



## OPINION ARTICLE

# Revisiting weed research: Aspiring for more scientific methods, quality observations, and data analysis

T.K. Das<sup>1</sup>, Tarun Sharma<sup>1</sup>, Rishi Raj<sup>1</sup>, Prabhu Govindasamy<sup>2</sup> and C.P. Nath<sup>3</sup>

Received: 15 July 2025 | Revised: 3 March 2026 | Accepted: 4 March 2026

### ABSTRACT

Crops and weeds may have differential response to resources/growth factors and environment under climate change, but little has been explored/investigated. The quantification of these effects/ responses needs rigorous basic and applied research. Necessarily, the weed research experiments should be pro-climate and tuned up to those directions, scales, and magnitudes, which could provide an edge to adapt to the changing climate and harness benefits more in favour of crops than weeds. Accordingly, the experiments and research methodologies/ observations need to be revisited/ reframed, having sound knowledge and science bases to make more authentic and climate-supportive recommendations. The pre-requisites are choosing pro-climate experiments and treatments, appropriate statistical design, relevant control/ check treatments for main and sub-plots, and precise sampling procedures, data tabulation and analysis, particularly for certain parameters like weed control efficiency, weed control index, weed index etc. The phytosociology study of weeds in crops across locations depict/ reveal community structure, diversity and similarity of weeds under changing climate and cropping practices and assumes huge significance. There is an utmost need to study the bio-efficacy of herbicides at weed species-level along with their effect on the categories of weeds and composite weeds to arrest species shift and dynamics. Studying the effect of herbicide/ weed control treatment on soil health (~carbon sequestration, physical, chemical and biological properties) and environmental health (herbicide residue in soil, water and crop produces, greenhouse gases emission, carbon footprints) has become highly pertinent and relevant now-a-days for climate resilient recommendation and sustainable crop production. Therefore, there is a need to pursue and expedite such research in collaboration with interdisciplinary sciences, which may be a comprehensive weed research model for future.

**Keywords:** Bio-efficacy, carbon footprint, data transformation, economic threshold, herbicide residue, weed interference indices

### INTRODUCTION

Agriculture is a more subsidized artificial ecosystem (Odum 1975). Its energy flow (~40x10<sup>3</sup> kcal/m<sup>2</sup>) has increased significantly compared to an unsubsidized natural ecosystem like grassland (~1x10<sup>3</sup> kcal/m<sup>2</sup>). Crop production technologies have undergone a tremendous change over the years in pursuit of achieving higher crop yield through using high-yielding varieties, higher cropping intensity, newer crop sequence and increased level of inputs (fertilizer, irrigation, pesticides/herbicides). These have resulted in huge disturbances in natural vegetation and soil. Weeds are ubiquitous and eternal pest and have wider ecological amplitudes. Their species diversity and density/intensity are changing

continuously due to birth, death, immigration and emigration of weeds (Das 2008). This causes weed dynamics through sudden appearance or predominance of certain weed or a class of weeds, or sudden disappearance of certain weed from a crop/ cropping system; appearance of more vigorous forms of weeds like perennial weeds, resistant weeds, invasive weeds with time and space (Das 2001a). Climate, soil, physiography, and agro-practices like tillage, irrigation, fertilization, herbicides, and cropping systems highly influence weed dynamics. Therefore, a precise estimation of weed interference in a crop/cropping system and the impact of weed management options exercised is of paramount importance, which needs a sound methodology for appraisal. To develop weed science more as science, certain firm/ unalterable principles, basic theories/concepts/hypotheses, and certain standard, workable, and proven methodologies need to be framed up additionally and enshrined in weed science. These may be followed in weed research as applicable to the nature of an experiment and duly analyzed by using sound statistical tools.

<sup>1</sup> ICAR-Indian Agricultural Research Institute, New Delhi 110012, India

<sup>2</sup> ICAR-National Research Centre for Banana, Tiruchirappalli, Tamil Nadu 639103, India

<sup>3</sup> ICAR-Indian Institute of Pulses Research, Kanpur, Uttar Pradesh 208024, India

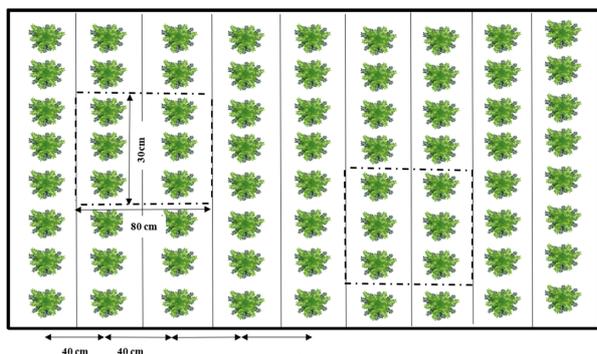
\* Corresponding author email: tarun.sharma06620@gmail.com

