maximum Anchorage Force					
	------------------ *N* ------------------					
	2019			2020		
	One	Two	Three	One	Two	Three
R. raphanistrum (RR)	0.55	0.73	1.13	0.71	0.95	1.20
G. flavescens (GF)	0.29	0.68	0.78	0.52	0.65	0.79
S. alba (SA)	0.44	0.52	0.80	0.38	0.60	1.02
B. napus (BN)	0.58	0.91	1.23	0.42	0.43	1.30
B. juncea (BJ)	0.45	0.41	0.74	0.24	0.42	0.71
Contrasts	------------------ P > F ------------------					
RR vs GF	0.162	0.755	**0.049**	0.177	**0.052**	**0.007**
RR vs SA	0.471	0.150	**0.070**	**0.023**	**0.021**	0.225
RR vs BN	0.842	0.207	0.573	**0.039**	**0.008**	0.508
RR vs BJ	0.552	**0.029**	0.033	**0.001**	**0.007**	**0.002**

Figure 2.5. The change in anchorage force as a *Guillenia flavescens* seedling at one true leaf was uprooted. The force exerted on the seedling increased linearly before decreasing sharply. Best fit line equation: y = 0.09358x + - 0.3738. R^2 0.958



Seed Mass. Both large- and small-seeded surrogate species were comparable to *R. raphanistrum* at the first leaf stage in root-to-shoot ratio, shoot surface area, root length, root surface area, and average root diameter (Table 2.11). At later leaf stages, large-seeded surrogates had similar total biomasses, root-to-shoot ratios and shoot surface areas while small-seeded surrogates had comparable root lengths and root surface areas (Table 2.11). Moreover, in 2019 both large- and small-seeded surrogates had comparable anchorage forces at the first leaf stage while varying at the second and third leaf stage in 2020 (Table 2.11).

As previous research has linked seed mass to the early growth and establishment of seedlings (Westoby 1998) and has been shown to influence root architecture (Leishman et al. 2000), we anticipated that seed mass could be an appropriate criterion for the selection of surrogates in a given experiment. However, given these inconsistent results, seed mass does not appear to be a useful metric for predicting which surrogate would more closely reflect the early growth characteristics of *R. raphanistrum* despite the influence of seed mass observed in past studies. Moreover, seed-size would appear to be even less consequential at the first leaf stage.

In summary, *R. raphanistrum* and the four included Brassica surrogate weed species were comparable in a number of parameters of biomass and root architecture. These similarities are especially true at earlier growth stages, at which PWC studies are predominately conducted. However, significant differences in anchorage force (Table 2.10), may advocate for caution and further research concerning using surrogates for PWC studies where uprooting is the primary mode of action. Additionally, seed mass may not be a useful component of the surrogate weed selection process.

Crops and weeds vary in susceptibility to PWC across species (Gallandt et al. 2018); therefore, the early growth and development, and susceptibility to PWC, of other commonly used surrogate species, such as winter wheat (*Triticum aestivum*) (Reid et al. 2014) or white proso millet (*Panicum miliaceaum*) (Brown and Gallandt 2018) should be included in future research. Additionally, we recognize that there may be cultivation modes of action other than uprooting (i.e., burial and slicing), for which other early growth characteristics may be of greater import, such as stem thickness.

Moreover, in our related study (Sanchez and Gallandt 2021), Brassica surrogates exhibited correlated rates of cultivation efficacy to *R. raphanistrum*, suggesting that the use of surrogates could generate useful data if paired with a related real weed as an internal reference. This could be accomplished by either sowing a small number of subsamples with real weed seeds, or counting ambient weeds, while primarily relying on the efficiency gained by utilizing surrogates.

Table 2.11. Biomass and Root Architecture measurements analyzed by seed mass, with means separated as appropriate. Data were square-root transformed to meet the assumptions of ANOVA. Back-transformed mean values are shown. Bold font indicates statistically significant P-values.

Species	Total Biomass	Root-to-shoot						Shoot Surface Area			Root Length			Root Surface Area			Average Root Diameter					
	g	*g/g*						*cm²*			*cm*			*cm²*			*mm*					
		2019			2020												2019			2020		
		One	Two	Three	One	Two	Three	One	Two	Three	One	Two	Three	One	Two	Three	One	Two	Three	One	Two	Three
RR	0.051	2.05	0.99	1.04	1.82	2.52	0.97	8.94	20.52	24.42	57.88	76.06	116.60	6.34	8.15	11.38	0.33	0.35	0.31	0.38	0.40	0.32
Large-Seeded[a]	0.049	1.39	1.23	1.97	2.35	1.85	1.09	7.89	12.44	24.11	69.73	101.87	275.61	8.32	12.42	29.26	0.39	0.43	0.38	0.39	0.40	0.34
Small-Seeded[b]	0.033	1.85	2.14	1.33	3.22	1.97	3.62	6.69	7.51	13.30	61.79	59.39	135.81	7.56	7.25	15.08	0.40	0.42	0.37	0.38	0.37	0.33
Contrasts	P>F																					
RR vs. Large-Seeded	0.997	0.630	0.202	0.158	0.392	0.176	0.844	0.740	**0.009**	0.847	0.453	0.159	**< 0.001**	0.242	**0.038**	**< 0.001**	**0.087**	**0.018**	**0.082**	0.939	0.896	0.467
RR vs. Small-Seeded	**0.032**	0.444	**0.015**	0.582	0.120	0.393	**0.001**	**0.078**	**< 0.001**	**< 0.001**	0.816	0.617	0.405	0.535	0.866	0.163	0.126	0.156	0.211	0.903	0.572	0.701

[a] *Sinapis alba* L., *Gullenia flavescenes* L., and *Brassica napus* L. were considered large-seeded.

[b] *Brassica juncea* L. was considered small-seeded.

CHAPTER THREE

A COMPARISON OF BRASSICA SURROGATE WEEDS AND WILD RADISH (*RAPHANUS RAPHANISTRUM*): II. RESPONSE TO FLEX-TINE HARROWS

INTRODUCTION

Interest in the development of improved implements for physical weed control (PWC) has increased in recent years due to a lack of effective herbicides and labor shortages (Fennimore et al. 2016). Tools for PWC vary in design and adjustability and have been known to range in weed killing effectiveness as much as 21 to 90% (Gallandt et al. 2018). Moreover, the efficacy of PWC tools can be affected by soil conditions (Duerinckx et al. 2005), weed growth stage (Rasmussen et al. 2008), and weed community composition (Mohler 2001). A better understanding of how PWC tools perform would aid in the development of improved cultivation tools (Kurstjens and Perdok 2000).

Due to the multi-faceted nature of evaluating PWC tools, researchers often use “surrogate” weeds to remove sources of variation often found among real weeds such as high rates of seed dormancy (Malik et al. 2010), variable stands (Myers et al. 2005), and heterogenous emergence patterns (Egley and Williams 1991). Surrogate weeds are domesticated species used in place of, or in addition to, their weedy counterparts (Gallandt 2010; Kolb and Gallandt 2012; Melander and McCollough 2020). However, while McCollough et al. (2020) noted similarities between real and surrogate weed responses to hoeing, explicit comparisons have yet to be made.

In an attempt to make these comparisons, we observed, in a related study, dissimilarities in the anchorage forces (i.e., the force necessary to uproot a plant) and the root architectures (i.e., the spatial configuration of the plant root system) of wild radish (*Raphanus raphanistrum* L.) and selected Brassica surrogates (Sanchez and Gallandt 2021). Past studies have linked plant anchorage force to susceptibility to PWC (Fogelberg and Dock Gutavsson 1998; Kurstjens and Kropff 2000; Kurstjens et al. 2004). Given these differences between an actual Brassica weed species and commonly used weed surrogate species, explicit comparisons in the field are necessary to justify the continued use of surrogate weeds in studies of PWC.

Variation is common not only between related species, but also within a species. To remove species variation, a number of studies have utilized "artificial" weeds, fashioned from simple and identical objects such as small wooden cylinders (Kshetri et al. 2019). Typically, artificial weeds have been used to assess mechanistic attributes of cultivation tools such as the capacity for soil upheaval (Zhang and Chen 2017) but also have potential for assaying PWC efficacy. However, the use of artificial weeds remains nascent, especially in field experiments, and requires further validation.

