Regular Article

Evaluating the quality of kiwifruit pollinated with an autonomous robot

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Abstract: The growing popularity of kiwifruit orchards in New Zealand is increasing the already high demand for traditional pollinators (bees), with alternatives currently too costly for most growers due to high labour requirements or inefficient usage of expensive pollen. A novel pollinating robot has been previously described to provide a more efficient, reliable and cost-effective means of addressing this problem. However, the pollinator suffered from a low fruit-set rate of 40% overall, well below commercial requirements of 80% to 90%. This paper presents two new developments for that system: a new, off the shelf spray nozzle (SS1504) to increase the overall pollen delivery and an automated height controller to keep the spray manifolds at a consistent distance below the canopy while avoiding obstacles. Furthermore, we have designed and conducted a more controlled, real-world evaluation of the pollination system to compare both nozzle variants and measure the commercial viability of the pollination platform. Final results show that, operating from a mobile platform at $2.5\,\mathrm{km\,h^{-1}}$, the new nozzle could consistently achieve a fruit-set rate only $16 \pm 2\%$ below the control samples in each test orchard ($82 \pm 2\%$ and $72 \pm 4\%$ absolute). Pollen consumption remains high, however, with estimates of up to $4.6\,\mathrm{kg\,ha^{-1}}$, thus preventing the system from being economically viable. While cost-effectiveness awaits substantial efficiency improvements, our work has demonstrated an automated pollinator that can produce commercial-grade kiwifruit.

Keywords: horticulture, robotics, neural networking, machine vision, pollination, convolution neural networks, orchards, kiwifruit

1. Introduction

While insects pollinate more than one-third of the food we eat—and our dependence on insect-pollinated plants is growing—wild pollinators are declining, resource-competition for managed

Received: 13 October 2020; revised: 07 March 2021; accepted: 08 April 2021; published: 01 November 2021.

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pollinators is increasing, and horticulture pollination services face growing risks from changing climate, disease, and predators (Aizen et al., 2009; Giannini et al., 2017; Klein et al., 2007; Leonhardt et al., 2013; Rader et al., 2013; Wienhold et al., 2018). Pollinating robots offer an alternative that is more flexible (selectively pollinating flowers to manage crop-load, for example) and may be more robust and reliable than insect-pollinators, which commonly shelter during poor weather.

New Zealand has built a strong kiwifruit export economy valued at $2.26 billion, with this value expected to double to $4.5 billion by 2025 (Zespri, 2016). The popularity of kiwifruit growing is driving a rapid increase in kiwifruit orchards being planted across New Zealand. A University of Waikato study has predicted this increase in orchards will require 29,000 new labourers by 2029/2030 (Scrimgeour et al., 2017).

Timely, efficient, and careful pollination of the kiwifruit flowers is critical to the growth of quality export kiwifruit. Kiwifruit flowers are typically pollinated by bees as seen Figure 1, however this approach is becoming less reliable. Bee hives are susceptible to diseases such as Varroa mite and colony collapse disorder, which vulnerability pose risks to growers requiring pollination services (Brown et al., 2018; Wilson, 2013). These risks are increasing the cost of obtaining the bees in the critically short two to three week pollination window. Furthermore, the number of hives available for the task of pollination has also reduced recently as more hive owners move towards the lucrative market of honey.

This trend has driven a move towards artificial pollination to supplement bee pollination with methods such as pollen blowers, dusters, and spray dispensers. Companies such as PollenPlus™ in New Zealand provide such pollination services to kiwifruit orchards. Their primary system is the "QuadDuster", a pollen blower mounted on a quad bike and capable of quickly and reliably blowing pollen throughout an entire orchard off the back of a vehicle, relying on bees and other insects to then help transfer the pollen to the flowers. However, the increasing cost of pollen (US$2500 per kg in 2016) makes this approach highly cost inefficient as, pollen is not targeted towards the flowers directly. Another approach is to use a human workforce with hand-held sprayers to manually pollinate each individual flower within the orchard. This enables an efficient and effective use of pollen but suffers a major drawback in the cost and recruitment of the labourers to carry out the task, making it infeasible for most orchards.

A novel robotic kiwifruit pollinator has been built to provide an efficient, cost-effective, and reliable means of full, autonomous pollination for kiwifruit orchards in the absence of insect pollinators (Williams, Nejati, et al., 2020). The work is a collaboration between the University of Auckland, the

Figure 1. Bee Hives within kiwifruit orchard for pollination.

University of Waikato, Plant & Food Research, and Robotics Plus Limited[1] (Williams et al., 2019; Williams, Nejati, et al., 2020; Williams, Ting, et al., 2020). Autonomous pollination of kiwifruit at $1\,\mathrm{km\,h^{-1}}$ was demonstrated in field-trials. However, the system achieved a fruit-set of only 40%, well below the 80% to 90% typically achieved with standard orchard practice (Gonzalez et al., 1998). This limitation arose, in part, due to errors in spray timing and scheduling. We then modified the system and subsequently demonstrated that the system was able to hit 79.5% of flowers with spray delivered by two nozzles when travelling at $3.5\,\mathrm{km\,h^{-1}}$. Unfortunately, we were not able to repeat the pollination trials in the same season due to the short window available for pollination.

In this paper, we present results from new field-trials designed to measure pollination performance for the previously employed air-assist nozzle, now equipped with the corrected spray timing and scheduling, and a new, off-the-shelf nozzle commonly used to deliver agri-chemicals. We also describe a spray-boom height controller capable of maintaining a consistent distance between the canopy and spray manifold. The autonomous-pollinator's performance is compared against normal orchard practice (that is, honeybee pollination) in two commercial orchards located in Tauranga, New Zealand.

2. Related work

The world's rapidly growing population is driving demand to develop efficient, reliable, and environmentally safe means to sustainably grow enough food to feed everyone. Work in precision agriculture has been conducted for a number of decades but has taken off more recently with significant advances in robotics and machine vision.

A wide range of robotic pollination systems are being developed to target and spray crops directly in order to reduce the reliance on unreliable natural pollinators, and to improve the quality and quantity of the developed fruit (Abutalipov et al., 2016; Amador & Hu, 2017; Berman et al., 2011; Kurosaki et al., 2012; Maghsoudi et al., 2015; Ohi et al., 2018). The majority of this work has focused on designing and developing drone based systems for pollination (Abutalipov et al., 2016; Amador & Hu, 2017; Berman et al., 2011). However, these systems have only seen small and limited real-world trials that have not conclusively demonstrated the ability to be commercially viable alternatives. One study even goes so far as to argue that drone based systems will never replace natural pollinators (Potts et al., 2018).

More promising is the development of ground based mobile pollinators (Amador & Hu, 2017; Ohi et al., 2018; Williams et al., 2019). In a similar vein a large amount of research has also been done for mobile based weed spraying robots (Berenstein et al., 2010; Bhong et al., 2020; Burgos-Artizzu et al., 2011; Fennimore et al., 2016; Lee et al., 1999; López-Granados, 2011; McAllister et al., 2019; Reiser et al., 2019; Slaughter et al., 2008; Urdal et al., 2014). In each application, the autonomous vehicle is attempting to detect, locate, and spray pollen or herbicide onto either a flower or weed within the orchard. Typically, these systems spray the target directly, instead of the normal commercial approach of blanket spraying, to reduce the total usage of the expensive pollen or harmful herbicides. In some cases the aim is to remove herbicides entirely by mechanically removing the weeds instead of spraying (Michaels et al., 2015).

Robotic fruit harvesters are also a popular area being developed to pick individual fruit from within a canopy without damage (Bac et al., 2014; Font et al., 2014; Longsheng et al., 2015; Oberti & Shapiro, 2016; Silwal et al., 2017). Some fruit varieties can be bulk harvested without much concern for damage of the fruit, e.g. wine grapes or nuts, however most fruit require careful selection for ripeness or to prevent damage to the fruit. The most advanced examples of these selective fruit harvesters are for apple and kiwifruit harvesting. An apple harvester has been shown to be capable of harvesting 84% of fruit attempted with an average picking time of 6 s per fruit (Silwal et al., 2017). A kiwifruit harvester has been shown to be capable of successfully harvesting 86.0% of reachable fruit, and 55.8% of all kiwifruit with a cycle-time of 2.78 s per fruit (Williams, Ting, et al., 2020).