## CROP-WEED INTERFERENCE APPRAISAL

### Sampling procedures

#### Sampling under row-sown crops

Standard procedures must be followed for sampling weeds/ crop plants from the row-sown/ row-planted crops for precisely estimating the crop-weed interference, weed control treatments effects, and herbicide bio-efficacy. The throwing/use of quadrat arbitrarily/randomly in a plot/treatment is of no meaning since the quadrat size may not match the crop sowing geometry (row-row, plant to plant spacing) and arbitrarily chosen area may not be representative for crop-weed interference on the ground of unequal distribution of crop plants and weeds. Therefore, for sampling weeds and crop from a treatment plot, at first, one, two, or three rows of the crop (as available/allowable) up to certain lengths, or as such the length of quadrat should be selected as length of the sample area, and the row-spacing of one, two, or three rows of that crop as the width of the sampling area in the central location or across locations from which weeds and crop plants may be sampled for observations and recording of data (Figure 1). For this kind of sampling, a quadrat may or may not be used/required and the area of sampling may or may not be equal to the area of quadrat as well. For example, in a maize crop having 60 cm (row-row) x 30 cm (plant-plant) spacing, a 90 cm or so (along the rows; ~3 plants or so) x 60 cm or so (across the rows; ~1 row or so) may be randomly selected from the central rows in each plot. Weed species and maize plants may be collected from that area. Individual weed species may be counted, categorized into grassy, broad-leaved, sedges or



**Figure 1.** Weed sampling technique for row-sown crops having distinct plant to plant spacing (40 cm row-row x 10 cm plant-plant; sampling area is 0.24 m<sup>2</sup>). In case of continuously-sown tillering crops like rice, wheat, row to row distance may be like this, but along the rows, length may be arbitrarily taken or taken as the length of the quadrat (if used)

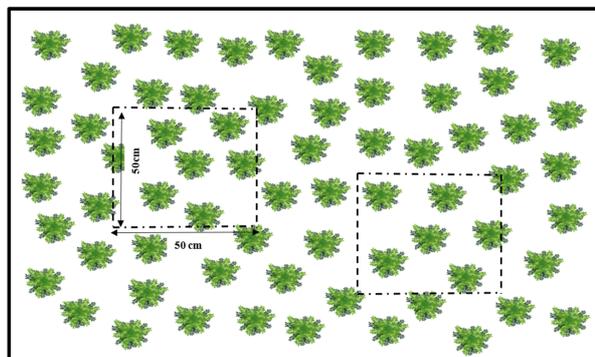
perennial weeds and summed up to total weed density across the treatments. Later the dry weight may be determined, following usual oven-drying procedure. Similarly, crop sample may be taken from that area for precisely estimating crop-weed interference (Figure 1). Multiple samples may be collected using quadrat from a plot bigger than 30 m<sup>2</sup>.

#### Sampling under broad-cast/mixed-sown crops

In broadcast/mixed-sown crops, a sampling area (without quadrat) having uniform crop stand and weeds may be randomly chosen or a quadrat of suitable size may be thrown randomly at the central locations of the plot avoiding borders rows and weeds may be collected from that area (Figure 2). For a bigger plot greater than 30 m<sup>2</sup>, multiple samples using quadrats from 3-4 locations of a plot/treatment may be collected. However, under the both row-sown and mixed-sown crops, the sampling area should be selected in such a way that it should have weed distribution representative to the whole plot/treatment. Similarly, crop samples may be taken from this area for appraising crop-weed interference.

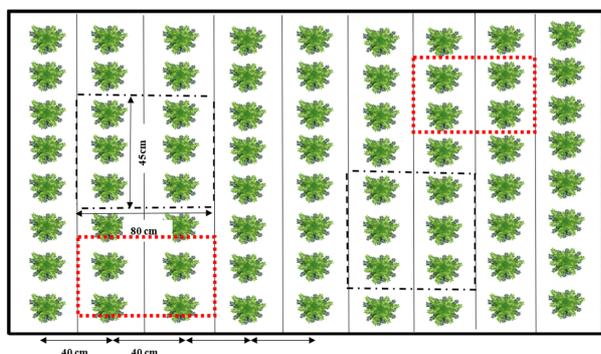
#### Fixed/tagged /undisturbed plot study

The tagged fixed/undisturbed plots constitute a kind of component study. This is usually done within an experiment having larger plot area, executed for a longer period and data need to be generated out of this experiment on treatments' effects, weed distribution and flora shift, weed seed bank, *etc.* (Figure 3). For this kind of experiment, a few small fixed/tagged plots (usually 2 m x 2 m or bigger) are randomly selected/ earmarked/ delineated in each treatment/ plot of larger dimension replication-wise, mainly, for non-destructive observations (*e.g.*, periodical weed and crop plants density, plants height, *etc.*). These plots may also be used for destructive sampling of weed dry weight, weed seed bank, crop plants tillering, branching, leaf area, yield attributes *etc.* For



**Figure 2.** Weed sampling technique for broadcasted single crop or mixed cropping plots using a quadrat of 50 cm x 50 cm

destructive sampling, the number of fixed plots per plot should be kept in large number or otherwise the fixed plot size may be kept larger. Interventions like inter-culture, herbicide application, hand weeding etc should not be done in these fixed plots except the treatments/ agro-practices being adopted since long time.



