Research Article

Comparison of Artificial Intelligence and Synthetic Herbicides for Weed Control in Wheat Crop

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Abstract | The use of artificial intelligence (AI) can prove to be the most economical and environment friendly weed management strategy in wheat crop in the long run. In order to assess the impact of artificial intelligence (AI) on wheat crop in comparison with certain synthetic herbicides, a field experiment was designed in the Farm of the University of Agriculture Peshawar, in the wheat growing season of 2020-21. A Randomized Complete Block design (RCBD) was used for the layout of the experiment, keeping four replications. The experiment consisted of six different treatments including three herbicides viz. Cut Out 40 EC (bromoxynil+MCPA) @ 500 ml ha^{-1} as a broad leaf weeds killer, Fenoxaprop-p-ethyl 6.9% EW (fenoxaprop-p-ethyl) as a grassy weeds killer applied @ 500 ml ha^{-1}, and Cleaner 6% OD (florasulam 2%+mesosulfuron methyl 4%) as a broad-spectrum herbicide @ 102 ml ha^{-1}. The fourth was an AI treatment (robotic weeding), along with a hand weeding (HW) and a weedy check (WC) treatments. The treatments had a significant effect on the performance of wheat crop and also on the weed control. The HW treatment was statistically the most significant in terms of reduction in weed density m^{-2}, weed abundance and weed frequency. Plant height of wheat crop and number of grains $spike^{-1}$ were non-significantly affected by the applied treatments. However, the tallest plants and the highest number of grains $spike^{-1}$ were observed in hand weeding. The highest thousand-grain-weight, biological yield and grain yield were recorded in the hand weeding treatments. However, the results of hand weeding treatments were statistically at par with the treatments of artificial intelligence (robotic weeding). The artificial intelligence got the highest CBR followed by the broad-spectrum herbicide and hand weeding. It can be concluded that the artificial intelligence could prove to be an economical as well as an environment friendly weed management strategy if applied on large scale. On the other hand, the hand weeding is generally not economical and the herbicides are not environment friendly.

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Introduction

These days, agriculture is undergoing a transformation towards the cutting-edge technologies like remote sensing etc. With the use of geographic information systems (GIS), remote sensing technologies, the global positioning system (GPS), and other technology, scientists have turned

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agricultural automation into precision agriculture (Zhang *et al*., 2002; Zhang and Kovacs, 2012).

Precision agriculture may be used to segregate weeds from crops in farmed areas (Guerrero *et al*., 2012). It involves a very accurate processing system that operates in a variety of soil moisture and sunshine conditions. In the field studies, the weed detection accuracy is 95% and the crop recognition accuracy is 80% (Burgos *et al*., 2011).

Another method is the uniformly herbicide spraying method in field crops (Tang *et al*., 2016). The chemical spraying method may cause environmental pollution that will eventually decrease the crop quality and quantity. The use of artificial intelligence for weed identification and precision spraying of herbicides can significantly minimize the environmental pollution caused by the general and indiscriminate use of herbicides (Gianessi and Reigner, 2007).

Robots can also be used in field operations for weed control or crop harvest (Emmi *et al*., 2014). The appearance and setup of such robots can vary from a tractor to small and specially designed platforms moving inside the fields. These robotic machines can locate crop and weed plants to perform all necessary chemical or mechanical tasks for weeding purposes (Ehsani *et al*., 2004). However, errors in the planting process can negatively affect the performance of AI based weed control processes. The crop grown by the broadcast method cannot be recognized by robots and consequently such crop plants can also be damaged. It is always a hard task to correctly design a weed management program for the use of AI.

For the treatment of annual weeds, the mechanical approaches are successful because it is difficult to get rid of every portion of a perennial plant or its root system i.e. the established perennial weeds are harder to control. In addition to preventing and reducing the population of seeds, mowing techniques such as removing weeds above the ground may also restrict weed growth and development (Nejati *et al*., 2011). Cutting or mowing weeds reduces their biomass, which weakens their resistance. This is true of both annual and perennial weeds. When the soil is turned over the sunlight damages or kills the vegetative or propagative sections of plants which help in controlling the weeds, particularly the younger ones (Alba *et al*., 2019; Rueda-Ayala *et al*., 2010).