[1] MBIE contract UOAX1414 Multi-purpose orchard robotics

However, these systems are still not commercially viable as pick rates are too slow, predominately due to the difficulty of physically harvesting fruit safely at a high speeds.

Overall, these robotic systems have yet to become commercial platforms however strong results are demonstrating that the future of robotics based agriculture is feasible. For pollination systems in particular, the largest hurdle appears to be a combination of accurately locating and applying the given spray, and managing to only utilise commercially viable levels of pollen.

3. Background: Pollinator overview

A robot moving at 5 km h^{-1} pollinating the flowers across the full-width (approximately 4 m) of each row as it went would traverse a hectare in about half an hour. A fleet of 20 robots working 10 hours each day could pollinate half the NZ crop (approximately 12,000 ha (Aitken & Warrington, 2019)) within the 14 day window available for pollination. Though there are many other factors to be taken into account for a commercial system (including: travel time between orchards, down-time for repair, boom width vs row width, etc), this scenario sets a practical speed target for our research. Successful pollination is determined by the quality and quantity of the kiwifruit produced for commercial export. In New Zealand, growers spend about $3,000 per hectare on honeybees for pollinating kiwifruit (Goodwin, 2012; MPI, 2018). Anecdotally, about half of New Zealand growers supplement honeybee pollination by broadcast spraying as described above. Application rate (and cost) varies among growers (and possibly season); we are not aware of any systematic study of this commercial practice.

Figure 2 presents the pollination system that was designed and built to meet these commercial requirements and was initially presented in Williams, Nejati, et al. (2020). The details of the pollination system and mobile robotic platform are each respectively described in detail in Jones et al. (2019), Lim et al. (2020), Nejati et al. (2020), and Williams, Nejati, et al. (2020). This section provides a brief summary of how the pollinator operates.

The pollination system consists of the base robotic platform and the two pollination modules on top. Each pollination module consists of a machine vision system for locating and tracking flowers, a spraying scheduler, boom height controller, and a pollination manifold with a series of nozzles. Each module is intended to independently locate, track, and spray individual flowers within the canopy while moving at 1.4 m s^{-1}. The following section presents the novel boom height controller and spray manifold contributed in this paper.

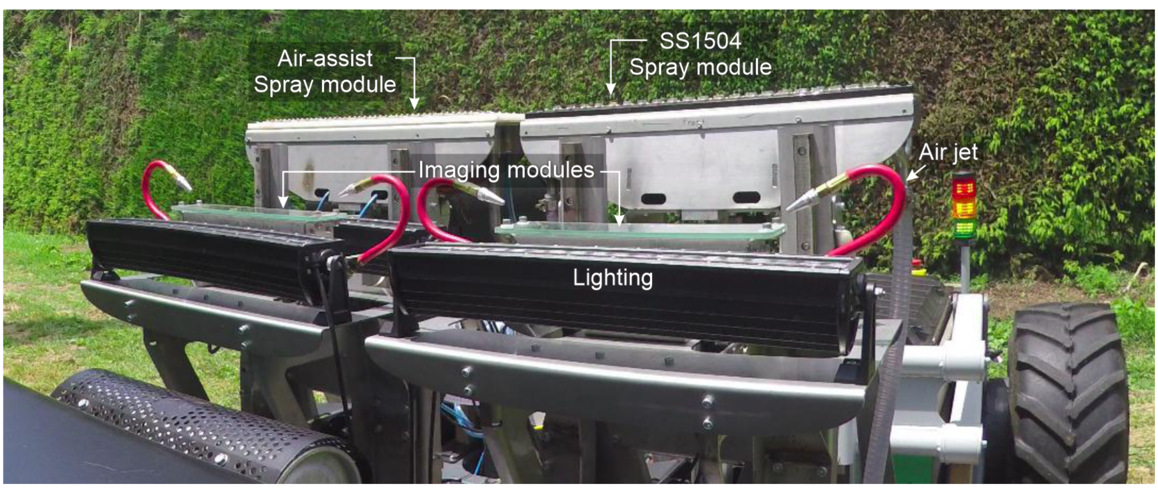

Figure 2. The pollinator module mounted on the autonomous platform. The spray modules consists of the air-assist (left) and SS1504 (right) spray manifolds. The image module comprises cameras to detect flowers, a protective cover, and air jets to keep water from accumulating on top of the cover.

The machine vision system detects and tracks flower positions in the canopy as the platform drives underneath. The vision system utilises a Fully-Convolutional Network (FCN) (Huang et al., 2017) and stereo cameras for locating flowers. The two cameras are mounted 300 mm in front of the spray manifold, and light bars (white light 6000 K) are placed either side of the cameras to add additional illumination and minimise the effect of varying ambient lighting as seen in Figure 2. The performance of the vision system is measured in detail and presented in Williams, Nejati, et al. (2020), with an overall precision 0.91 and recall of 0.80.

The spray-timing control then utilises the odometry, boom height, spray characteristics, and flower positions to determine when and which nozzle to fire in order to individually pollinate each flower as described in Williams, Nejati, et al. (2020). We presume that all flowers are facing downwards, and do not consider the orientation of the flowers—a reasonable assumption given the overhead structure of a kiwifruit canopy. Ideally, the spray from the nozzles would act like a laser and could spray straight up into the flower when it is directly underneath the nozzle. However, the spray takes an appreciable amount of time to travel from the nozzle to the flower, causing an offset between the firing position and strike position as the spray continues to travel forward. Furthermore, the spray is not instantaneous and delays in activation of the nozzles and the emergence of the spray add additional offsets. Figure 3 shows a single frame of a video capturing this process.

The concept of utilising a wet, pollen based solution is derived from commercial practice of using a Cambrian sprayer, a manual, hand-held device to spray the pollen onto the flowers within the canopy. This wet solution has proved to be a commercially effective means of directing the pollen solution onto the flowers over the alternative, dry pollen based approaches. The wet-pollen approach also provides an easier medium of delivering controlled pollen doses at speed. The pollination manifolds control the characteristics of the spray via servo-controlled nozzles. The initial spray manifold consisted of 20 independently controlled air-assisted nozzles linearly spaced 25 mm apart, covering 500 mm of the canopy as detailed in Williams, Nejati, et al. (2020). The new pollination manifold presented in this paper is described in Section 4.1. During operation the pollen solution can drip onto the cameras and cover and obscure their visibility. To mitigate this issue two nozzles are directed over the cover to