**Figure 3. Weed sampling technique from a fixed/undisturbed plot in long-term studies for generating data on weed diversity, succession/flora shift, weed seed bank, etc. Main plot treatments like cropping practices, nutrients management etc may be applied to whole plot including the Red-bordered area, which will be kept fixed/undisturbed over the years and blanket weed management practice may be adopted to keep the plot free from weeds or a few other weed control treatments superimposed in this plot.**

**CROP-WEED INTERFERENCE INDICES**

**Weed control efficiency (WCE) and per cent reduction in weed density**

Weed control efficiency (WCE) is derived from weed density for studying the performance of a treatment in terms of reduction in weed density compared to weedy check/ unweeded control (Mani *et al.* 1973). Weed density although may not be an accurate and reliable estimate for studying weed interference/control in a crop, the trend in the efficiency of the methods/treatments adopted may be appraised in terms of their superiority/inferiority. The WCE may be calculated using the following formula (Eq.1):

$$WCE = \left[ \frac{WD_c - WD_T}{WD_c} \right] \times 100 \quad (1)$$

Where,  $WD_c$  and  $WD_T$  are weed density (number/m<sup>2</sup>) in control and treated plots, respectively; The unit in both  $WD_c$  and  $WD_T$  should be same.

This derived parameter may strictly be pronounced as WCE, when the per cent reduction in weed density of the treated plots/ treatments is

compared based on a weedy check/unweeded control treatment adopted in the experiment. Otherwise, it may be pronounced as the per cent reduction in weed density of a treatment compared with another treatment adopted in the experiment, having no absolute weedy check/unweeded control treatment. The similar formula (Eq.1) may be used with no mention of weedy check /unweeded control treatment (Eq.2).

Per cent reduction  
in weed density =  $\left[ \frac{(WD_{Tc} - WD_{Tn})}{WD_{Tc}} \right] \times 100 \quad (2)$

Where,  $WD_{Tc}$  is weed density in  $T_c$  treatment based on which the per cent reduction is being calculated in another treatment  $T_n$  having weed density  $WD_{Tn}$ ; The unit in both  $WD_{Tc}$  and  $WD_{Tn}$  should be same.  $T_c$  is the control/check treatment whose density is taken as base value for calculating the per cent reduction in the “n<sup>th</sup>” number of treatment (where  $n = 1 \dots n$ ).  $T_n$  is the n<sup>th</sup> treatment for which the per cent reduction is being calculated over the  $T_c$ .

**Weed control index (WCI) and per cent reduction in weed dry weight**

Weed control index is calculated based on reduction in weed dry weight compared to weedy check/ unweeded control (Misra and Tosh 1979). In the formula of WCE of Mani *et al.* (1973), weed density has been replaced with dry weight to calculate WCI. It is a more reliable estimate for studying weed interference /control in crops across the treatments than WCE. The WCI may be calculated using the following formula (Eq.3):

$$WCI = \left[ \frac{(WDW_c - WDW_T)}{WDW_c} \right] \times 100 \quad (3)$$

Where,  $WDW_c$  and  $WDW_T$  are weed dry weight (unit/m<sup>2</sup>) in control and treated plots, respectively; The unit in both  $WDW_c$  and  $WDW_T$  should be same. The similar formula (Eq.3) may be used where weedy check /unweeded control treatment has not been considered (Eq.3).

Per cent reduction  
in weed dry weight =  $\left[ \frac{(WDW_{Tc} - WDW_{Tn})}{WDW_{Tc}} \right] \times 100 \quad (4)$

Where,  $WDW_{Tc}$  is weed dry weight in  $T_c$  treatment based on which the per cent reduction is being calculated in another treatment  $T_n$  having weed dry weight  $WDW_{Tn}$ ; The unit in both  $WDW_{Tc}$  and  $WDW_{Tn}$  should be same.

The values of WCE and WCI usually vary from 0 (zero) to 100. On principle, the WCE and WCI of

the weedy check should be always zero (0) and that of the weed-free check treatment always 100. Thus, higher the WCE or WCI of a treatment, greater is its weed control potential. However, there are instances in which the WCE and WCI have been found to be negative (-ve) for a treatment, which was worse than weedy check. It may happen in field experiments. They can be worked out for both sole and intercropping situations. In a crop/season, the WCE/WCI of a treatment, particularly, herbicide may increase/ decrease over time depending on the growth/vigour of a crop, nature and spectrum of weeds, herbicides, growing season/environment, *etc.*

It would be always better/wiser to use the original non-transformed data for calculating the WCE and WCI, although a researcher can use both transformed and non-transformed original data. This would reflect the actual WCE/WCI of a particular treatment. This would hardly be reflected by using the square-root or logarithmically transformed weed data. Using the transformed weed data, the WCE/WCI of a treatment would never become 100% as usually obtained for the weed-free check treatment. However, the non-transformed original data would always lead to 100% WCE/WCI for the weed-free check treatment.