The objective of this study was to evaluate the ability of two broadleaf, Brassica surrogate weeds to accurately reflect the cultivation susceptibility of a related weedy species, wild radish. To assess a wide range of PWC intensities, six different flex-tine harrows, with varying designs, were tested. Additionally, we assessed the suitability of seed mass as a metric for surrogate weed selection and the ability of golf tees to act as artificial weeds. We hypothesized that the included Brassica surrogate weed species would not vary significantly in response to cultivation from that of wild radish and expected that larger-seeded surrogate species would more closely reflect the rates of cultivation efficacy for the relatively large-seeded wild radish. Additionally, we expected artificial weeds to effectively simulate both surrogate and real weeds and to be less variable.

METHODS AND MATERIALS

Field Preparation. Field trials were conducted at the University of Maine Rogers Farm (44.93°N, 68.70°W) in July 2019 and August 2020. Soils were a Pushaw-Boothbay silt loam in 2019 and a Nicholville very fine sandy loam in 2020. In both years, fields were prepared by shallow rototilling, perfecta harrowing (Perfecta Field Cultivator, Unverferth Manufacturing Company, Kalida, OH), and culti-packing with an empty Brillion Sure Stand Grass Seeder (Landoll, Marysville, KS, USA). Due to the short duration of the experiments, and because we did not plan to take test crops to yield, soil amendments were not added to fields in either year. Treatments were established in a split-plot randomized complete block design with four blocks. The main-plot factor was flex-tine harrow while the subplot factor was weed species: wild radish, surrogate weed, or artificial weed. Test crops included bush beans (‘Provider’) in 2019 and beets (‘Chioggia Guardsmark’) in 2020, which were both sown with a Wizard Vacuum Seeder (Sutton Ag, California) and planted in two rows 50 cm apart on beds 127 cm wide.

Real, Surrogate, and Artificial Weeds. Two commonly used surrogate weeds, condiment mustard (*Guillenia flavescens* Hook.) and canola (*Brassica juncea* L.), were broadcast at a rate of 60 seeds 0.25 m^{-2} and raked into the soil to simulate a stand of wild radish (*Raphanus raphanistrum* L.) (Brown and Gallandt 2018; Kolb et al. 2010; McCollough et al. 2020). *R. raphanistrum* was sown in each plot at a target density of at least 60 plants per 0.25 m^{-2} (Vanhala 2004). To ensure surrogate weeds and *R. raphanistrum* were in the cotyledon to first true leaf stage at the time of cultivation, and therefore simulate weed emergence after a pre-emergence harrowing (Lundkvist 2009; Meier 2001), they were broadcast by hand and subsequently incorporated into the soil 5-7 days after test crop emergence (Brown and Gallandt 2018). Each species was sown in 0.25 m^{-2} subplots which were placed in random locations centered over the crop row in each plot.

Designation of surrogates as large- or small-seeded was based upon measurements of the 100-seed masses, using a precision balance (Sartorius, Germany) (Sanchez and Gallandt 2021). *G. flavescens* (5.32 mg $seed^{-1}$) was considered the large-seeded surrogate while *B. juncea* (2.64 mg $seed^{-1}$) designated as small-seeded.

In 2020, 35 mm long wooden golf tees were also included, as an additional analogue for ambient weeds, herein referred to as "artificial weeds" to differentiate from the surrogate weed species above (Kshetri et al. 2019). Artificial weeds were placed in the soil at a depth of 33 mm and at a density of 25 per 0.125 m^{-2} subplots.

Cultivation. Cultivation was conducted when a majority of surrogates and real weeds reached the cotyledon to first leaf stages (Meier 2001). Due to poor *R. raphanistrum* germination in a number of attempted experiments in both field seasons, bush beans were in the fourth true leaf stage (i.e., the second trifoliate leaf was unfolded) (Feller et al. 1995) and beets were in the fifth leaf stage (i.e., five true leaves were unfolded) (Meier et al. 1993) at the time of cultivation.

To include a range of designs, six flex-tine harrows were used in this study: the Johnny's Selected Seeds Tine Weeding Rake (Johnny's Selected Seeds, Fairfield, ME), Terrateck Double Wheelhoe with flex-tines (Terrateck, Lestrem, FR), Terrateck Tine Rake (Terrateck, Lestrem, FR), Tiny Treffler (Man@Machine, Molenstraat, NL), Two Bad Cats Tine Weeder (Two Bad Cats LLC., North Clarendon, VT), and Williams Tine Harrow (Market Farm Implement, Friedens, PA, USA). All flex-tine harrows were handheld and operated by a single individual except for the Williams Tine Harrow. Forward speeds for handheld tools ranged from 4.5 to 5.4

kph. The Williams Tine Harrow was mounted to a Case IH 265 Offset Cultivation Tractor driven at 5.4 kph. Varying design characteristics between tools were noted and settings deemed to be optimal were adjusted in the field (Table 3.2). The manufactured tine angles ranged from 27° to 79°, spanning what has been used in other studies to represent the spectrum of harrowing intensity based on tine angle (Gerhards et al. 2020).

Data Collection. Real and surrogate weeds were counted using 0.25 m^{-2} quadrats centered across the crop row. Stand counts were conducted before and after plots were harrowed. Due to low and variable stands, ambient weeds were not counted in either year of this study.

Artificial weed mortality was scored using a qualitative scale wherein golf tees were considered “dead” when either fully uprooted (i.e., the pointed tip was visible) or when fully buried (i.e., the head of the golf tee was fully obscured with soil). Golf tees which were only partially uprooted or buried were considered “live.”

Weed control efficacy and crop mortality were determined by the percentage of plants killed (Evans et al. 2012; Kolb et al. 2010). Within subplots, pre- and post-treatment counts for crop plants, surrogate weeds, and artificial weeds were conducted, which were then used to calculate the percent efficacy and percent crop mortality using the following equation:

$$\text{Efficacy (\%)} = ((D_b - D_a) / D_b) \qquad [1]$$

Where D_b was the pre-treatment density in each quadrat and D_a was the post-treatment density.

Statistical Analysis. Statistical analyses were conducted in JMP 15 Pro (SAS Institute Inc., Cary, NC, USA). Cultivation efficacy was analyzed using an Analysis of Variance (ANOVA). Explanatory variables included in the ANOVA were block, year, species, and tool treatment. Assumptions of normality, constant variance, and independence of errors were evaluated using

Shapiro-Wilkes tests, Levene's tests, residual-by-fitted plots, and q-q plots (Quinn and Keough 2014). Data failing to meet the assumptions for ANOVA were subjected to Box-Cox and power transformations, as necessary (Box and Cox 1964). Means were compared using orthogonal contrasts and Tukey's HSD, where appropriate. A significance level of 0.05 was used throughout the analyses for this study.

RESULTS AND DISCUSSION

Flex-tine Harrow Efficacy. Flex-tine harrow efficacy ranged from 23 to 53% across the tools (Figure 3.1). This range of weed control efficacy is comparable to results of previous flex-tine harrow studies (Brown and Gallandt 2018; Fontanelli et al. 2015; Pardo et al. 2008). The Tiny Treffler had a higher rate of efficacy than the Johnny's Selected Seeds Tine Rake, the Two Bad Cats Tine Rake, and the Terrateck Tine Rake; there were no differences between the remaining tools (Figure 3.1). Additionally, while the tools performed in nearly identical rank orders in both years, rates of efficacy were higher in 2019 than 2020 (Table 3.1). Differences between the two years may be attributable to different soil types or amounts of precipitation, as total precipitation at the study site was 28% more in 2020 than in 2019 (Kurstjens and Perdok 2000).

The design characteristics of the individual tools may have affected efficacy and crop mortality (Table 3.2). For instance, the implement with the greatest efficacy, the Tiny Treffler, had the longest and most rigid tines. Differences in tine angle have also been shown to influence tool aggressiveness (Peruzzi et al. 2010; Rasmussen and Svenningsen 1995).

Figure 3.1. Cultivation efficacy of flex-tine harrows. Means from two study years, averaged over real and surrogate weed species. Error bars show the standard error of the mean. Tools not connected by the same letter are statistically different.