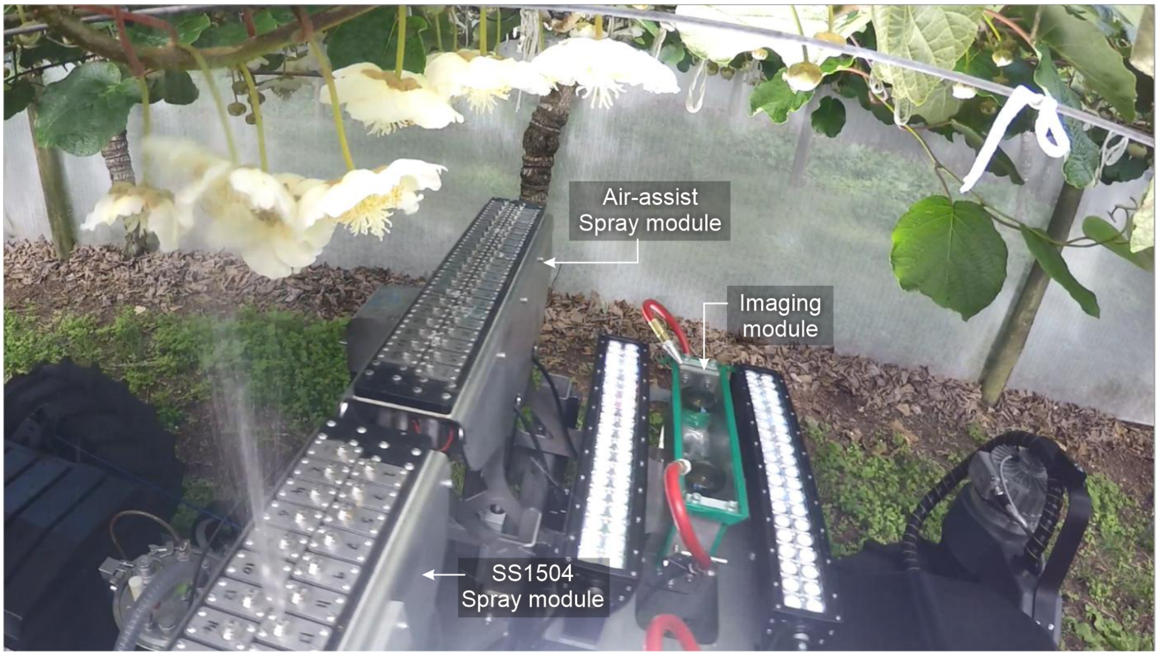

Figure 3. An example of the pollinator successfully tracking and spraying a cluster of flowers within the canopy.

blast air onto it at regular intervals to clear any build up of fluid. The intention for a full commercial pollinator is to have a number of these modules spaced across the autonomous platform to cover the full width of a 4 m canopy.

4. Contributions

4.1. SS1504 spray manifold

The sprayer is required to apply an effective dose of pollen to each of the flowers' stigma at a range of about 200 mm. Two nozzles' variations were evaluated for delivering pollen to flowers in this work: the Air Assist and the SS1504.

The Air Assist is a custom nozzle previously described in Williams, Nejati, et al. (2020). Briefly, it consists of a central liquid stream surrounded by a column of air. The air causes the liquid stream to break up into fine droplets, a design motivated by the assumption that smaller droplets would be more easily captured by the stigma on the flowers. The manifold comprised a single row of 21 nozzles, each 25 mm apart.

The SS1504 is a standard commercial nozzle used for delivering agri-chemical sprays with a nominal 15° spray cone angle and orifice diameter of 1.3 mm. The SS1504 nozzle was selected to deliver droplets in a narrow cone that minimises over-spray and pollen waste while providing a "reasonable" mass, this momentum sufficient to reach the flower without wind deflection, and sufficient volume to deliver approximately 7000 pollen-grains to the styles of kiwifruit flowers, an amount sufficient to produce export-quality fruit (Hii, 2004). We designed a custom, proof-of-concept manifold, arranging SS1504 nozzles into two rows of 21 nozzles for field testing (Figure 4). The manifold spanned 500 mm with an effective pitch of 12.5 mm, approximately half the diameter of a kiwifruit flower's style-bush (Hii, 2004). This pitch is half that of the air-assist manifold and chosen to reduce the chance of missing flowers positioned halfway between two nozzles.

Spray delivery through each nozzle was controlled by an individual valve drawing pollen solution from a central channel in the manifold. Pollen solution is circulated continuously through the manifold from a 4 L reservoir, to keep it well mixed.

Figure 4. The SS1504 spray manifold consisting of 42 nozzles (21 in each row).

Table 1. Spray Characteristics for SS1504 nozzle.

Variable	Description	Value
T_{spray}	Time from liquid ON signal to OFF signal	40 ms
T_{OtL}	Time from liquid ON signal to liquid start latency	10 ms
T_{OtS}	Time from liquid OFF signal to liquid stop latency	28 ms
$v_{centroid}$	Centroid vertical velocity	$9.5\,\mathrm{m\,s^{-1}}$
T_{delay}	Software latencies	10 ms
V_{shot}	Liquid volume delivered in a single shot	1.4 mL
$N_{nozzles}$	Number of nozzles fired for each flower	1

Table 2. Spray Characteristics for air-assist nozzle.

Variable	Description	Value
T_{spray}	Time from liquid ON signal to OFF signal	40 ms
T_{OtL}	Time from liquid ON signal to liquid start latency	13 ms
T_{OtS}	Time from liquid OFF signal to liquid stop latency	29 ms
$v_{centroid}$	Centroid vertical velocity	$18.6\,\mathrm{m\,s^{-1}}$
T_{air}	Time from Air ON signal to OFF signal	70 ms
T_{AtO}	Time from Air ON signal to liquid ON signal	15 ms
T_{delay}	Software latencies	10 ms
V_{shot}	Liquid volume delivered in a single shot	0.36 mL
$N_{nozzles}$	Number of nozzles fired for each flower	2

In order to calculate the spray control timings for the pollination system, the spray characteristics of the SS1504 nozzle were measured (Tables 2 and 1). In brief, the timing controller determines the distance (anticipation distance) before the flower the nozzle needs to be triggered in order to land the “spray centroid” on the flower. The “spray centroid” is measured here as the approximate centre of mass of the spray droplets. Under ideal conditions, this strategy will distribute spray evenly across the target flower.

A Phantom Miro high speed camera (Vision Research, Wayne, NJ 07470, USA) was used to capture images of droplets in the spray at 1000 Hz. Mean droplet velocity was estimated by calculating spatial correlations between consecutive images. A median droplet velocity of $9.5\,\mathrm{m\,s^{-1}}$ was measured for the SS1504 nozzle. Using an LED to indicate control signal activations, the timing between the software triggering the nozzle and the spray physically emerging from the nozzle could be measured. This timing is critical, as at the desired velocity ($2.5\,\mathrm{km\,h^{-1}}$), the time delay between activation and spray (10 ms) equates to a significant distance travelled (approximately 7 mm), which would put the spray centroid past the centre of the flower.

4.2. Spray-boom height controller

The height of flowers and branches varies throughout kiwifruit orchards. To keep a high proportion of the flowers in range of the spray nozzles, the pollinator was mounted on an actuated boom that could be raised and lowered. However, as the pollinator traverses through the orchard, obstructions in the form of low hanging branches or canes can interfere or collide with the sprayer.

The spray booms were independently raised up to 400 mm from their lowest height to keep the pollen spray from the nozzles in range of the flowers to be pollinated. In addition, the spray booms were independently lowered in order to avoid collisions with the kiwifruit canopy. Initially, this functionality was achieved by having a LIDAR with a vertical scan plane, mounted 1.5 m ahead of the spray booms, detecting the height of canopy points in a region of interest. The boom height controller tracked an offset from a percentile of these heights. However, it was found that with this approach the

Figure 5. Examples of a soft (left) and solid (right) hanging branch. Soft hanging branches should not be avoided by the boom height controller. The low solid-branch caused an unwanted collision with the spray boom when using a lidar sensor to control the spray-boom height.

booms would tend to avoid all collisions with the canopy, including avoiding soft hanging branches, which could safely be impacted, such as that shown in Figure 5. The resulting behaviour kept the booms too low for the pollen spray to consistently reach the flowers. To improve the system, the output was averaged across multiple frames of LIDAR data and hence the booms tended to track the average height of the canopy better, including correctly driving through low hanging soft vines. However, it was also found during field testing that a relatively rare case of a low hanging solid branch (Figure 5) could cause an unwanted collision with the spray booms. A typical commercial orchard does not contain obstructions more than 200 mm below the canopy as they are pruned for the safety of human operators; however, rare cases of lower solid branches still exist.