### Weed index (WI) and per cent reduction in yield

Weed index (WI) is crop yield reduction across the treatments compared to weed-free check treatment in weed control experiments (Gill and Vijayakumar 1969). It is also called as weed competition index (WCI). Here the control treatment is always weed-free check. The WI appraises the superiority/ inferiority of a treatment in terms of crop yield and is worked out in almost all weed control studies. The WI may be calculated based on the following formula (Eq.5):

$$WI = \left[ \frac{Y_{WF} - Y_T}{Y_{WF}} \right] \times 100 \quad (5)$$

Where,  $Y_{WF}$  and  $Y_T$  are crop yield in weed-free plot and treatment plot, respectively; The unit should be same in both  $Y_{WF}$  and  $Y_T$ .

$$\text{Per cent reduction in crop yield} = \left[ \frac{(Y_{Tc} - Y_{Tn})}{Y_{Tc}} \right] \times 100 \quad (6)$$

Where,  $Y_{Tc}$  is crop yield in treatment control based on which the per cent reduction is being calculated in another treatment  $T_n$ , whose yield is  $Y_{Tn}$ ; The unit should be same for both  $Y_{Tc}$  and  $Y_{Tn}$ .

Weed index (WI) is determined in several experiments, which do not have any weed-free treatment. In such cases, the best weed control treatment or the lowest weed-infested plot such as

two/three hand weeding or alike has been considered as weed-free control. Theoretically/on principle, weed-free check is completely free from weeds and can hardly be substituted/replaced with any weed control treatment even though it is assumed to be the best weed control treatment. In that case, it should be strictly pronounced as the per cent yield reduction rather than WI. In an extreme case of weedy check where no yield is obtained, WI becomes 100. The WI of weed-free check is always 0 (zero). However, certain treatments, particularly some efficient herbicides, in which higher yields obtained than in season-long weed-free control, may have WI values negative (-ve), which indicates superiority of that treatment than even weed-free check. WI could be worked out for both sole and intercropping situations.

### Species- and category-wise weed appraisal

For determining WCE and WCI, respectively, the density and dry weight of composite culture of weeds across the treatments are taken into consideration. This ignores the importance/ effect of specific/single weed species. For this, the species-wise density and dry weight of weeds are considered and could be achieved through sampling of weed species individually from a certain area using quadrat. This, upon summing up of weeds of particular category, may further lead to category-wise density and dry weight of weeds. The relative density (Rdn) (Eq.7) and relative dry weight (Rdw) (Eq. 8) of a weed species can be studied to evaluate its effect to the overall total effect of composite weed community.

$$Rdn = \left( \frac{W_{dn}}{TW_{dn}} \right) \times 100 \quad (7)$$

$$Rdw = \left( \frac{W_{dw}}{TW_{dw}} \right) \times 100 \quad (8)$$

Where,  $W_{dn}$  and  $TW_{dn}$  are densities of a weed species and total composite weeds present in that area, respectively;  $W_{dw}$  and  $TW_{dw}$  are dry weight of a weed species and total composite weeds present in that area, respectively.

Several other indices related to weed interference, crop tolerance/ competitiveness (Mishra and Misra 1997) or weed control performance (Krishnamurthy *et al.* 1975) are weed smothering efficiency (WSE) in intercropping situations), weed persistence index (WPI), crop resistance index (CRI), pest/weed management index (PMI/WMI), agronomic management index (AMI), integrated pest/weed management index (IPMI/IWMI), and herbicide efficiency index (HEI) (Eq.9-Eq.15). All these have got enough relevance to study the aspects

of weed management on comparative basis/scale among treatments.

$$WSE = \left[ \frac{(M_{dw} - I_{dw})}{M_{dw}} \right] \times 100 \quad (9)$$

$$WPI = \frac{\text{Weed density in control plot}}{\text{Weed density in treated plot}} \times \frac{\text{Weed dry weight in treated plot}}{\text{Weed dry weight in control plot}} \quad (10)$$

$$CRI = \frac{\text{Crop dry weight in treated plot}}{\text{Crop dry weight in control plot}} \times \frac{\text{Weed dry weight in control plot}}{\text{Weed dry weight in treated plot}} \quad (11)$$

$$PMI/WMI = \frac{\text{Per cent crop yield over control}}{\text{Per cent control of weeds/other pests}} \quad (12)$$

$$AMI = \frac{\text{Per cent crop yield over control} - \text{Per cent control of weeds/other pests}}{\text{Per cent control of weeds/other pests}} \quad (13)$$

$$IPMI/IWMI = \frac{(PMI + AMI)}{2} \quad (14)$$

$$HEI = \left[ \frac{\left( \frac{Y_T - Y_C}{Y_T} \times 100 \right)}{\left( \frac{Wdw_T}{Wdw_C} \times 100 \right)} \right] \quad (15)$$

Where,  $Y_T$  is crop yield from the treated plot;  $Y_C$  is crop yield from the weedy check;  $Wdw_T$  is weed dry weight in the treated plot; and  $Wdw_C$  is weed dry weight in the weedy check plot.