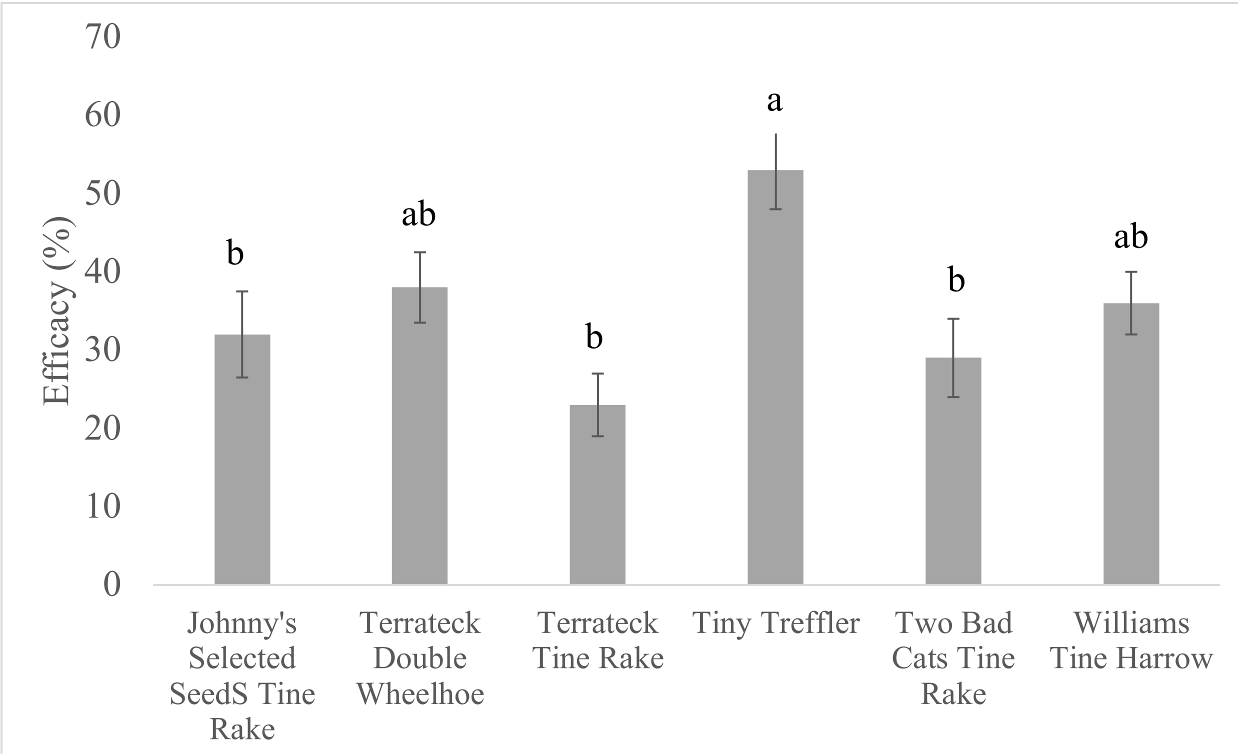


Table 3.1. Analysis of variance of the cultivation efficacy by six flex-tine harrows with *Raphanus raphanistrum* and Brassica surrogate weeds. Bold font indicates statistically significant P-values.

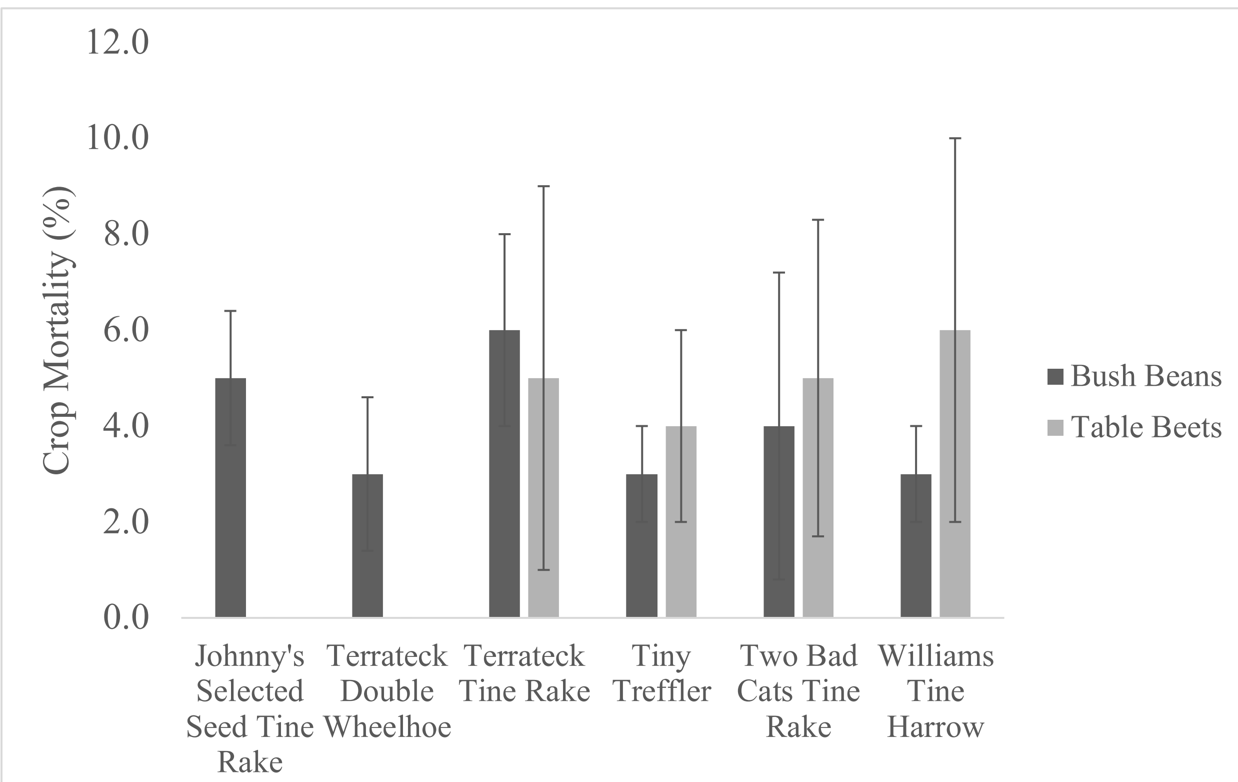
Source	df	Efficacy
Block	3	0.122
Year	1	**< 0.001**
Tool	5	**0.002**
Species	2	0.098
Year*Tool	5	0.473
Year*Species	2	0.198
Species*Tool	10	0.945
Year*Species*Tool	10	0.867

Table 3.2. Design characteristics of selected flex-tine harrows.

Tool	Diameter	Length	Angle	Rigidity	Total Number of Tines
	-- mm --	*-- cm --*	*-- Degrees --*	*-- N --*	*-- no. --*
Johnny's Selected Seeds Tine Rake	1.9	7.5	56.1	2.2	28
Terrateck Double Wheelhoe	3.1	9.5	27.1	4.4	14
Terrateck Tine Rake	3.3	9.5	28.4	4.4	14
Tiny Treffler	8.1	21.0	57.5	26.6	32
Two Bad Cats Tine Rake	3.3	12.0	54.9	1.1	21
Williams Tine Harrow	6.2	17.0	79.4	8.9	27

Crop Mortality. Based on the results of previous studies, we expected to observe crop mortality rates in the range of 12 to 18% (Melander and Hartvig 1995; Dastheib 2004). However, the mortality of bush beans ranged from 3 to 6% across the tools while that of table beets ranged from 0 to 6% (Figure 3.2). Due to their advanced size, test crops in both years resulted in low and highly variable rates of crop mortality across tools.

Figure 3.2. Crop mortality of flex-tine harrows. To address the range in cultivation susceptibility in crop species, bush beans ('Provider) were used as a test crop in 2019 while table beets ('Chioggia Guardsmark') were used in 2020 however, the experiment was conducted only once with each test crop due to constraints caused by low and variable weed germination. Error bars show the standard error of the mean.



Surrogate Weeds. The rate of cultivation efficacy for *R. raphanistrum* ranged across tools from 21% with the Two Bad Cats Tine Rake to 45% with the Tiny Treffler (Table 3.3). Rates of efficacy for both *G. flavescens* and *B. juncea* were comparable to those of *R. raphanistrum* (Table 3.3), indicating that these species are useful surrogates for this weed species.