Analysis of the LIDAR data showed that this sensor did not capture point measurements of the canopy with sufficient resolution to reliably distinguish a new shoot with a diameter less than 10 mm from a solid branch with a diameter of more than 30 mm. Hence it was decided to investigate the use of other sensors. In order to get higher resolution depth measurements of the canopy in high contrast lighting conditions, stereo-cameras were used, as shown in Figure 6. A fully convolutional neural network was trained for semantic segmentation of solid branches in one of the camera images (Figure 7). The heights of the corresponding segmented solid branch points were measured using stereo-vision. Different stereo-matching methods were tested including variants of block matching, semi-global block matching and belief propagation; however, it was found that all of these stereo-matching methods produced significant matching errors, which caused parts of branches to be measured to be closer than they actually were. This behaviour caused the booms to stay low and hence the spray could not reach the flowers. To overcome this issue, both block matching and constant space belief propagation were used and a threshold was set for the difference in disparity at each pixel, so that disparity calculations were only kept at points where the stereo matching methods were in close agreement (Figure 7). Using this technique, the boom navigation system was able to specifically avoid collisions with solid branches in the kiwifruit canopy.

5. Pollinator evaluation

A controlled pollination experiment was conducted to evaluate the pollination platform as it would be used in commercial operation. That is, the robotic platform drives straight down a row at constant

Figure 6. Parts of the spray boom height controller hardware on the front of the mobile robot platform.

speed while the pollinator autonomously detects and sprays individual flowers. The performance of the pollination system is then measured in four ways:

1. the proportion of flowers hit by pollen solution (hit-rate),
2. the proportion of flowers that subsequently set fruit (fruit-set),
3. seed count of the kiwifruit produced, and
4. the weight of the kiwifruit produced.

Hit-rate measures the ability of the pollinator to find and deliver pollen to flowers within the canopy. A score of 0 (miss), 0.5 (no dye visible on styles), 1 (dye on styles) or 2 (excess of dye on styles) was assigned to each tagged flower (Section 5.1) immediately after autonomous pollination (Figure 8). This is a refinement of our previous scoring system (Williams, Ting, et al., 2020), which did not distinguish between dye on the style-bush and an excess of dye on the style-bush. Loosely speaking, a hit-score of 0 or 0.5 here corresponds to a score of 1 or 2 in Williams, Ting, et al. (2020) while a hit-score of 1 or 2 here corresponds to a score of 3. However, it is very difficult to maintain consistency across seasons for this very subjective measurement. Instead, we use hit-score as a tool to dissect the results within an experiment.

Fruit-set assesses whether enough pollen was delivered to the stigma to fertilise the flower. Fruit-set is calculated as the number of tagged flowers recovered from, divided by the number of flowers tagged in, each treatment region (see experimental setup). The Hayward kiwifruit variety can set fruit with as few as 100 pollen grains (Hopping & Hacking, 1983). Although relatively few pollen grains are required to set a fruit, poorly pollinated fruit will not grow to commercial size. Seed count provides a more precise method to assess pollination, as the pollen tubes germinated from viable pollen grains grow down the flowers styles to fertilise eggs and produce seeds. Fruit that were obvious mutations (fused stigma bush, for example) were excluded from the seed count as part of standard orchard practice.

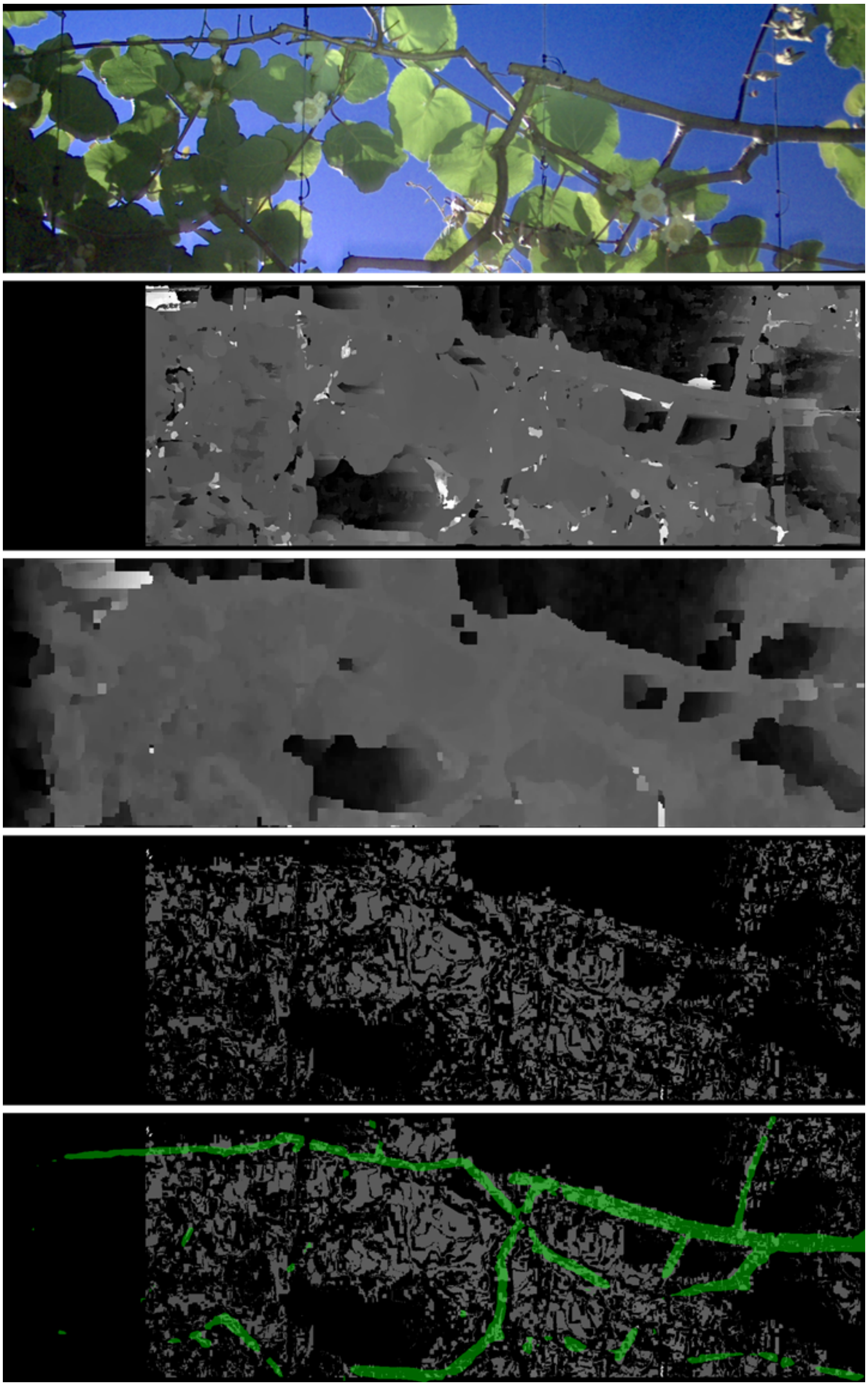

Figure 7. An input image from a stereo pair used for spray boom height control, followed by the disparity from Block Matching, followed by the disparity from Constant Space Belief Propagation, followed by the disparities that matched from Block Matching and Constant Space Belief Propagation, followed by the semantic segmentation result, overlaid on the matching disparities and used to measure the height of solid branches for spray boom collision avoidance.

Figure 8. Hit scores assigned to flowers were based on the amount of pollen visible on stigmas.

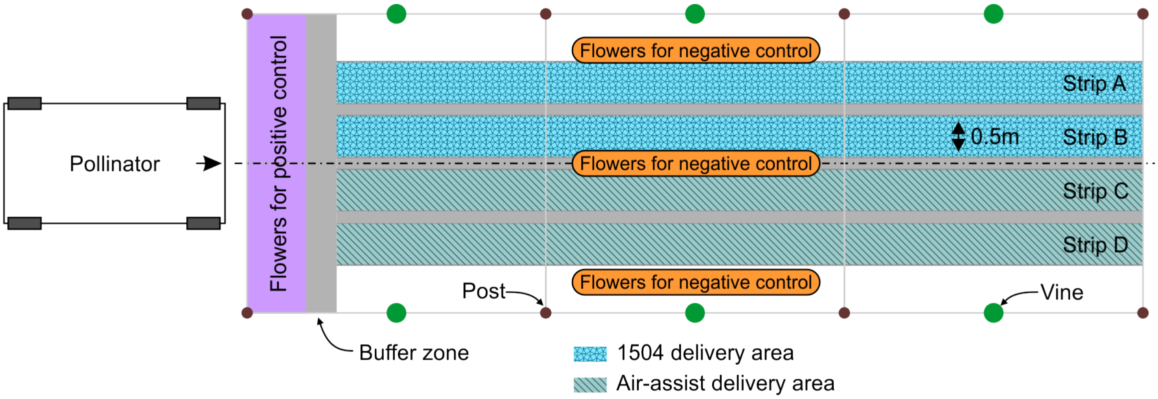

Figure 9. Schematic diagram of the layout for each test area.