## WEED INTERFERENCE STUDY

### Agronomic non-weed control experiments

In several agronomic experiments so-called not purely weed control experiments, researchers strive to study relative weed control effects of the treatments so-called non-weed control treatments without adopting any designated weed control check treatment like weedy check, weed-free check, standard herbicide check as applicable. Weed population and dry weight are studied as additional/extra data to highlight the effects of some non-weed control treatments like fertility levels, nutrients, cropping systems, or agro-practices on weed interference/ weed growth reduction. Also, weed control efficiency (WCE), weed control index (WCI), and weed index (WI) are calculated in these experiments. The WCE and WCI based on weed population and dry weight, respectively are calculated/reported across the treatments considering one traditional treatment (like no or full nutrients application against other set of nutrients, no or full water application against other water treatments, conventional till agriculture against no/minimum tillage practices etc.) as control out of a set of treatments adopted. However, this should not be so. Therefore, an attempt has been made here to highlight

the myth and reality of WCE versus per cent reduction in weed density, WCI versus per cent reduction in weed dry weight, and WI versus per cent reduction in crop yield. These experiments do not have the requisite control or check treatments like weedy check/ unweeded control for studying WCE/ WCI and weed-free check for studying WI. No disagreement/worry in that the basic/elementary data on weed population and dry weight are observed across the treatments in these experiments and the superiority or inferiority of a treatment is compared with other treatments based on the reduction in weed population and dry weight. But, giving term as WCE, WCI or WI, is not appropriate when these are calculated considering one treatment out of the whole set of treatments as control, which is not the absolute control. The WCE, WCI and WI are derived parameters using appropriate formulae and should not be same/similar with what has been calculated without having a designated control treatment. For these cases, the designated term should be the per cent reduction in weed population instead of WCE, per cent reduction in weed dry weight instead of WCI, and the per cent reduction in crop yield instead of WI considering that traditional control treatment. Otherwise, it has been seen that the results/ data calculated from these experiments may lead to some arbitrary, absurd, and illogical inferences. Therefore, the derivation of per cent reduction in weed density, per cent reduction in weed dry weight, and per cent reduction in crop yield uniformly apply to all experiments, irrespective of agronomic and weed control research with or without designated control treatments and sound more universal than WCE, WCI and WI, respectively.

### Scenario 1: Experiment in randomized complete block design, considering one non-weed control treatment as control but not an absolute control

Recently, research is being carried out in several frontier areas such as conservation agriculture, organic farming, natural farming, precision farming on several aspects of agronomy, soil health, crop protection, environmental implications, etc. This large theme area usually entertains a number of objectives to be investigated on a time-scale. Therefore, under a long-term bigger experiment of this kind, several small component trials are undertaken to satisfy several objectives or sub-objectives. In several agronomic non-weed control experiments, researchers intend to study weed control efficiency/weed control index (WCE/WCI) without an absolute control treatment. Experiments are laid out in randomized complete block design and

considered a non-weed control treatment as control and analysed for WCE/WCI. An experiment of this kind is of Ghosh *et al.* (2022), involving several conservation agriculture practices (Table 1), and WCE/WCI was studied. Treatments were conventional tillage flatbed without residue (CT); ZT permanent narrow bed without residue (PNB) and with residue (PNB+R), ZT permanent broad bed without residue (PBB) and with residue (PBB+R); ZT flatbed without residue (PFB) and with residue (PFB+R). The 100%N (100N) and 75% (75N) of the recommended doses were applied to residue-retained conservation agriculture (CA) plots like PNB+R, PBB+R and FB+R treatments. To assess WCE/ WCI of this experiment, an area (~mini plot/ spot) of 2 m x 2 m was tagged/ earmarked in each treatment plot, which remained unsprayed/ unweeded throughout the crop cycle and weed data were collected from these spots to find out the effect of these non-weed control CA treatments. The CT had higher weed growth but the CA-based practices had lower weed growth and variable weed suppression ability. Therefore, CT was considered as the control, although it was not an absolute control like unweeded/weedy check control but a relative one for the purpose of studying WCE and WCI. In this kind of evaluation of relative weed suppression ability of the treatments, WCE and WCI may not sound appropriate as followed for the true weed control experiments. It would be better if per cent reduction in weed density instead of WCE, and per cent reduction in weed dry weight instead of WCI are mentioned/ used in this kind of studies. However, in this kind of experiment involving required absolute controls like weedy check (WC) or unweeded control (UWC), and weed-free check (WFC) along with these treatments (CT, PNB, PNB+R, PBB, PBB+R, FB, FB+R), the WCE, WCI, and weed index (WI) may be worked out.