While not statistically different than the surrogate species, generally the rate of cultivation efficacy for *R. raphanistrum* was lower than that of either surrogate weed species (Table 3.3). Cultivation efficacy can be affected by many plant factors, including biomass, root architecture, and anchorage force (Mohler et al. 1997; Mohler et al. 2016). Anchorage force is particularly important for tools in which uprooting is an important mechanism (Kurstjens and Kropff 2000). In our related studies of the early growth of *R. raphanistrum* and Brassica surrogates, anchorage forces of *R. raphanistrum* were greater than *G. flavescens* and *B. juncea*, at the first leaf stage (Sanchez and Gallandt 2021). Field measurements of anchorage forces corroborated these results as *R. raphanistrum* had higher anchorage forces than *B. juncea* and comparable anchorage forces as *G. flavescens* (data not shown). Differences in the anchorage forces of *R. raphanistrum* and surrogate weeds could affect flex-tine harrow efficacy, but such an effect was not detected in our experiments.

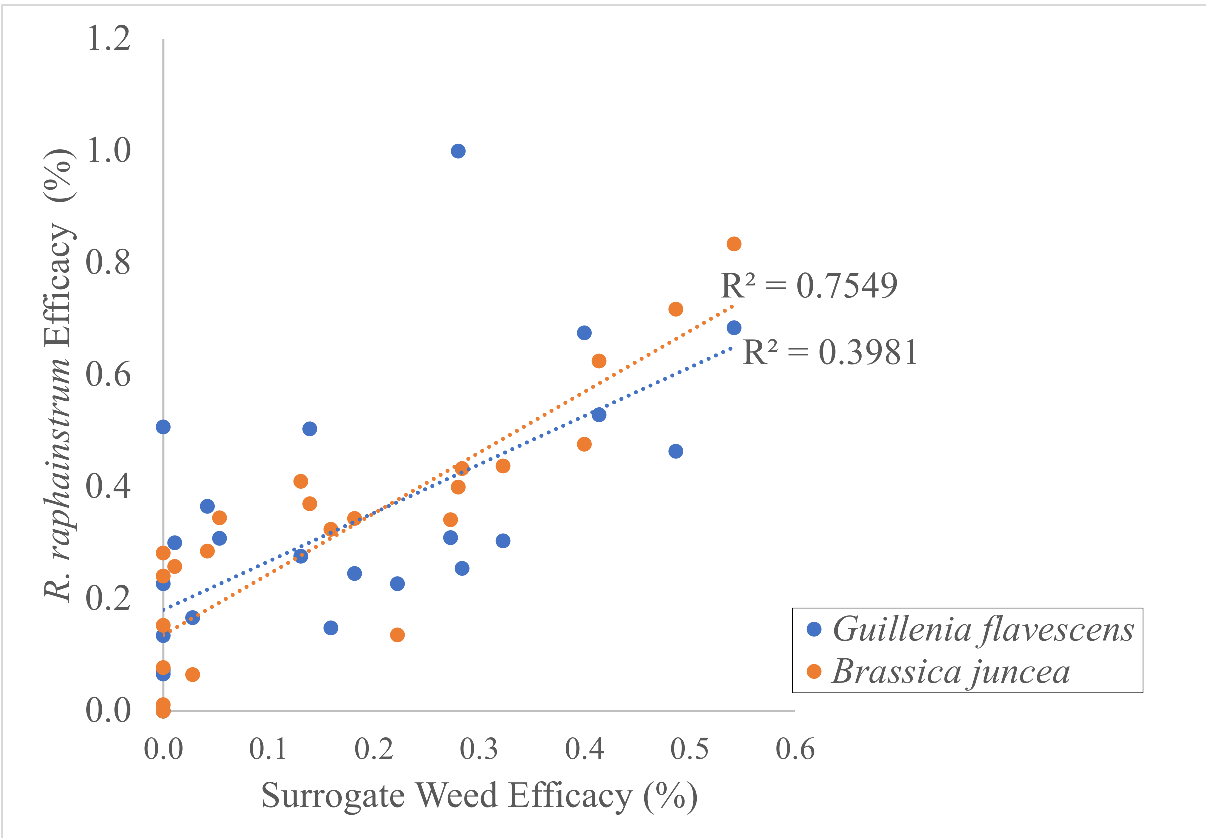
Moreover, rates of cultivation efficacy, averaged across all flex-tine harrows, for both *G. flavescens* and *B. juncea* were positively correlated with that of *R. raphanistrum* ($r = 0.63$, $P = 0.0009$; $r = 0.86$, $P = 0.0001$, respectively) (Figure 3.3), possibly due to similarities in biomass allocation and root architecture (Sanchez and Gallandt 2021). Comparable rates of cultivation efficacy and positive correlations between the two surrogate species and *R. raphanistrum* support our hypothesis that selected Brassica surrogate weeds can accurately reflect the cultivation of *R. raphanistrum* with flex-tine harrows.

Table 3.3. Efficacy of selected flex-tine harrows on *Raphanus raphanistrum*, selected Brassica surrogate weeds, and artificial weeds.

Species	Johnny's Selected Seeds Tine Rake	Terrateck Double Wheelhoe	Terrateck Tine Rake	Tiny Treffler	Two Bad Cats Tine Rake	Williams Tine Harrow
	------------------------------- Efficacy (%) -----------------------------					
R. raphanistrum (RR)	30	25	33	45	21	24
G. flavescens (GF)	38	40	38	56	22	36
B. juncea (BJ)	27	45	43	60	26	29
Artificial Weeds (AW)[a]	41	26	17	48	10	63
Contrasts	--------------------------------- P > F ----------------------------------					
RR vs GF	0.507	0.161	0.650	0.391	0.919	0.283
RR vs BJ	0.792	0.065	0.359	0.185	0.656	0.664
RR vs AW	**0.004**	0.092	0.783	0.293	0.349	**< 0.001**

[a] Efficacy data for artificial weeds is only for 2020 and was square-root transformed to meet the assumptions of ANOVA. Presented data are back-transformed least square means.

Figure 3.3. Cultivation efficacy of *G. flavescens* and *B. juncea,* across flex-tine harrows, plotted against that of *R. raphanistrum.* Best fit line equations: y = 0.865x + 0.180 and 1.085x + 0.135, for *G. flavescens* and *B. juncea,* respectively. R^2 = 0.754 and R^2 = 0.398 for *G. flavescens* and *B. juncea*, respectively.



Seed Mass. Due to the strong relationships among seed mass and biomass allocation, and therefore anchorage force and cultivation efficacy (Leishman et al. 2000; Stromberg et al. 2008; Westoby 1998), we anticipated that seed mass might be a good predictor of a surrogate for PWC assays.

G. flavescens and *B. juncea* reacted similarly to cultivation with the six flex-tine harrows (Table 3.3). Mortality of *B. juncea* – the surrogate with the largest difference in seed mass from *R. raphanistrum* – was more strongly correlated with that of *R. raphanistrum* than *G. flavescens,* which has a similar seed mass to *R. raphanistrum* (Figure 3.3). Contrary to expectations, seed mass did not appear to be a useful metric for selecting either *G. flavescens* (large-seeded) or *B. juncea* (small-seeded) as a surrogate weed to simulate *R. raphanistrum*.

Artificial Weeds. Rates of efficacy for the artificial weeds and both surrogate species were comparable (Table 3.4) and were positively, albeit weakly, correlated ($r = 0.432$; $P = 0.035$ and $r = 0.419$; $P = 0.041$, respectively) (Figure 3.4). However, cultivation efficacy for *R. raphanistrum* and the artificial weeds were not correlated ($r = 0.388$; $P = 0.061$) (Figure 3.5). Unexpectedly, we observed higher variability in efficacy for artificial weeds, relative to surrogate weeds (Table 3.5).

While acknowledging that artificial weeds do not need to perfectly reflect the reaction to cultivation of real weeds, they should at least be strongly correlated. Our golf tee weed mimics failed to accurately simulate weed seedling response to cultivation, and their response was highly variable. Our study does not support the use of golf tees to simulate the effect of flex-tine harrows on broadleaf weed species. Future research into artificial weeds that more closely reflect the intricacies of the root system architecture and anchorage forces of real weeds may result in more accurate artificial weeds. It is important to note that the primary mechanisms of harrowing are burial and uprooting (Kurstjens and Kropff 2001; Leblanc et al. 2011), and therefore artificial weeds should also be evaluated using cultivation tools with different modes of action.

Table 3.4. Main effect of efficacy averaged over tool for Brassica surrogate weed species and golf tee artificial weeds. As artificial weeds were only included in 2020, the rate of cultivation efficacy for artificial weeds is only compared to the efficacy rates of real and surrogate weeds from the 2020 study year. Data were square-root transformed to meet the assumptions of ANOVA. Presented data are back-transformed means.