Fruit are sold by weight, making it an important measure of fruit quality. However, a variety of factors, including pollination, growing conditions, and vine health, influence fruit weight. So it is not always a good measure for pollination. The quality of the kiwifruit produced by the pollinator is compared against the control fruit pollinated by bees to account for these external factors.

The performance of the individual components of the pollination system were out of scope for this particular experiment due to time constraints (two week pollination window), insufficient manpower, and limited access to orchards. The focus on this experiment were to evaluate the overall performance of the pollinator for producing quality fruit with a high fruit-set. However, the pipeline is the same as in our prior experimentation and Williams, Nejati, et al. (2020) covers the performance of the individual systems in detail.

5.1. Experimental setup

The pollinator was evaluated in three areas on two orchards—two areas at Newnham (N1, N2) and one area at Hua Kiwi (H1) orchards—in the Tauranga region, New Zealand during November 2018. Each area was approximately 3.5 m by 10.5 m, spanning three bays. An example of the row breakdown is shown in Figure 9 and example of an orchard, marked out and flowers bagged, in Figure 10. The areas were divided into four strips, lengthwise, approximately 0.5 m to match the manifold's width using string stretched between vine support structures. The two strips to the left of centre in each area were pollinated with the SS1504 nozzle; the two strips to the right of centre were pollinated by pairs of air-assist nozzles. Area N1 was only pollinated with SS1504 nozzles as the air-assist nozzle was not configured correctly when this area was pollinated. This configuration issue was resolved before areas N2 and H1 were pollinated.

Figure 10. Experimental setup for pollination experiment. Four strips with bagged and tagged flowers for tracking the outcome of the pollination runs.

Starting four to nine days before autonomous pollination, flower buds within each strip were marked with numbered tags and covered with a paper bag approximately 1 day before anthesis (the "pop-corn" stage) as shown in Figure 11. The numbered tags were tied to one end of an approximately 300 mm length of string; the other end was tied securely to the stem above the flower. The paper bags excluded other pollination vectors (insects, wind) while numbered tags allowed us to track the flowers throughout the experiment and determine fruit set. A positive control area in each orchard was marked out at the start of one of the areas. Positive control flowers were covered during robotic pollination, but otherwise were left to be pollinated by bees as part of the orchard's normal pollination operation. A gap of approximately 150 mm was left between each strip and flowers in this region were tagged for negative controls. The negative controls were uncovered at the same time as the treatment flowers but not sprayed by the robotic platform. The intent was to demonstrate the kiwifruit set by the targeted flowers were the result of the robotic pollination and not a contamination from external pollinators. This method for negative controls proved unsuccessful (see discussion).

A fresh batch of pollen solution was prepared to pollinate each strip. The pollen solution was prepared at a concentration of $8\,\mathrm{g\,L^{-1}}$ male Chieftain pollen with $20\,\mathrm{mL\,L^{-1}}$ of PollenAid solution and approximately 40 mL of red dye in 4 L of deionized water. The solution was mixed for 15 min using a magnetic bead stirrer. The dye provided a visual indication of pollen delivery to the flowers. Paper bags were removed from flowers immediately before autonomous pollination of each strip by the robot and replaced quickly (within 30 minutes) to prevent pollination of these flowers by honeybees.

Immediately after pollinating each strip with the robot, the amount of pollen delivered to tagged flowers was visually assessed and recorded. A score of 0 (miss), 0.5 (no pollen visible on styles), 1 (pollen on styles) or 2 (excess of pollen on styles) was assigned (Figure 8). A single observer performed all visual assessments for consistency.

Figure 11. Bagged kiwifruit flower (with identification tag) to prevent external pollination.

Fruit were harvested in April (Newnham) and May (Hua Kiwi) of 2019, approximately 10 days before the commercial harvest. At harvest the tag number was written on the fruit using a permanent marker. All tags that were not attached to fruit were recovered from the ground and canopy. More than 95% of the tags were recovered.

Following harvest the fruit were weighed and the number of seeds in each fruit was counted. Seeds were counted by over-ripening the fruit (using ethylene as an accelerant), peeling then spreading the flesh in a thin layer inside a large, clear plastic bag. Each bag was photographed and the seeds counted using ImageJ.

6. Results

Pollen was delivered to a total of 799 flowers by the robot pollinator across the three areas (N1, N2, H1) and treatments (SS1504, air-assist). An additional 307 flowers were tagged as positive controls.

The proportion of flowers hit by the robot, assessed visually, is shown in Figure 12. The proportion of flowers that were hit by pollen solution (hit-score of 1 or 2) was consistent across both orchards for each type of nozzle. Deliveries from $60 \pm 3\%$ pairs of air-assist nozzles resulted in either pollen visible on the flower styles or an excess of pollen on the stigma bush. Similarly, deliveries from SS1504 nozzles hit $73 \pm 2\%$ of flowers.

Table 3 summarises the proportion of all tagged flowers (regardless of hit-score) in each treatment area that set fruit. The positive controls set fruit for $98.7 \pm 0.9\%$ and $87.1 \pm 2.7\%$ of the tagged flowers in the Newnham and Huakiwi orchards, respectively. Fruit-set varies between orchards (and areas within orchards), making the robot's performance relative to naturally pollinated control samples a more useful metric than absolute fruit-set. SS1504 nozzles set $16 \pm 2\%$ and $15 \pm 5\%$ fewer fruit than the controls samples in the Newnham and Huakiwi orchards respectively while pairs of air-assist nozzles set $10 \pm 2\%$ and $30 \pm 5\%$ fewer fruit.

Seed counts for each treatment group and orchard are summarised in Table 4 and Figure 13. Notches on the box-plots were used as evidence of statistically significant differences where the notches

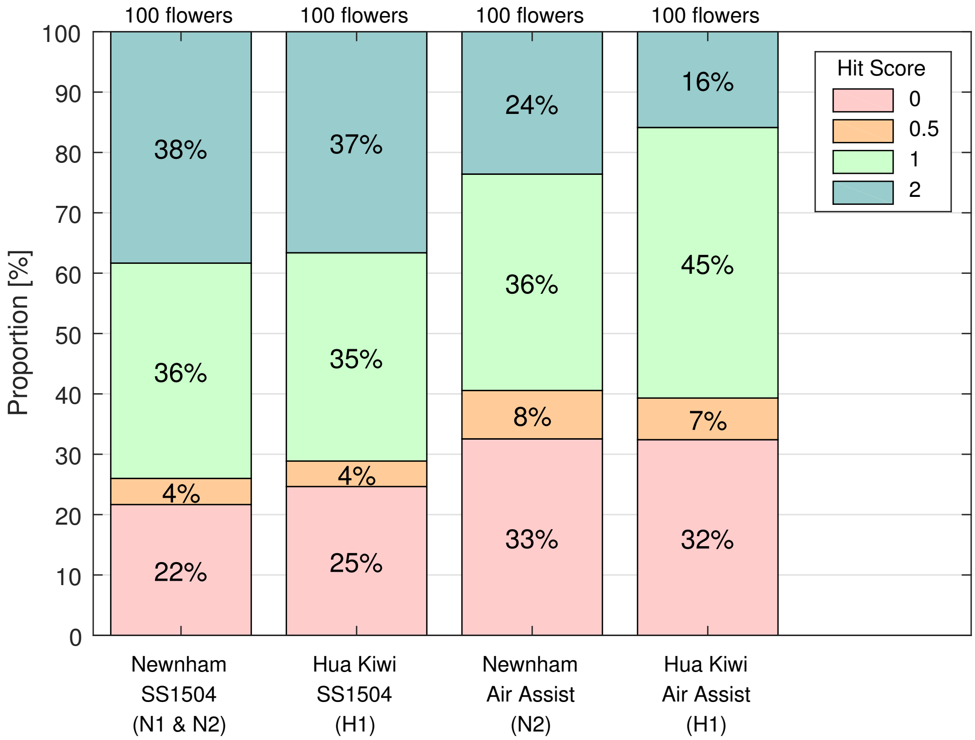

Figure 12. The distribution of pollen solution volume delivered to flowers (assessed using visual hit-score) is shown for each treatment area and nozzle using stacked bars. Flowers with no pollen solution visible scored 0 while those with an excess of pollen scored 2. The number of flowers in each treatment group is noted at the top of the plot; the proportion of flowers for each hit-score is noted on each bar.