**Table 2. Total weed population and weed control efficiency (WCE) and index (WCI) at 40 DAS of maize (Part of the Table 1 of Susha *et al.* 2014)**

Treatment	WCE (%)	WCI (%)
Weedy check	0	0
Atrazine 0.75 kg/ha + pendimethalin 0.75 kg/ha (tank-mix PE)	69.6	74.4
Atrazine 1.0 kg/ha + hand weeding at 30 DAS	78.4	87.0
Atrazine 1.0 kg/ha +mustard residue mulch 5 t/ha	66.4	74.8
Pendimethalin 0.75 kg/ha + imazethapyr 0.050 kg/ha (tank-mix PE)	90.6	90.9
*KNO <sub>3</sub> (6%) + pendimethalin 0.75 kg/ha + imazethapyr 0.050 kg/ha (tank-mix PE)	89.2	87.3
Pendimethalin 0.75 kg/ha + chlorimuron 0.006 kg/ha (tank-mix PE)	85.6	85.3
Pendimethalin 0.75 kg/ha PE followed by imazethapyr 0.050 kg/ha PoE with sand	78.1	76.8
Pendimethalin 0.75 kg/ha PE <i>fb</i> chlorimuron 0.006 kg/ha POE with sand	75.5	74.0
Brown manuring ( <i>Sesbania</i> 5 kg/ha+ 2,4-D 0.75 kg/ha at 25 DAS)	59.8	60.3
Brown manuring ( <i>Sesbania</i> 10 kg/ha+ 2,4-D 0.75 kg/ha at 25 DAS)	64.6	67.7
Weed-free check	100.0	100.0

\*KNO<sub>3</sub> was applied separately; PE - pre-emergence; PoE – post-emergence; \*\*Data were subjected to square-root ( $\sqrt{x+0.5}$ ) transformation; Figures in the parentheses are original values

**Table 1. Conservation agriculture treatments effects on weed control efficiency (WCE)/per cent reduction in weed population, weed control index (WCI)/ per cent reduction in weed dry weight (WCE) in mungbean (Part of the Table 1 of Ghosh *et al.* 2022)**

Treatment	WCE (%) in 2018-19	WCI (%) in 2018-19
CT	0	0
PNB	16.3	6.7
PNB+R+75N	38.0	42.2
PNB+R+100N	30.4	47.3
PBB	44.6	36.7
PBB+R+75N	51.1	50.2
PBB+R+100N	45.7	48.9
FB	31.5	35.1
FB+R+75N	37.0	39.3
FB+R+100N	34.8	38.3

### Scenario 2: Experiment in randomized complete block design having absolute controls (WC/ UWC, WFC)

A case in point is the experiment of Susha *et al.* (2014), which is a pure/true weed control trial (Table 2), involving 11 weed control treatments including two controls such as WC and WFC. Here studying WCE and WCI is very appropriate, which really gives a measure of relative weed control ability of these treatments. For example, highest WCE and WCI were obtained from the tank-mix pre-emergence application of pendimethalin 0.75 kg/ha + imazethapyr 0.050 g/ha. With respect to WCE and WCI, all the weed control treatments including brown manuring showed superiority over weedy check (WC).

### Scenario 3: Experiment in split plot design considering only one control for both main plot and sub-plot treatments (may/may not be absolute control)

In some experiments in split plot design, one set of weed control treatments are adopted out of two

sets of treatments and analyzed, taking only one control for both main plot and sub-plots treatments (Table 3). Fazil *et al.* (2022) conducted an experiment involving three weed management options in main plots, and four N levels in sub-plots in barley. For both main plot and sub-plot treatments, weedy check was taken as control for determining WCE and WCI, whereas WFC was the control for determining WI. It showed that the IWM significantly increased WCE and WCI. On the contrary, the effect of nitrogen levels was not significant although the N-treatments gave considerably higher WCE/WCI values ranging from 34-52%. In this case, the effect of each main plot weed control treatment averaged over four sub-plot N treatments and compared with WC is alright and acceptable as the efficacy/effect of the weed control treatments got tested/ evaluated over a range of N doses. But, the effect of each sub-plot N treatment averaged over three main plot treatments and compared with WC gave values hardly acceptable as their individual effect since the values are quite higher and could hardly be achieved under field conditions.

For example, it shows that N<sub>120</sub> can lead to 51.6% WCE and 44.3% WCI, which hardly can happen in reality. This could happen due to the statistical analysis. The effects of all weed control treatments have been averaged and reflected in the N doses. In this sort of experiment, the WCE/WCI should be worked out only for the factor, main plot or sub-plot that involves the weed control treatments with WC (~W<sub>1</sub>) as the control, which will be quite realistic and reasonable. The WCE/WCI of the other

**Table 3. Weed control efficiency (WCE), weed control index (WCI) at 40 DAS and weed index/WI in barley (Part of the Table 1 of Fazil *et al.* 2022) (considering one absolute control for both main plot and sub-plot treatments)**