Species	Efficacy
	------- % -------
R. raphanistrum (RR)	16
G. flavescens (GF)	32
B. juncea (BJ)	31
Artificial Weeds (AW)	34
Contrasts	----- P > F -----
AW vs. RR	**< 0.001**
AW vs. GF	0.828
AW vs. BJ	0.672

Figure 3.4. Cultivation efficacy of artificial weeds by flex-tine harrows. Means averaged over four blocks. Error bars show the standard error of the mean. Tools not connected by the same letter are statistically different.

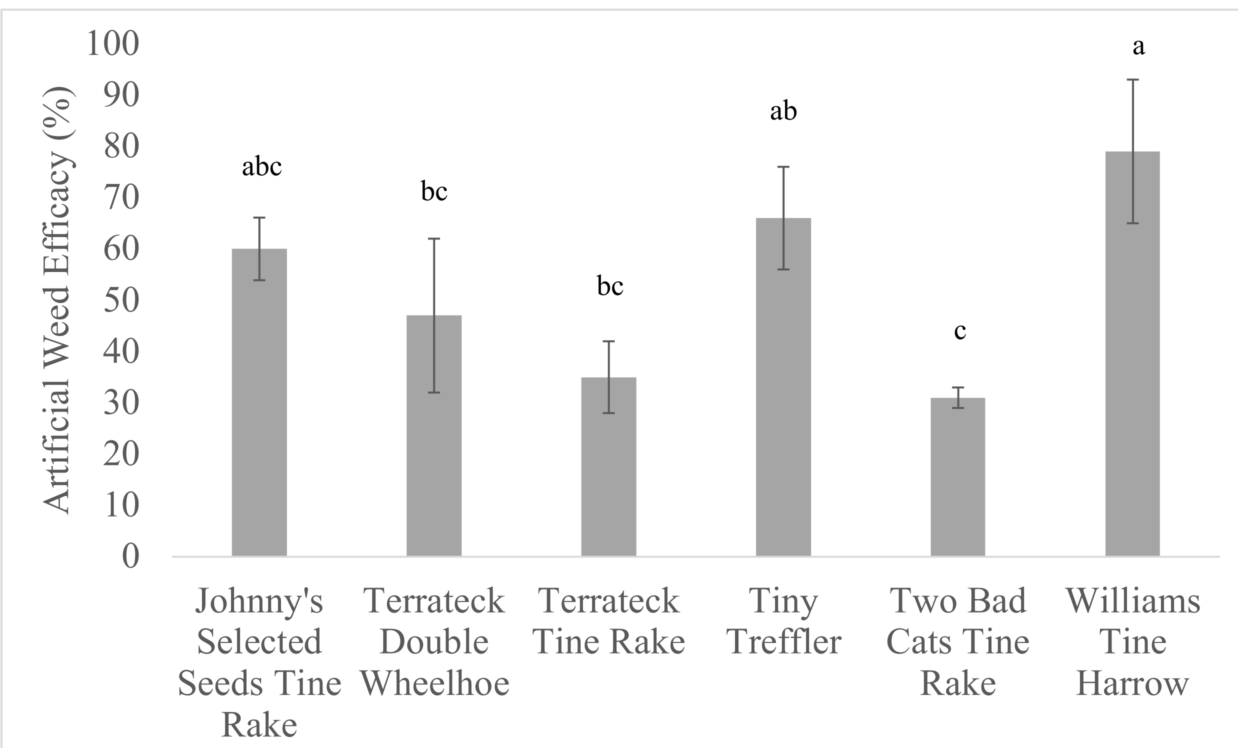


Figure 3.5 Cultivation efficacy of *R. raphanistrum*, *G. flavescens,* and *B. juncea*, across flex-tine harrows, plotted against that of the Artificial Weeds. Best fit line equations: y = 0.257x + 0.077; y = 0.394x + 0.189; y = 0.348x + 0.196, for *R. raphanistrum, G. flavescens, B. juncea*, respectively. $R^2 = 0.15$; $R^2 = 0.18$; and $R^2 = 0.17$, for *R. raphanistrum, G. flavescens, B. juncea*, respectively.

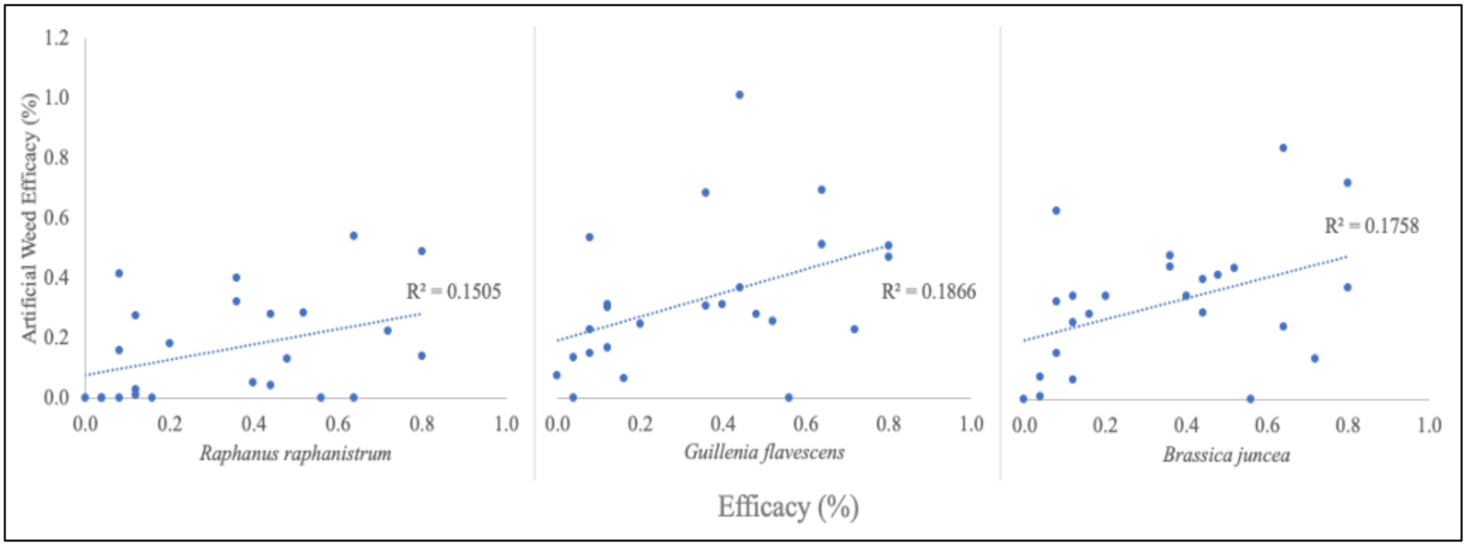


Table 3.5 Coefficients of variation for *R. raphanistrum*, selected Brassica surrogates, and artificial weeds.

Species	Coefficient of Variation
Raphanus Raphanistrum	79.7
Guillenia flavescens	62.2
Brassica juncea	67.3
Artificial Weeds	76.4

Overall, we conclude that selected Brassica surrogate weeds can be useful analogues for PWC studies of a related weedy species, in this case, *R. raphanistrum*. Additionally, seed mass was not a useful metric for the selection of surrogate weeds to simulate *R. raphanistrum*. Moreover, our results demonstrate a need for further research and development in the manufacturing of suitable artificial weeds that will be both accurate and less variable.

CHAPTER FOUR

EVALUATING THE POTENTIAL OF INEXPENSIVE, WEARABLE GPS TECHNOLOGIES TO MONITOR ON-FARM ASSETS

INTRODUCTION

Organic farms often have diverse enterprises that provide economic benefits by expanding markets and reducing risk (Kremen and Miles 2012). Diversification presents challenges, including opportunity costs if less lucrative enterprises are chosen in lieu of more profitable ones, or if significant inefficiencies are present therein (Carsan et al. 2014). Farmers may not be aware of the real-time elements that contribute to profit, and expenses associated with individual enterprises because performance is highly context specific (Rosa-Schleich et al. 2019). Ideally, farmers would monitor each of their ventures, adapting them through changes in pricing or the reduction of expenses (Wiswall 2009). Such nimble decision making requires access to reliable and timely data regarding farm assets, including inputs such as fertility, seed, equipment use and labor.