Table 3. Summary statistics for the proportion of flowers that set fruit, as mean and standard-error of the mean, in each treatment group and area.

Orchard	Treatment	Area	Flowers	Average Fruit Set (%)
Newnham	Positive control		152	98.7 ± 0.9
	Negative control*		56	37.5 ± 12.7
	SS1504	N1	111	82.0 ± 7.2
		N2	189	82.5 ± 5.4
		N1 + N2	300	82.3 ± 2.2
	Air assist	N2	212	88.7 ± 2.2
Hua Kiwi	Positive control		155	87.1 ± 2.7
	Negative control*		30	73.3 ± 15.8
	SS1504	H1	142	71.8 ± 3.8
	Air assist	H1	145	57.2 ± 4.1

*Negative controls did not work as expected; see discussion

do not overlap. Data for the two SS1504 treatment areas demonstrated no significant differences and has been combined to improve statistics (t-test, 5% significance level). The number of seeds in 35 grossly oversized deformed fruit, which typically arise when two flowers fuse during development, were not counted. These fruit are normally removed by the grower during thinning. The seed count in fruit from the Hua Kiwi orchard was about 20% higher than the Newnham orchard across both treatments and the positive control group. This difference may be caused by environmental effects such as the local climate during pollination, which can affect pollen tube growth (Jansson & Warrington, 1988),

Table 4. Seed counts (μ: mean with standard-error of the mean, σ: standard deviation, minimum and maximum count) are summarised by treatment group and area.

Orchard	Treatment	Seed Count				
		Count	μ	σ	Min	Max
Newnham	Positive control	139	977.2 ± 21.8	257	270	1421
	Negative control*	17	735 ± 91	364	35	1236
	SS1504	229	917.2 ± 21.2	321	36	1496
	Air assist	178	761.1 ± 21.2	350	10	1590
Hua Kiwi	Positive control	129	1192.2 ± 19.4	220	624	1663
	Negative control*	21	971 ± 70	311	252	1382
	SS1504	100	1090.3 ± 29.2	291	113	1397
	Air assist	81	912.9 ± 31.5	282	35	1236

*Negative controls did not work as expected; see discussion

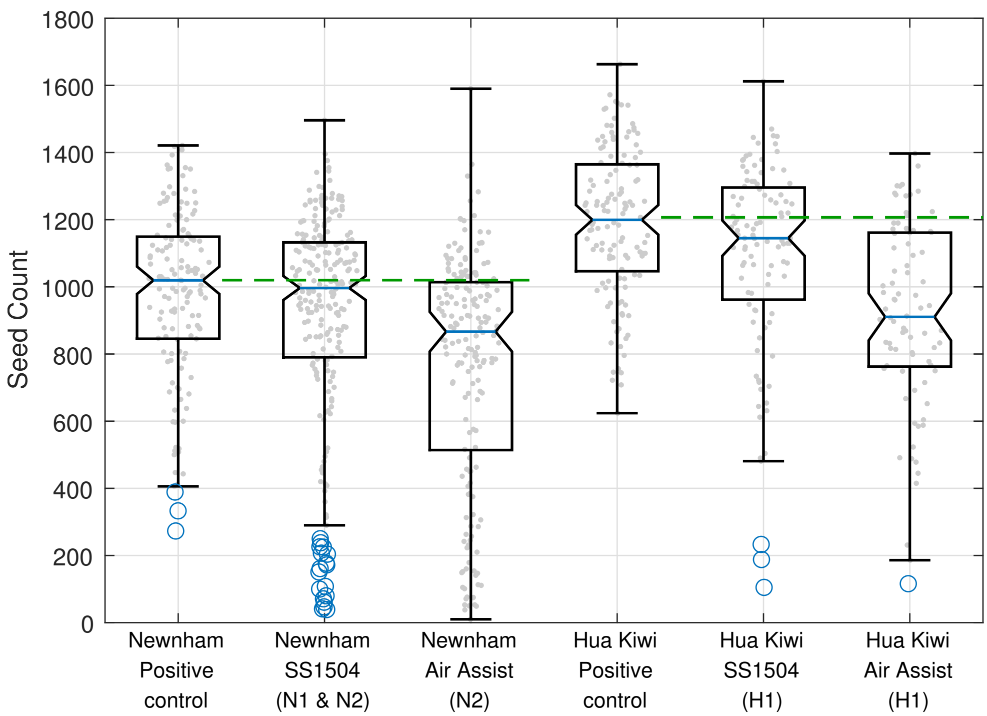

Figure 13. The seed count of fruit in each treatment group is plotted with a superimposed boxplot. Median is indicated with a blue horizontal line, boxes extend to the interquartile range (IQR), notches extend to $\pm 1.58 \times \mathrm{IQR}/\sqrt{N}$, possible outliers are indicated with circles. The green dotted line extends the median of the relevant control group for reference.

and underscores the importance of local, relevant control samples when assessing pollination. There was no evidence of a difference in the median number of seeds in fruit pollinated with SS1504 nozzles and control flowers (t-Test, 5% significance level) at either site, though the SS1504 produced far more fruit with low seed counts (below 300). The median seed-count for fruit pollinated by air-assist nozzle pairs was 15% and 24% below the control fruit at the Newnham and Hua Kiwi orchards, respectively.

Fruit weight for each treatment group and orchard are summarised in Table 5. The difference in average fruit weight between control fruit from the two orchards was not significant. However, we found that autonomously pollinated fruit were between 7% and 24% lighter than naturally pollinated

Table 5. Fruit weights (μ: mean with standard-error of the mean, σ: standard deviation, minimum and maximum count) are summarised by treatment group and area.

Orchard	Treatment	Fruit Weight				
		Count	μ (g)	σ (g)	Min (g)	Max (g)
Newnham	Positive control	150	107.1 ± 1.9	23.8	50.1	202.1
	Negative control*	22	87 ± 6	28	27.5	139.6
	SS1504	242	93.1 ± 1.7	25.7	15.8	185.7
	Air assist	185	81.6 ± 1.9	25.3	9.3	148.7
Hua Kiwi	Positive control	132	106.3 ± 1.3	14.4	67.0	147.9
	Negative control*	22	97 ± 4	16	61.8	138.0
	SS1504	101	98.9 ± 1.5	14.8	45.4	129.6
	Air assist	81	96.9 ± 1.9	17.4	23.0	136.8

*Negative controls did not work as expected; see discussion

fruit. There was no significant difference between the weight of fruit pollinated with the two nozzles at the Hua Kiwi orchard but fruit pollinated by pairs of air-assist nozzles at the Newnham orchard were 12% lighter than fruit pollinated with SS1504 nozzles (t-Test, 5% significance level).