Treatment	WCE (%)	WCI (%)	Weed index (%)
<i>Weed management (W)</i>			
Weedy check (W <sub>1</sub> )	0	0	24.1
Chemical weed management (W <sub>2</sub> )	60.7	58.6	6.6
Integrated weed management (W <sub>3</sub> )	81.9	72.6	0.0
LSD (p=0.05)	7.96	14.8	10.4
<i>Nitrogen doses (N)</i>			
N <sub>0</sub>	40.0	44.3	41.1
N <sub>40</sub>	43.9	34.2	18.5
N <sub>80</sub>	54.8	52.2	-6.7
N <sub>120</sub>	51.6	44.3	-11.9
LSD (p=0.05)	NS*	NS*	19.8
<i>Interaction (WxN)</i>			
LSD (p=0.05)	NS*	NS*	NS*

\* Non-significant

factors should not be studied/reported. To establish their actual WCE/WCI, they should be studied as an individual treatment solely in a randomized complete block design and compared with WC. However, their combined interaction effect if at all exists on WCE/WCI may be studied and reported. Furthermore, in this case, the calculation is more complex and each pair of W<sub>1</sub>N<sub>0</sub>, W<sub>1</sub>N<sub>40</sub>, W<sub>1</sub>N<sub>80</sub>, and W<sub>1</sub>N<sub>120</sub> have to be taken as control for determining the WCE/WCI of respective pairs of W<sub>2</sub> with N<sub>40</sub>, N<sub>80</sub>&N<sub>120</sub>, and W<sub>3</sub> with N<sub>40</sub>, N<sub>80</sub> & N<sub>120</sub> treatments (Table 3a). For easy and quick analysis, sometimes only one combination of main plot control and sub-plot control such W<sub>1</sub>N<sub>0</sub> is taken as single control, and the WCE/WCI of rest of the combinations are worked out. This may lead to erroneous analysis and inference (Table 3b) and should not be adopted in any case/ experiment. Doing this, the mean value of WCE/WCI even for the weedy check control (W<sub>1</sub>) treatment does not become zero. Another analysis could be that two controls are chosen separately, such as W<sub>1</sub> for main plot (weed control treatments) and N<sub>0</sub> for the sub-plot (N doses) treatments and both factors' effects are analyzed separately (Table 3c). This has been presented in Table 4.

**Table 3a. WCE or WCI calculated considering only one main plot treatment as control for combination with each of the sub-plot treatments**

Treatment	WCE or WCI across the combinations of treatments				Mean
	N <sub>0</sub>	N <sub>40</sub>	N <sub>80</sub>	N <sub>120</sub>	
W <sub>1</sub>	0	0	0	0	0
W <sub>2</sub>	a <sub>1</sub>	a <sub>2</sub>	a <sub>3</sub>	a <sub>4</sub>	A
W <sub>3</sub>	b <sub>1</sub>	b <sub>2</sub>	b <sub>3</sub>	b <sub>4</sub>	B
Mean	C	D	E	F	

Here W<sub>1</sub> to W<sub>3</sub>; N<sub>0</sub> to N<sub>120</sub> are taken from Table 3; Each pair of W<sub>1</sub>N<sub>0</sub>, W<sub>1</sub>N<sub>40</sub>, W<sub>1</sub>N<sub>80</sub>, and W<sub>1</sub>N<sub>120</sub> are taken as control; a<sub>1</sub>- a<sub>4</sub> & b<sub>1</sub>- b<sub>4</sub> are replication-wise values of WCE/WCI calculated based on weed density or dry weight; and A-F are respective mean values of WCE/WCI of the main plot and sub-plot treatments.

**Table 3b. WCE or WCI calculated considering only one combination of treatments (W<sub>1</sub>N<sub>0</sub>) as control**

Treatment	WCE or WCI across the combinations of treatments				Mean
	N <sub>0</sub>	N <sub>40</sub>	N <sub>80</sub>	N <sub>120</sub>	
W <sub>1</sub>	0	a <sub>1</sub>	a <sub>2</sub>	a <sub>3</sub>	A
W <sub>2</sub>	b <sub>1</sub>	b <sub>2</sub>	b <sub>3</sub>	b <sub>4</sub>	B
W <sub>3</sub>	c <sub>1</sub>	c <sub>2</sub>	c <sub>3</sub>	c <sub>4</sub>	C
Mean	D	E	F	G	

Here W<sub>1</sub> to W<sub>3</sub>; N<sub>0</sub> to N<sub>120</sub> are taken from Table 3; Only W<sub>1</sub>N<sub>0</sub> is taken as control; a<sub>1</sub>- a<sub>3</sub>; b<sub>1</sub>-b<sub>4</sub>&c<sub>1</sub>-c<sub>4</sub> are replication-wise values of WCE/WCI calculated based on weed density or dry weight; and A-G are respective mean values of WCE/WCI of the main plot and sub-plot treatments.