Historically, farmers have recorded and reviewed budget information using pen and paper crop journals, often with spreadsheet software. Today, there are a vast array of digital farm management information systems (FMIS), including dozens designed specifically for diversified fruit and vegetable producers; examples include Granular® (Corteva Agriscience, Wilington, DE, USA), EasyFarm® (Vertical Solutions, Minot, ND, USA), Croptracker® (DragonFly Inc, Kingston, Ontario, Canada), and FarmOS® (farmos.org) that allow farmers to track many assets across their farms. While these tools effectively manage data, expenses and revenue must be manually entered, a task that often is relegated to a "rainy day."

Tracking labor expenses can be especially complicated. Analyzing payroll records (Wiswall 2009) is straightforward, but it is difficult to differentiate between time spent on disparate farm tasks. Moreover, these records do not allow farm managers to understand inefficiencies in a timely manner. Crop-specific labor assessments are also complicated because activities are temporally sporadic and can span months or even years of work.

Wearable GPS devices, including watches, pendants, and bracelets, are routinely used to locate and monitor individuals, and also for post-hoc tracking of activities (Stopher et al. 2018). GPS tracking has been used to better understand the effects on physical movement of cognitive disorders due to multiple sclerosis (MS) and advanced age (Neven et al. 2012; Williamson et al. 2017). These studies suggest that wearable GPS devices are a viable method of spatial data collection while remaining non-hindering to the wearer. Given this, we hypothesized that wearable GPS devices could be used to track the time employees spent at particular farm locations, and by extension on specific farm tasks, throughout the day.

Our objective specifically was to determine the viability of a relatively inexpensive system for monitoring farm labor expenses, using Garmin Instinct® watches. We hypothesized that the use of commercially available GPS technologies would be an improvement upon typical farm labor tracking methods by acquiring farm asset information more efficiently and could potentially be integrated into existing farm management information systems.

MATERIALS AND METHODS

A field experiment was conducted at the University of Maine Rogers Farm (44.93°N, 68.70°W) during the summer of 2020. A "model farm" was established across two fields (54 x 20 m and 70 x 17 m, respectively); soils were a Nicholville very fine sandy loam (coarse-silty, isotic, frigid Aquic Haplorthods). Initial tillage was done with a tandem off-offset disk to control winter annual weeds. Nutri-wave™ 4-1-2 organic fertilizer (Envirem Organics, Fredericton, NB, Canada) was applied at 50.4 kg ha^{-1} and incorporated using a Perfecta Harrow mounted to a John Deere 6300. Feather meal (13-0-0) was applied by hand at 39.2 kg ha^{-1} to individual carrot beds and incorporated by hand. Immediately prior to crop planting, the study area was rototilled and culti-packed to firm the beds. Seeds were sourced from Johnny's Selected Seeds (Winslow, ME). In field A, beds 152 cm on center were established and sown to eight different crops with a Jang Seeder (Jang Automation Co., LTD, Chungcheongbuk-Do, Korea) and, in field B, three beds were prepared similarly and sown to beet (Chioggia Guardsmark) with a Wizard vacuum seeder (Sutton Ag Enterprises Inc., Salinas, CA, USA). To represent a small, diversified vegetable farming operation, nine crops were sown, maintained, and harvested (Table 4.1).

Labor inputs included planting, fertilizer applications, hand pulling weeds, weeding with scuffle hoes, weeding with wheelhoes, and harvesting. All labor inputs were tracked using Garmin Instinct® watches (Garmin Ltd., Olathe, Kansas, USA). The Garmin Instinct® is a single frequency device, capable of utilizing three global positioning systems – GPS, GLONASS, and GALILEO – which we believed made it well suited to tracking labor in rural locations. The Garmin Instinct® has a noted error margin of about 3 m, typical of commercially available navigational devices (Uradzinki and Bakuła 2020). Therefore, buffer beds of each crop were also planted to minimize overlap in GPS data collection (Figure 4.1). The GPS tracked data were compared to a reference system in which paper records were kept throughout the season and the data was later uploaded to the online FarmOS® software.

Table 4.1. Time spent within the boundaries of each crop and the associated cost of labor, as recorded with the paper reference. Labor rates were based on farm worker wage estimates by the USDA in 2019.

Test crop	Cropped Area	Tasks Tracked	Cumulative Labor Time	Total Labor Cost
	m^2		min	$
Arugula	33.9	Planting, weeding, harvesting	22.95	5.42
Bean	248.1	Planting, weeding	163.11	38.52
Beets	90.6	Weeding, harvesting	105.48	24.91
Broccoli	41.8	Planting, weeding, row covering, harvesting	63.28	14.95
Carrot	48.8	Planting, weeding, fertilizing, harvesting	76.26	18.01
Chard	82.7	Planting, weeding, harvesting	49.53	11.70
Kale	41.8	Planting, weeding, row covering, harvesting	122.05	28.82
Kohlrabi	18.6	Planting, weeding, row covering, harvesting	35.05	8.28
Radish	64.1	Planting, weeding, row covering, harvesting	68.91	16.28

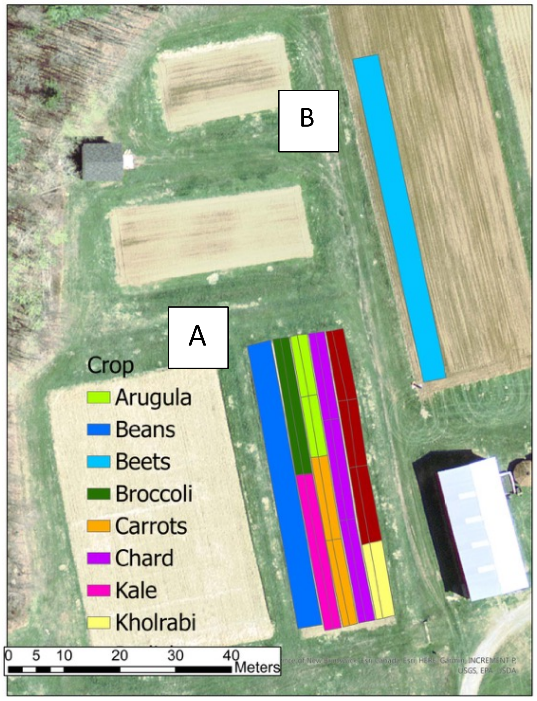


Figure 4.1. Georeferenced, digitized map of fields A and B, depicting separate polygons for each included test crop, produced from surveyed points, projected with Maine East Mercator NAD (2011 realization) in U.S. survey foot.

Prior to beginning any farm tasks, participants were asked to note the name of the task and start time in a provided notebook before engaging the GPS function on a provided watch and allowing it to acquire the position, via satellite connectivity. Participants were required to wear the watch, or have it on their person, before engaging the GPS tracking mode. To increase the accuracy of the position data logging, watches were set to record a data point every second, regardless of changes in direction or speed. While the watch tracked their movements, participants were asked not to leave the designated crop area, which included only the bed in which the crop was being grown and the wheel tracks on either side which were used as walking pathways. Upon the completion of each farm task, participants disengaged the GPS and noted the end time of the event.

Data acquired by tracking the spatial movements of workers within the farm, using worker-worn personal GPS receivers, was overlaid onto the time-stamped location data output on a georeferenced, digitized map delineating the different crops and other work areas within the farm (Figure 4.2). Prior to any analysis, the location of the corners of each crop area were precisely georeferenced using a NET-G5 GNSS reference receiver and an FC-5000 field controller, capable of referencing all GNSS constellations using GPS, GLONASS, and GALILEO (Topcon Electronics, Livermore, CA, USA). The spatial boundaries of individual crops within the farm were defined as separate polygons in a GIS. The intersection of each worker's location history, stored as points, with the crop polygons was calculated to determine the time spent in each crop. Spatial data manipulation was conducted in ArcGIS (ESRI, Redlands, CA, USA). Labor expenditures within different arenas of farm operations were calculated by quantifying time spent by individual workers on specific activities and multiplying by the relevant labor rates (Table 4.1). Labor rates were based on farm worker wage estimates by the USDA (USDA 2019).