7. Discussion

For pairs of air-assist nozzles and a $2.5\,\mathrm{km\,h^{-1}}$ speed, the portion of flowers hit ($60 \pm 3\%$) is a little lower than the previous result of $75 \pm 5\%$ (Williams, Nejati, et al., 2020). The hit-rate for SS1504 nozzles ($73 \pm 2\%$) was higher than the previous result of $52 \pm 7\%$ for single air-assist nozzles, possibly because the inter-nozzle spacing on the SS1504 manifold (12.5 mm) was half the spacing of air-assist nozzles, making it less likely for a flower to be caught halfway between two nozzles. This still leaves a substantial number of flowers (22% to 33%, depending on orchard and nozzle; Figure 12) where no pollen was observed.

Fruit are set when viable pollen delivered to the stigma grow down the style structures to fertilise a flower. Flowers that should have escaped robotic pollination (negative controls) nevertheless set a large proportion of fruit. This likely arose as these flowers were immediately adjacent to, and easily within reach of the robot if it strayed slightly while traversing the treatment area. The negative control region was only 150 mm wide; the treatment area and spray-boom were the same width (500 mm). This could also explain some absent fruit where flowers near the edge of the treatment area were missed. Cross-pollination between treatment areas was excluded by paper bags, which were removed and replaced on the flowers in each area in turn.

The naturally pollinated flowers (positive control) fruit set is within the 80% to 90% range typically seen in commercial orchards (Gonzalez et al., 1998). Fruit set by the robot is higher than the 40% achieved in the previous work, despite an increase in ground-speed from $1\,\mathrm{km\,h^{-1}}$ to $2.5\,\mathrm{km\,h^{-1}}$, although pollen concentration was increased from $4\,\mathrm{g\,L^{-1}}$ to $8\,\mathrm{g\,L^{-1}}$ in this work to (partially) compensate for the increase in speed. Flower recognition and hardware calibration have been improved substantially since the earlier result. However, robust pollen delivery, while managing pollen consumption, remains a key challenge as any difference in fruit set between autonomously and naturally pollinated flowers would be a financial loss to growers.

Generally, the proportion of fruit not-set is similar to the proportion of fruit with no pollen visible (hit score 0) for all treatments and areas except air-assist nozzle pairs in area N2. Pairs of air-assist nozzles in area N2 set 90% of the tagged flowers despite no pollen observed on 30% of them. Although 100 pollen-grains is sufficient to set fruit (Hopping & Hacking, 1983), well below the threshold of visibility, this discrepancy and inconsistency between the two orchards may indicate flowers received pollen from another source, such as spray drift, reducing our confidence in this data point.

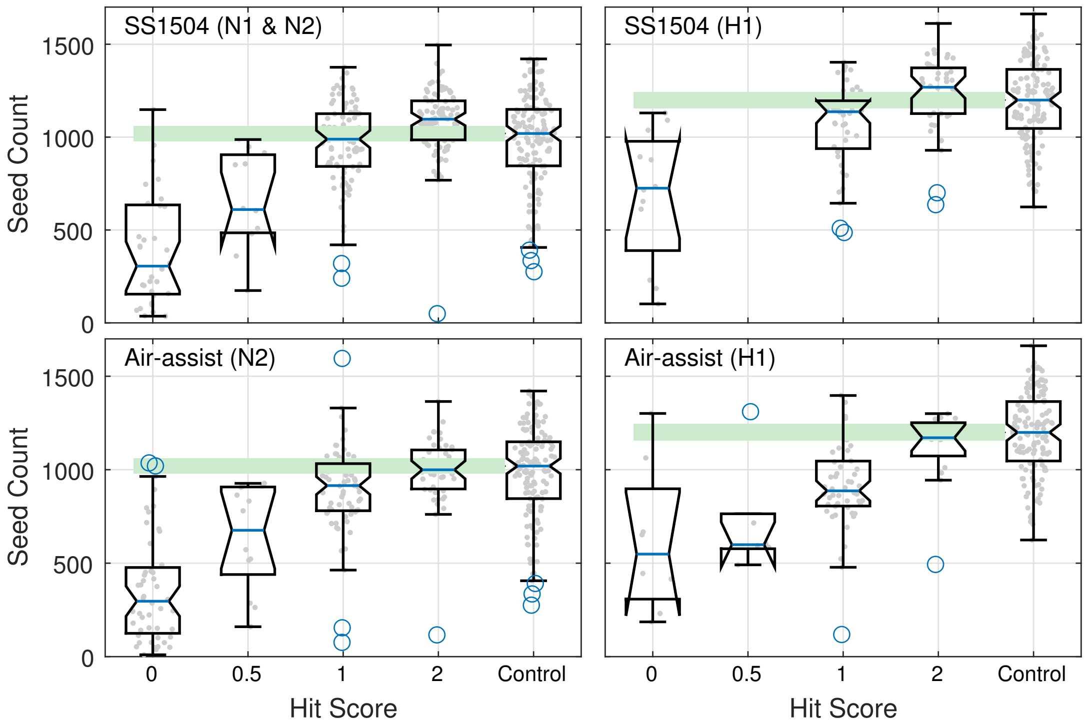

Figure 14. The seed count for fruit, grouped by hit-score, is plotted with a box-plot superimposed for each treatment and site. Non-overlapping notches in the box-plots provide evidence of a statistically significant difference between medians; the notch in the control-samples is extended across for reference (green band). Note: no SS1504 observations had a hit-score of 0.5 at site H1.

The ability to set fruit, albeit low quality fruit, with relatively little pollen makes fruit-set a crude measure of pollinator efficacy. Each successful fertilisation during pollination produces a seed, thus suggesting seed count as a straight forward and more nuanced measure of pollination. A fully pollinated kiwifruit typically contains 700 seeds to 1400 seeds (Holcroft & Allan, 1994). In general, all treatment groups produced some fruit having seed-counts within this range, however, there was considerable variation in seed-count. Some fruit contained fewer than 200 seeds, for example. Figure 14 illustrates the strong influence of hit-score on seed count. With a hit-score of 2, both nozzles achieved a seed-count similar to naturally-pollinated fruit (positive controls) (t-Test, 5% significance level). At a hit-score of 1, only flowers pollinated by SS1504 nozzles produced fruit with a similar seed-count to control fruit; those pollinated by a pair of air-assist nozzles were 10% to 27% below the seed count of the control samples. Both nozzles produced fruit with far fewer seeds than naturally pollinated flowers when the hit-score was 0 or 0.5. The spread in the group with a hit-score of 2 was smaller than other groups across all treatments, including the control samples. These results demonstrate that pollination by an autonomous system can be as effective as natural pollinators, provided sufficient pollen is delivered, and may indicate more consistent pollination is possible with an autonomous system. They also show that visual assessment provides a simple and effective indicator of poor pollen delivery and may prove beneficial in understanding delivery failures, because dye assessment alone does not require bagging flowers nor waiting for fruit to develop.