In order to compare the effects of AI with those of chemical weed control methods and manual weeding, the experiment was carried out with the objective of evaluating the impact of these treatments on crop and weed performance.

Materials and Methods

An experiment was carried out in the wheat cropping season of 2020-21 at the farm of the University of Agriculture Peshawar with the collaboration of GIK Institute of Engineering Sciences and Technology, Swabi, KP, Pakistan to comparatively study weed control through artificial intelligence, hand weeding, and herbicides. The wheat variety, 'NARC-1 Khaista 17' was selected for the experimentation. A seed rate of 120 kg ha^{-1} was used for the sowing of the wheat seeds. A row-to-row distance of 30 cm was maintained in the whole experiment. In each unit plot (sub-plot), a total of 10 rows of wheat plants were kept with a row length of 5 m, making the sub-plot size 15 m^2.

There were a total of six treatments including three herbicides viz. Cut Out 40 EC (bromoxynil + MCPA) @ 500 ml ha^{-1} as a broad leaf weeds killer, Fenoxaprop-p-ethyl 6.9% EW (fenoxaprop-p-ethyl) as a grassy weeds killer applied @ 500 ml ha^{-1}, and Cleaner 6% OD (florasulam 2% + mesosulfuron methyl 4%) as a broad-spectrum herbicide @ 102 ml ha^{-1}; along with a treatment of AI (robotic weeding), a hand weeding (weed free) and a weedy check (weedy) treatments. The herbicide treatments were applied after one month of the crop sowing using all the required protocols for herbicide application. For AI application, firstly drones were flown to collect aerial images of the weeds in the field. Later on, weeds were identified from the drone images and these images were made recognized by robots for final plucking of weeds in the field (Bhongal and Gore, 2017). The robots having a height of one foot only were locally developed by the experts of GIK institute.

Weed identification through object recognition can be done through various approaches. First approach is through weed detection by training the CNN model over the fatal weed types (Ambika and Supriya, 2018) and the second approach is to identify between the crop (wheat) and the non-crop plants (weeds). The first approach requires the model to be trained for the weed species (Ferreira *et al*., 2017). On the contrary, the second approach can be done to develop a generic model which will label every weed as not a crop and can be done to remove even the weed type is out of the bound (not one of the weeds defined in first approach).

Data were collected on the parameters of weed diversity, weed density (m^{-2}) and importance value indices (IVI) of the weeds, and also on the crop plant height (cm), number of grains spike^{-1}, biological and grain yields (kg ha^{-1}), and thousand grains weight (g).

Statistical analysis

The data were analyzed by the statistical software called statistix 2.0, using a randomized complete block design (RCBD). The LSD test was conducted for comparison of the treatment means, at a 5% or 1% probability level, after achieving the significant results of the F-test (Steel *et al*., 1997). The means are displayed in relevant Tables.

Results and Discussion

Weeds diversity

In the experimental plots, several weed species were seen. These species were recognized and grouped based on their physical traits and life cycle. The infesting weeds are categorized in Table 1 into broad-leaved and grassy weeds, whereas weeds that are annuals, biennials, or perennials are categorized in Table 2. The broad leaved weeds dominated the weed infestation.

Weed density (m^{-2})

Data pertaining to weed density was significantly influenced by the different treatments applied. Table 3 showed the highest weed density (193 m^{-2}) obtained in weedy check and the lowest (16 m^{-2}) observed in HW treatments, which was however statistically similar to broad-spectrum herbicide treatment (58 m^{-2}). The broad leaf and grassy herbicide treatments have also effectively suppressed the weeds and reduced their population in comparison with the control treatments. When there are empty niches available to the weed plants, there occurs more germination of weeds. The AI treatment with 16 weeds m^{-2} was statistically similar to the HW, showing the best performance among the applied treatments, as compared to WC plots, which always generated more weeds than other treatments (Hashim *et al*., 2002; Hassan *et al*., 2003).