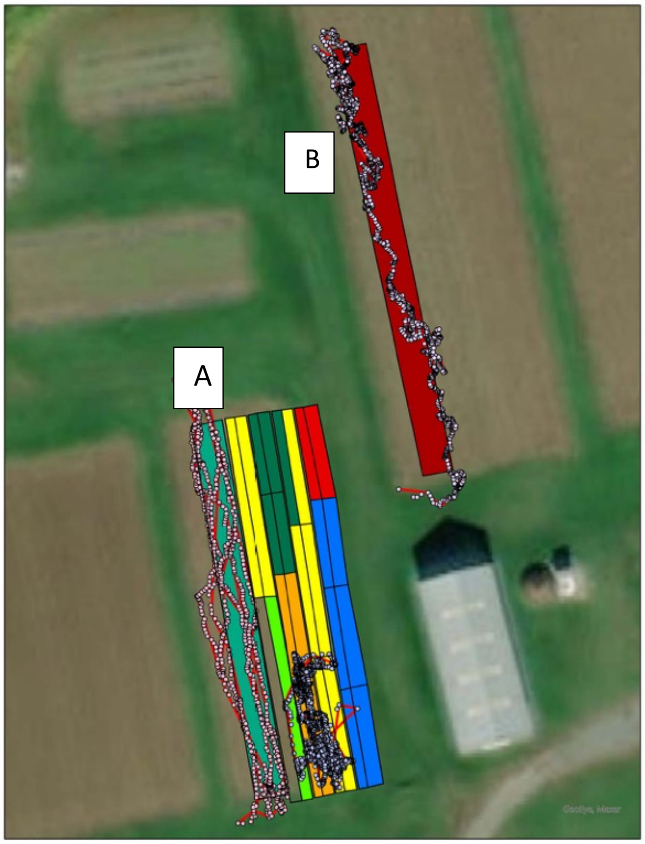


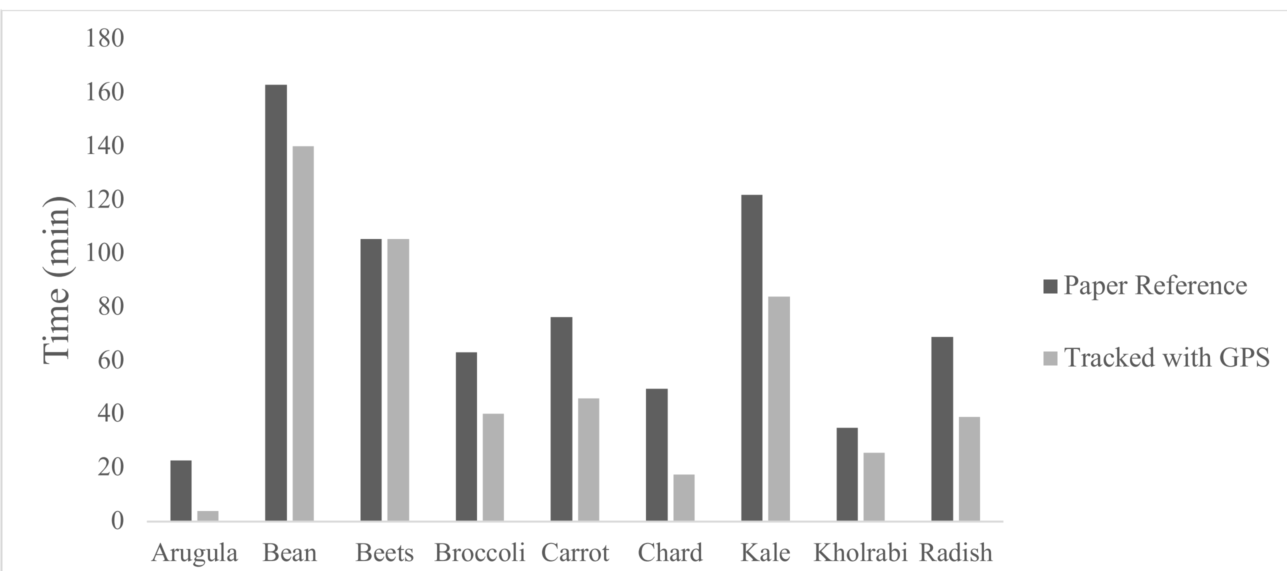
Figure 4.2. Digitized map of fields A and B overlaid with time-stamped location data acquired with Garmin Instinct® watches for beets, beans, and carrots.

RESULTS AND DISCUSSION

A total of 11.9 hours were recorded using the reference system while conducting farm tasks across all crops grown. Labor requirements across crops varied from 22 minutes to 2.7 hours of cumulative labor time and labor expenditures that ranged from \$5.42 for arugula to \$38.52 for beans, respectively. Cumulative labor times were similar to labor rates recorded in vegetable field operations for previous studies (Sørensen et al. 2005). Pen and paper records for each of the 83 farm tasks conducted over the season required approximately 3 minutes to be transferred to farmOS®, resulting in a cumulative 4.15 hours per season spent digitizing data for the reference system.

While data collected with the GPS receivers were correlated with the reference system ($r = 0.9642$, $P = 0.0001$), there was an associated average error rate of 37% across all crops (Figure 4.3). Rates of error, by crop, ranged from zero for beets to 83% for beans. Moreover, the GPS devices tended to underestimate time spent within crop bed. The noted rates of error may be an inherent problem with using commercially available GPS devices which primarily utilize frequencies from only one satellite constellation at a time. This can potentially limit their viability in tracking labor on small farms where error may result in significant inaccuracies in the acquired data. Additionally, it should be noted that, because the data acquisition of this system was limited to the spatial boundaries of the crop bed, it did not take into account a number of labor tasks associated with each crop that would take place following harvest, such as washing and packaging.

Figure 4.3. Time spent within the boundaries of each crop bed, as recorded with the paper reference and tracked by Garmin Instinct® watches.



Despite this error, the Garmin Instinct® may be a viable GPS receiver on somewhat larger farms where field sizes are proportionally larger than the radius of error. This was apparent in the absence of any deviation from labor tracked with watches and the reference system in the beet plot (Figure 4.3) where the cropped area was roughly five times that of smaller areas in field A. However, the risk of overlapping labor tracks remains an issue if cropped areas are directly adjacent, as demonstrated by the considerable level of error associated with the relatively large area designated for beans. Alternatively, differentiation through the timing of the crops for which labor is tracked may be a useful method to avoid overlap in GPS tracks. For instance, if a farmer were to plant a crop that is typically harvested later in the season and requires minimal labor inputs earlier in the season directly adjacent to another crop with contrasting labor needs, it would be possible to distinguish GPS pathways and subsequently calculate labor expenditures accurately.

There is potential for the further development of global navigation satellite systems (GNSS) to obviate these limitations as satellite constellations transmitting signals on two or more frequencies become more common (Chen and Chang 2020). Combining satellite constellations, essentially increases the number of visible satellites and therefore improves the precision of positioning systems (Hou et al. 2021). For nearly 20 years, only GPS and GLONASS transmitted dual frequency signals (Johnston et al. 2017), and recently, the use of three or more frequency signal transmitting systems have been shown to provide more robust positioning observations (Zeng et al. 2021). However, while GNSS technology has developed significantly in recent decades, multiple frequency systems have not been available in commercial grade devices, such as smartphones, tablets, or portable navigation systems. Today, dual frequency systems are available in commercially available devices, such as the Mi 8 (Xiaomi Corporation, Beijing, China), the first smartphone capable of utilizing dual frequency technology, and have proven to be viable (Montenbruck et al. 2019). Given these developments, there is potential for this system to be adapted to FMIS which already utilize smartphone applications such as FarmOS Field Kit®.

In summary, tracking on-farm assets can be difficult and expensive, making it less likely for farmers to do, and while an FMIS can facilitate data storage and description, data acquisition for labor is often challenging. A labor tracking system that is used at a suitable scale, or utilizes technology, that circumvents the limitations of contemporary GPS and is integrated into an FMIS in such a manner that removes the need for specialized spatial analysis skills could be a useful decision-making tool for vegetable farmers.

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APPENDIX

Appendix A. Literature review of studies using surrogate weeds for research involving physical, chemical, and cultural weed management as well as crop-weed competition.