Fruit weight was also significantly related to hit-score, see Figure 15. There is a strong relationship between fruit weight and seed count (Hopping & Hacking, 1983), so this is expected. However, fruit weight was lower than control samples for flowers that received a hit-score of 1 from SS1504 nozzles even though seed counts were similar. Fruit weights were lower at a hit-score of 2 for both nozzles

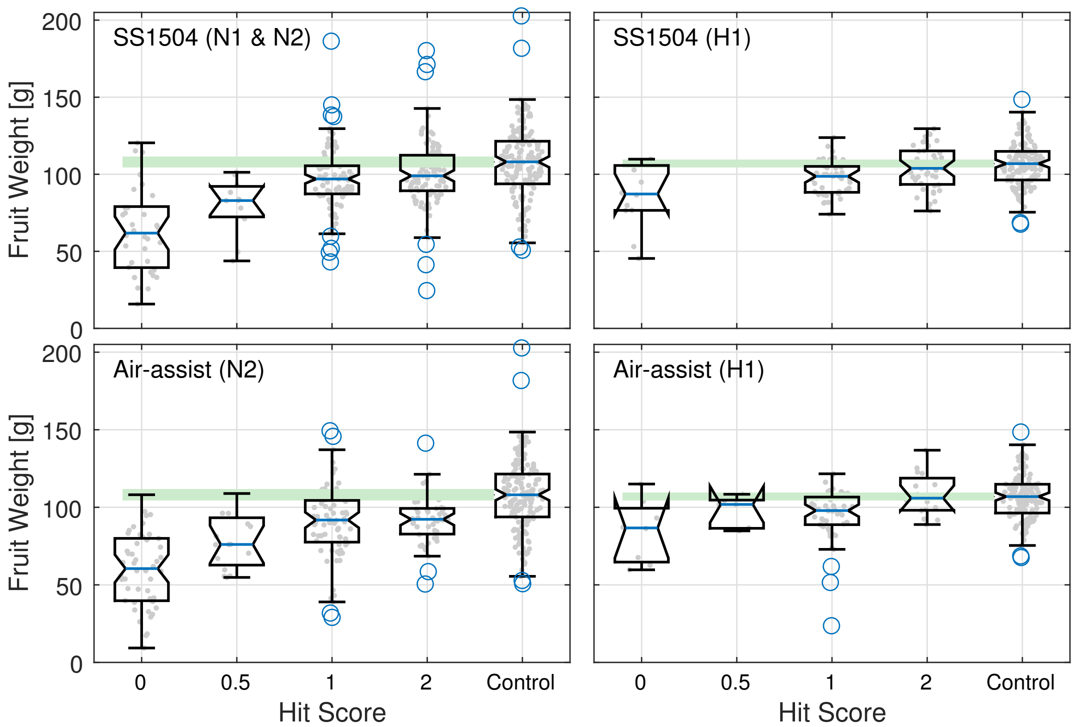

Figure 15. Fruit weight, grouped by hit-score, is plotted with a box-plot superimposed for each treatment and site. Non-overlapping notches in the box-plots provide evidence of a statistically significant difference between medians; the notch in the control-samples is extended across for reference (green band). Note: no SS1504 observations had a hit-score of 0.5 at site H1.

than control samples in the Newnham orchard again despite similar seed counts. Other factors such as crop-load, flowering stage, and application time can affect fruit weight but were not controlled in this experiment (Asteggiano et al., 2011; Tacconi et al., 2016). Further work is required to establish the effect (if any) of full artificial pollination on fruit weight and other properties, such as quality and storage, that were beyond the scope of this work.

In 2019, Sáez et al. (2019) reported a comparison of artificial and bee pollination of kiwifruit in Argentina. Normal pollination practice in this region involves spraying pollen suspended in a water based solution at a concentration of $3\,\mathrm{g\,L^{-1}}$. They obtained a fruit set of $65 \pm 5\%$ for artificially pollinated flowers. This was 28% below the fruit set of bee pollinated flowers and similar to our result with pairs of air-assist nozzles in the Hua Kiwi orchard. It is below the fruit set we measured for flowers pollinated with SS1504 nozzles delivering $8\,\mathrm{g\,L^{-1}}$ pollen solution with targeting guided by the AI vision system, however, Sáez et al. found a significant difference in seed count and fruit weight with 35% more seeds and 34% greater weight in fruit pollinated by bees. Again, we found a much smaller difference between natural and artificial pollination. This may be, in part, due to the higher concentration of pollen in the suspension we used. The volume delivered to the flower's stigma will also play a critical role in the amount of pollen available for fertilisation. Unfortunately this volume remains a difficult quantity to measure.

Approximately 11.2 mg and 5.8 mg of pollen is delivered for each flower identified, though hit-scores illustrate that not all of this pollen reaches the stigma, or even the flower (Figures 8 and 12). Improving the targeting system further should enable more reliable delivery leading the way to reducing pollen concentration in the suspension and thereby pollen consumption. Current pollen consumption can be estimated from kiwifruit production data. At 12,373 $\mathrm{trays\,ha^{-1}}$ and 33 $\mathrm{fruit\,tray^{-1}}$ (Aitken &

Warrington, 2019), the robot will use approximately $4.6\,\mathrm{kg\,ha^{-1}}$ and $2.4\,\mathrm{kg\,ha^{-1}}$ for SS1504 nozzles and pairs of air-assist nozzles respectively. At \$NZD4750 $\mathrm{kg^{-1}}$ pollen cost alone will exceed the cost of bee-pollination (\$NZD1400 $\mathrm{ha^{-1}}$ to \$NZD4800 $\mathrm{ha^{-1}}$ (Goodwin, 2012; MPI, 2018)). In the absence of other drivers, these costs may be a barrier to adoption.

Generally SS1504 nozzles produced better pollination results than the air-assist nozzles, with a higher proportion of flowers receiving pollen, higher and more consistent fruit-set, seed-count, and fruit weight. However, SS1504 nozzles use considerably more pollen than pairs of air-assist nozzles. Although we saw an improvement in most metrics for flowers with a hit-score of 2 instead of 1, the differences tended to be small. More consistent hits may enable a reduction in pollen concentration, and hence pollen consumption, without compromising efficacy. However, pollen consumption was too high for commercially practical autonomous-pollination of kiwifruit with either nozzle. A greater understanding of how nozzles use and deliver pollen to flowers is required.

The results presented here indicate that flowers identified as being hit by the pollinator (hit score - via visible dye) do produce commercial grade kiwifruit. The hit score is the result of the performance of the vision system and targeting control. The performance of the vision system as described in the previous work (Williams, Nejati, et al., 2020) demonstrates the vision system is capable of detecting 79.8% of all the kiwifruit flowers with a recall of 0.91. These results indicate that the amount of pollen being used on false positives is relatively low, compared to total pollen consumption. Although not specifically measured due to the complexity of measuring system accuracy in the real-world, the primary limitation of the vision system likely comes from the accuracy of the targeting system. The current targeting approach makes a number of simplifications and assumptions that can be improved in future work:

1. The spray dynamics for the targeting system are only modelled as a projectile. A more accurate representation of the spray may provide better spray timings for the system, albeit at the potential trade-off of run time.
2. The tracking and targeting systems do not account for disturbances in the roll, pitch, or yaw of the platform and presumes the travel is flat. The impact of these errors are not easy to measure, but the addition of inertial measurement systems can assist the pollinator to determine which nozzle should be triggered to hit a flower.

Overall, the primary challenges identified to make this robotic platform commercial viable rely on improving the fruit-set (hit rate) of the platform, and reducing the pollen consumption. Currently, the system's fruit-set and pollen consumption are the primary hurdles to commercial viability.

8. Conclusion

The results of this trial demonstrate that the pollination platform is capable of producing commercially viable kiwifruit, with fruit weight and seed counts similar to those for conventionally pollinated fruit. We demonstrate consistency in fruit set up to $16 \pm 2\%$ below naturally pollinated flowers from an autonomous platform moving at $2.5\,\mathrm{km\,h^{-1}}$, however pollen consumption remains high at up to $4.6\,\mathrm{kg\,ha^{-1}}$. Significant improvements in delivery accuracy and reductions in pollen consumption will be required for a commercially viable autonomous pollination platform. This may require completely new nozzle designs that can delivery pollen more efficiently and tracking flowers to ensure delivery remains on-target when the platform is travelling over uneven terrain.

Acknowledgments

This research was supported by the New Zealand Ministry for Business, Innovation and Employment (MBIE) on contract UOAX1414. A very special thank you to Curtis Reed, Sam Coysh, and Steven Farrow from the University of Waikato for their diligent work assisting the pollination field-trial experiments and managing the bagging of the flowers.

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How to cite this article: Williams, H., Bell, J., Nejati, M., Hussein, S., Penhall, N., Lim, J., Jones, M. H., Ahn, H. S., Bradley, S., Schaare, P., Martinsen, P., Broussard, M., Seabright, M., Duke, M., Scarfe, A., & MacDonald, B. (2021). Evaluating the quality of kiwifruit pollinated with an autonomous robot. *Field Robotics*, *1*, 231–252.