Table 1: *Weeds categorization on basis of morphology.*

Broad leaf	Grassy
Anagallis arvensis (pimpernel)	*Avena fatua* (wild oats)
Chenopodium album (lambs-quarters)	*Cynodon dactylon* (Bermuda grass)
Cirsium arvense (Canada thistle)	*Digitaria sanguinalis* (Large crabgrass)
Convolvulus arvensis (Field bindweed)	*Phalaris minor* (Canary grass)
Coronopus didymus (Swinecress)	*Poa annua* (Annual bluegrass)
Euphorbia helioscopia (Sun spurge)	
Fumaria indica (Fumitory)	
Parthenium hysterophorus (Carrot grass)	
Rumex crispus (Curly dock)	
Silybum marianum (Milk thistle)	

Table 2: *Weeds categories on basis of life cycle.*

Annuals	Perennials
Anagallis arvensis (Pimpernel)	*Cirsium arvense* (Canada thistle)
Avena fatua (wild oats)	*Convolvulus arvensis* (Field bindweed)
Chenopodium album (lambs-quarters)	*Cynodon dactylon* (Bermuda grass)
Coronopus didymus (Swinecress)	*Digitaria sanguinalis* (Large crabgrass)
Euphorbia helioscopia (Sun spurge)	*Rumex crispus* (Curly dock)
Fumaria indica (Fumitory)	
Parthenium hysterophorus (Carrot grass)	
Phalaris minor (Canary grass)	
Poa annua (Annual bluegrass)	
Silybum marianum (Milk thistle)	

Table 3: *Weed density m^{-2} as influenced by the various mechanical and chemical weed control methods.*

S. No.	Treatments	*S. marianum*	*C. arvensis*	*R. crispus*	*A. arvensis*	*C. album*	*P. minor*	*C. arvensis*	*C. didymus*	*A. fatua*	*F. indica*	*C. dactylon*	*P. hysterophorus*	Total
1	BL	6.5bc	6.7 c	4.5c	4.5c	8.5bc	7.2bc	8.2c	11.2bc	11.6b	8b	5.5bc	6.2bc	88
2	G	10.2ab	11.5b	8.1b	8.1b	12ab	10b	11b	14.2ab	8.7b	12.2a	8.5ab	8.2b	124
3	BS	4.2c	4cd	1.7cd	1.7cd	6.7c	5.5cd	5.5cd	10bc	4.2c	6bc	4.2bc	4.7cd	58
4	HW	1.75	0.2e	0.5d	0.5d	0.7d	1.2d	3.d	3d	1.2c	1.5d	1c	1.2e	16
5	WC	15a	17.7a	16.a	16.2a	16a	17.7a	17a	18a	18a	15.2 a	11a	14.2a	193
6	AI	2.5c	2.5de	1.1d	1.1d	5cd	2.2d	5.5cd	7.5cd	2.7c	4.2cd	3c	3de	40
	LSD	5.7	3.4	2.8	2.8	4.6	4.5	3.4	6.5	5.6	3.6	5	3.2	

BL, broad leaf herbicide; G, grassy; BS, broad spectrum herbicide; HW, hand weeding; WC, weedy check; AI, artificial intelligence.

Table 4: *Important value indices (IVI) as affected by different mechanical and chemical weed control methods.*

S. no.	Treatments	*S. marianum*	*C. arvensis*	*R. crispus*	*A. arvensis*	*C. album*	*P. minor*	*C. arvensis*	*C. didymus*	*A. fatua*	*F. indica*	*C. dactylon*	*P. hysterophorus*	Total
1	BL	4.1	4.1	4.6	4.3	4.4	4.1	5.2	5.5	4.4	4.7	3.2	3.7	52.3
2	G	6.4	6.1	5.9	7.6	6.3	5.8	7.2	6.9	5.3	5.5	4.5	5.0	72.5
3	BS	2.8	2.9	2.7	2.6	3.1	3.1	3.7	4.2	2.5	3.1	2.2	2.8	35.7
4	HW	1.1	1.2	0.6	0.9	0.5	0.8	1.8	1.3	0.4	0.9	0.7	1.0	11.2
5	WC	8.7	8.6	7.4	12.3	8.0	8.6	10.1	8.7	8.7	6.7	6.4	7.4	101.6
6	AI	1.6	2.3	1.9	1.4	2.3	1.5	2.9	3.0	1.3	1.9	1.6	1.8	23.5

BL, broad leaf herbicide; G, grassy; BS, broad spectrum herbicide; HW, hand weeding; WC, weedy check; AI, artificial intelligence.