Study	Objectives: Physical/ Chemical Management	Cultural Management	Weed Competition	Surrogates Used
Rasmussen (1993) Yield response models for mechanical weed control by harrowing at early crop growth stages in peas. Weed Res 33: 231-240.	X			Oilseed rape (*Brassica napus* L.)
Ascard (1994) Dose-response models for flame weeding in relation to plant size and density. Weed Res 34: 377-385.	X			Condiment mustard (Sinapis alba L.)
Pullen and Cowell (1997) An evaluation of the performance of mechanical weeding mechanisms for use in high-speed inter-row weeding of arable crops. J Argic Engin Res 67: 27-34.	X			Oilseed rape (*Brassica napus* L.)
Perez-Ruiz et al. (1997) Highlights and preliminary results for autonomous crop protection. Comp Electron Agric 110: 150-161.	X			Condiment mustard (Sinapis alba L.)
Plaggemeyer (2003) Grasslands of the Missouri Coteau and their relationship to environment. Doctoral Dissertation.		X		Big bluestem grass (*Andropogon gerardi*); Mosquito grass (*Bouteloua gracilis*)
Busey et al. (2003) Cultural management of weeds in turfgrass: a review. Crop Sci 43: 1899-1911.		X		Ryegrass (*Festuca perennis*)
Vanhala (2004) Guidelines for physical weed control research: flame weeding, weed harrowing and intra-row cultivation. 6th EWRS Workshop on Physical and Cultural Weed Control. Lillehammer, Norway, 8-10 March 2004.	X			Condiment mustards
Myers et al. (2005) The effect of weed density and application	X			Sorghum (*Sorghum*

timing on weed control and corn grain yield. Weed Technol 19: 102-107.				*bicolor* L.)
Spies et al. (2007) Branching in field pea. Soils and Crops Workshop.			X	Oilseed rape (*Brassica napus* L.)
Gallandt (2010) Evaluation of scale-appropriate weed control tools for the small farm. SARE Final Report ONE09-098.	X			Condiment mustard (Sinapis alba L.)
Kolb et al. (2010) Improving weed management in organic spring barley: physical weed control vs. interspecific competition. Weed Res 50: 597-605.	X			Condiment mustard (Sinapis alba L.)
Giambalyo et al. (2010) Nitrogen use efficiency and nitrogen fertilizer recovery of durum wheat genotypes as affected by interspecific competition. Agron J 102: 707-715.		X	X	Barley (*Hordeum vulgare*)
Dillehay et al. (2011) Critical period for weed control in alfalfa. Weed Sci 59: 68-75.				Millet (*Panicum miliaceum*)
Page et al. (2012) Why early season weed control is important in maize. Weed Sci 60: 000-000.	X			Winter wheat
Sanderson et al. (2012) Grass-legume mixtures suppress weeds during establishment better than monocultures. Agron J 104: 36-42.		X	X	Oilseed rape (*Brassica napus* L.)
Kolb et al. (2012) Impact of spring wheat planting density, row spacing, and mechanical weed control of yield, grain protein, and economic return in Maine. Weed Sci 60: 244-253.	X			Condiment mustard (Sinapis alba L.)
Bullied et al. (2012) Hydrothermal modeling of seedling emergence timing across topography and soil depth. Crop Ecol Phys 104: 423-436.			X	Spring wheat
Brainard et al. (2013) Temperature and relative humidity affect weed response to vinegar and clove oil. Weed Technol 27: 156-164.		X		Brown mustard (*Brassica juncea* L.)
Munakamwe et al. (2013) Low input weed management in field peas. Open Agric J 7: 53-64.		X	X	Oilseed rape (*Brassica napus* L.)
Reid et al. (2014) Delaying weed control lengthens the anthesis-	X		X	Winter wheat

silking interval in maize. Weed Sci 62: 326-337.				
Saito and Futakuchi (2014) Improving estimation of weed suppressive ability of upland rice varieties using substitute weeds. Field Crops Res 162: 1-5.			X	Purple-leaf rice (*Oryza sativa*); Cowpea rice (*Vigna unguiculata*)
Munakamwe et al. (2014) The effect of genotype and agronomic factors on crop growth and yield in field peas as influenced by radiation interception and utilization. Aus J Crop Sci 8: 680-688.			X	Oilseed rape (Brassica napus L.); Italian ryegrass (*Lolium multiflorum*); Common vetch (*Vicia sativa*)
Smith et al. (2014) Increased productivity of a cover crop mixture is not associated with enhance agroecosystem services. PLoS ONE 9: e97351.		X	X	Brown mustard (*Brassica juncea* L.)
Smith et al. (2015) Cover-crop species as distinct biotic filters in weed community assembly. Weed Sci 63: 282-295.		X		Brown mustard (*Brassica juncea* L.)
Böhm (2016) Development of a testing system for the documentation and evaluation of the weed-suppressing ability of blue lupins. Julius Kuhn Institut.		X	X	Oilseed rape (*Brassica napus* L.)
Merfield et al. (2017) Efficacy of heat for weed control varies with heat source, tractor speed, weed species and size. New Zea J Agric Res 60: 437-448.	X			Brown mustard (*Brassica juncea* L.)
Brainard et al. (2017) Combining strip-tillage and zonal cover-cropping for soil moisture conservation in organic vegetable systems. Ceres Trust Final Report.	X			Condiment mustard (*Sinapis alba* L.); millet (*Panicum miliaceum*)
Brown and Gallandt (2018) Evidence of synergy with "stacked" intrarow cultivation tools. Weed Sci 58: 284-291.	X			Condiment mustard (*Sinapis alba* L.);

Appendix A continued.

				millet (*Panicum miliaceum*)
Melander et al. (2018) Inter-row hoeing for weed control in organic spring cereals Influence of inter-row spacing and nitrogen rate. Euro J Agron 101: 49-56.	X			Condiment mustard (Sinapis alba L.)
Tilton et al. (2018) Improving weed management in carrots with stacked in-row weeding tools and cultivation-tolerant cultivars. Doctoral Dissertation.	X			Millet (*Panicum miliaceum*)
Hunter al et. (2019) Integration of remote-weed mapping and an autonomous spraying unmanned aerial vehicle for site-specific weed management. Pest Manag Sci 76: 1386- 1392.	X			Tobacco (*Nicotiana tabacum* L.)
Hodge et al. (2019) The potential of culinary vegetable oils as herbicides in organic farming: the effect of oil type and repeated applications on plant growth. Doctoral Dissertation.	X			Poppy (*Eschscholzia californica* Cham.); white clover (*Trifolium repens* L.); alyssum (*Lobularia maritima* L.); blue lupin (*Lupinus angustifolius*); buckwheat (*Fagopyrum esculentum* Moench.); mustard (*Sinapis alba* L.); oats (*Avena sativa* L.); perennial ryegrass (*Lolium*

Appendix A continued.

				perenne L.); tall fescue (*Festuca arundinacea* Schreb.)
McCollough et al. (2020) Band sowing with hoeing in organic grains: I. Comparisons with alternative weed management practices in spring barley. Weed Sci 68: 285- 293.	X			Condiment mustard (Sinapis alba L.)
McCollough et al. (2020) Band sowing with hoeing in organic grains II. Evidence of improved weed management in spring wheat, oats, field peas, and flax. Weed Sci 68: 294-300.	X			Condiment mustard (Sinapis alba L.)
Melander and McCollough (2020) Influence of intra-row cruciferous surrogate weed growth on crop yield in organic spring cereals. Weed Res 60: 262-274.	X			Condiment mustard (Sinapis alba L.)
Kshetri (2020) Study of soil-tine interaction for the application of automated mechanical weeder. Doctoral Dissertation. Iowa State University.	X			Artificial Weeds
Babiker (2020) Dandelion weed detection and recognition for a weed removal robot. Graduate Thesis. Concordia University.	X			Artificial Weeds
Klaiss et al. (2020) Organic soybean production in Switzerland. Oilseeds Fats Crops Lipids 27: 64.			X	Lentil (*Lens culinaris*); Flax (*Linum usitatissimum*); buckwheat (*Fagopyrum esculentum*)
Sanchez and Gallandt (2020) Functionality and Efficacy of Franklin Robotics' Tertill robotic weeder. Weed Technol 35: 166-170.	X			pearl millet and condiment mustard

BIOGRAPHY OF AUTHOR

Johnny Sanchez was born in Albuquerque, New Mexico on September 24, 1995, and raised on the Ohkay Owingeh reservation by parents, John and Yvette Sanchez. Prior to attending university, Johnny gained an appreciation for agriculture by spending his summers on his grandparents' farm. Johnny graduated from the Santa Fe Indian School in 2014 and attended Dartmouth College, graduating with a Bachelor of Arts degree in Environmental Studies and Psychology. Before beginning a Master's program at the University of Maine, Johnny worked on organic farms in Honokaa, HI, Vershire, VT, and co-managed a maple sugaring operation in Hanover, NH. Agriculture remains an important part of Johnny's life and he plans on gaining further experience in operating organic farms and has aspirations of owning his own. Johnny is a candidate for the Master of Science degree in Ecology and Environmental Sciences from the University of Maine in May 2021.