Importance value index (IVI)

Table 4 demonstrated that the administered treatments had a substantial impact on IVI. The HW treatments had the lowest IVI (11.2), while WC had the highest IVI (101.6). The IVI in AI plots was 23.5 which was at par with the herbicidal treatments.

Plant height (cm)

Wheat plant height was significantly affected by none of the chemical weed control methods (Table 5). The HW plots had the tallest plants (92 cm), followed by the AI (89 cm), broad spectrum (85.2 cm), broad leaf (84 cm), and grassland herbicide (90.4 cm) treatments. The control plots had the shortest plant height (78.5 cm). Usman *et al*. (2010) found that different herbicide treatments resulted in statistically comparable plant heights. The application of artificial intelligence in weed control programs for agricultural crops was encouraged by Norremark *et al*. (2012).

Number of grains spike^{-1}

The data on the number of grains spike^{-1} was significantly affected by the treatments (Table 5). Mean values showed the highest number of grains spike^{-1} (55) observed in HW treatments, while the lowest number of grains spike^{-1} (46) was recorded in weedy check. The no. of grains spike^{-1} in AI, broad-spectrum herbicide, and broad leaf herbicide was 50.0, 51.5, and 48.0, respectively, though statistically similar to each other. The decline in the number of grains spike^{-1} in the weedy check was due to weed competition that consequently adversely affected the grains spike^{-1} (Tunio *et al*., 2004). Norremark *et al*. (2012) advocated the use of AI in the weed management program in crops.

Table 5: *Plant height (cm) and no. of grains spike^{-1} as influenced by different weed control methods in wheat.*

Treatments	Plant height (cm)	No. of grains spike^{-1}
Broad leaf herbicide	84.00 bc	48.0 ab
Grassy herbicide	81.25 c	47.0 b
Broad spectrum herbicide	85.25 abc	51.5 ab
Hand weeding	92.00 a	55.0 a
Weedy check (control)	78.50 c	46.5 b
Artificial intelligence	89.00 ab	53.0 ab
$LSD_{0.05}$	7.5	7.6

Biological yield (kg ha^{-1})

The ANOVA indicated a significant influence of the chemical and mechanical weed control treatments on the biological yield (BY) of wheat crop. The Table 6 indicated the highest BY (9333 kgha^{-1}) produced in hand-weeded treatments that was however statistically at par with the AI and herbicide treatments. In addition, the lowest BY (4333 kg ha^{-1}) was produced in a weedy check. The weed competition with crop plants in weedy check plots might be the key reason that lowered the BY, because the crop plants got less nutrients due to the weed competition in weedy check. The conditions in control plots are always favorable for weed competition. The herbicides and AI were statistically at par. Artificial intelligence could be a better weed management strategy with cost-effectiveness because herbicide use is a hazardous method for human health and environmental safety (Norremark *et al*., 2012). The herbicides should be used only on casual basis or when no option is left.

Grain yield (kg ha^{-1})

As shown in Table 6, the highest GY (2466 kg ha^{-1}) was obtained in hand weeding treatments, statistically at par with AI (2283 kg ha^{-1}), followed by broad-spectrum herbicide (2083 kg ha^{-1}). The lowest GY (1450 kg ha^{-1}) was obtained in control plots due to the intensive weed competition with crop plants. The crop plants achieved nutrients in less amounts than the required, as weeds are more efficient in receiving the soil nutrients and water. The herbicides and AI were statistically at par. Therefore, the AI has to be preferred over herbicides for weed management to overcome the chances of herbicide resistance development in weeds, also to overcome the environmental pollution and other health hazards in the long run. The AI can prove to be an effective weed control tool especially when applied at large scale (Norremark *et al*., 2012), although Arif *et al*. (2004) and Tunio *et al*. (2004) reported the best effect of herbicides on grain yield of wheat crop.

Table 6: *Biological and grain yields (kg ha^{-1}) as affected by weed control methods in wheat.*

Treatments	Biological yield (kg ha^{-1})	Grain yield (kg ha^{-1})
Broad leaf herbicide	6666 b	2033 b
Grassy herbicide	6333 bc	1966 b
Broad spectrum herbicide	8333 ab	2083 ab
Hand weeding	9333 a	2466 a
Weedy check (control)	4333 c	1450 c
Artificial intelligence	8333 ab	2283 ab
$LSD_{0.05}$	1333	183

Thousand grains weight (g)

The mechanical and chemical weed control methods had a significant effect on the thousand-grain weight (TGW) of wheat. Table 7 exhibited the highest TGW (40.18 g) obtained from the hand-weeding plots, which was however statistically at par with that of artificial intelligence (37.89 g) and broad-spectrum herbicide (34.10 g). While the weedy check plots gave the lowest TGW (28 g). The results showed that the grain weight was improved when the weed competition was reduced which is very much obvious from the TGW in the hand-weeding plots. As a result, sufficient nutrients and space are made available to the crop plants that improved the TGW. Hassan *et al*. (2003) reported the importance of herbicides in the direct increase of the TGW, still the artificial intelligence was statistically at par with the herbicide treatments that support the effectiveness of AI as a good tool for environment-friendly and cost-effective weed management strategy in wheat crop (Norremark *et al*., 2012).

Table 7: *Thousand grains weight (g) under the influence of different weed control methods in wheat.*

Treatments	Thousand grains weight (g)S
Broad leaf herbicide	32.99 cd
Grassy herbicide	30.10 e
Broad spectrum herbicide	34.24 bcd
Hand weeding	40.18 a
Control	28.00 f
Artificial intelligence	37.89 ab
$LSD_{0.05}$	3.82

Cost-benefit ratio (CBR)

The cost-benefit ratio for all the treatments was calculated to find out their anticipated economic benefits. The highest CBR of 17.9 was observed in AI, followed by broad-spectrum herbicide (10.87). In fact, all the treatments showed CBRs in the range of 9.69-17.90. The means in Table 8 showed that the additional income achieved from all the treatments was more than the obtained yield in the weedy check. Generally, weed control treatments are more economical (with higher CBR) than weedy checks (Usman *et al*., 2010). The study suggests that AI can efficiently reduce the reliance on herbicides for weed control and can sufficiently diminish production cost. Also, AI is an eco-friendly method of weed management. Zhang and Zhang (2016) advocated the use of AI in weed management programs of a crop.

Table 8: *Cost benefit ratio of treatments used for weed control in wheat.*

Treatments	Yield (kg ha^{-1})	[1]Added income (Rs. ha^{-1})	[2]Added cost (Rs. ha^{-1})	CBR (Added income/ Added cost)
B/L herbicide	2033.4 b	43896	4530	9.69
Grassy herbicide	1966.7 b	53638	4970	10.79
B/S herbicide	2083.4 ab	64664	5950	10.87
Hand weeding	2466.7 a	94032	9300	10.11
Artificial intelligence	2283.4 ab	85572	4775	17.90
Weedy check	1450 c			

[1]Prices of wheat grain @ Rs. 40/kg and Straw (Rs. 15 kg^{-1}) @ Rs. 34020 ha^{-1}; [2]Added cost includes cost on the weed control treatments or labor (in the hand weeding). Labor charges @ Rs. 600 day^{-1}. For artificial intelligence the expenses are measured hourly by 1000 per hour (in 1 hour, the estimated area covered is 1 Ja or 0.5 ac).

Conclusions and Recommendations

Physical and mechanical weed management techniques are efficient and beneficial; however, they are often not cost-effective. In terms of weed control, yield enhancement, and CBR, manual weeding performed the best. The broad-spectrum herbicide did the best overall among the herbicide applications. Since the outcomes of AI weed control were comparable to those of chemical weed control, this supports the usage of Artificial intelligence (AI) for weed control in the next weed management techniques. The AI consequently seems to be superior to the use of herbicides for large-scale agriculture in terms of weed control, grain yield, and CBR.

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Novelty Statement

The use of artificial intelligence (drones and robots) for weed control in wheat is an innovative endeavor in Pakistan.

Author's Contribution

Shujaullah Khan conducted the research and collected the data, Zahid Hussain supervised the research and analyzed the data (corresponding author too), Haroon Khan wrote the manuscript and worked on the literature review, and Omer Suha USLU reviewed the paper and made improvement in the final manuscript.

Conflict of interest

The authors have declared no conflict of interest.

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