**Table 3c. WCE or WCI calculated considering two controls one each for main plot and sub-plot treatments**

Treatment	WCE or WCI across the combinations of treatments				Mean
	N <sub>0</sub>	N <sub>40</sub>	N <sub>80</sub>	N <sub>120</sub>	
W <sub>1</sub>	0	0	0	0	0
W <sub>2</sub>	0	a <sub>1</sub>	a <sub>2</sub>	a <sub>3</sub>	A
W <sub>3</sub>	0	b <sub>1</sub>	b <sub>2</sub>	b <sub>3</sub>	B
Mean	0	C	D	E	

Here W<sub>1</sub> to W<sub>3</sub>; N<sub>0</sub> to N<sub>120</sub> are taken from Table 3; Each pair of W<sub>1</sub>N<sub>0</sub>, W<sub>1</sub>N<sub>40</sub>, W<sub>1</sub>N<sub>80</sub>, and W<sub>1</sub>N<sub>120</sub>, and N<sub>1</sub>W<sub>1</sub>, N<sub>1</sub>W<sub>2</sub>, and N<sub>1</sub>W<sub>3</sub> are taken as control; a<sub>1</sub>- a<sub>3</sub>& b<sub>1</sub>- b<sub>3</sub> are replication-wise values of WCE/WCI calculated based on weed density or dry weight; and A-E are respective mean values of WCE/WCI of the main plot and sub-plot treatments.

There is no WFC treatment in this experiment (Table 3), but WI has been calculated. The IWM treatment being most superior in terms of higher WCE/WCI and crop yield, was considered as the control, i.e. WFC. This, however, should not be followed. In reality, an IWM treatment can never substitute WFC theoretically. This has been found in many weed experiments and two hand weeding, three hand weeding, or the best weed control treatment have been considered as control/WFC treatment and WI calculated. There is nothing wrong in determining this parameter. But, in this case as there was no WFC treatment, it would be more appropriate to mention it as the per cent reduction in crop yield based on the so-called control. This can be compared with all other treatments in randomized complete block design, and across the main plot treatments or across the sub-plot treatments as applicable in split plot design. The per cent reduction in crop yield is more universal than WI and can be applicable/determined uniformly in all weed/non-weed agronomic experiments.

#### Scenario 4: Experiment in split plot design taking two controls one each for main plot and sub-plot treatments (may or may not be absolute control)

In some experiments in split plot design, involving two sets of treatments as main plot and sub-plot, WCE/WCI or WI are worked out considering two controls, one main plot treatment as control for the main plots and one sub-plot treatment as control for the sub-plots and statistical analysis is done. Kumar *et al.* (2012) had undergone similar analysis in an experiment involving five main plot and four sub-plot treatments (Table 4). By doing this, the main plot treatments averaged over sub-plots treatments are compared among themselves, while sub-plot treatments averaged over main plot treatments are compared among themselves.

**Table 4. *Cyperus rotundus* control efficiency (CCE) and *C. rotundus* control index (CCI) of different treatments in soybean (Part of the Table 6 of Kumar *et al.* 2012) considering one control each for main plot and sub-plot treatments)**

Treatment	CCE (%)	CCI (%)
<i>Summer season</i>		
Cowpea cropping	13.9	12.3
Deep disking <i>fb</i> glyphosate at 1.0 kg/ha once	25.5	19.2
Deep disking <i>fb</i> glyphosate at 1.0 kg/ha twice	55.0	48.5
Soil solarization for one month <i>fb</i> glyphosate at 1.0 kg/ha	83.5	83.1
Farmers' practice	-	-
<i>Rainy season</i>		
Unweeded control	-	-
Imazethapyr at 0.075 kg/ha at 20 DAS	51.5	77.9
<i>In situ Sesbania</i> grown and mulched	55.5	72.1
Two hand-weeding at 25 and 35 DAS	83.8	91.4

#### WEED DATA TRANSFORMATION: MYTHS AND REALITY

The non-uniform scattered distribution and periodicity of germination of weeds coupled with the effect of treatments like weed-free check, weedy check, adopted in most experiments often results in large variation. Transformation helps to normalize these data. Several transformations, *viz.*, square-root, logarithmic, angular or reciprocal are advocated for different purposes (Table 5). Therefore, an analytical exercise (Das 1999) had been undertaken to find out whether transformation could change the significance of weed data across treatments; whether the square-root transformations varied among themselves; whether a wider variation in significance of data existed between the square-root and logarithmic methods *vis-à-vis* between the split plot and randomized complete block design. Original and transformed data through  $(X+1.0)^{1/2}$ ,  $(X+0.5)^{1/2}$ ,  $(X+0.05)^{1/2}$  and  $\log(X+1)$  were subjected to analysis of variance (ANOVA) and the significance was tested by variance ratio/ F value. The summum bonum of the ANOVA revealed that (i) the significance for treatment variation of the main plots, sub-plots and their interaction did not differ between original and transformed data, irrespective of square-root and logarithmic methods up to a coefficient of variation (CV) nearly 70%; (ii) at the CV higher than 100%, the square-root transformed data behaved similarly with original data, but the logarithmic transformation differed with original data (Das 1999); (iii) different square-root methods tried did not differ among themselves; and (iv) transformation could reduce CV by 50% in square-root methods and by 75% in logarithmic method and standard error drastically.

**Table 5. Different methods of data transformation (Das 2008)**

Transformation method	Formula	Data to be transformed
Square-root methods	$(X+1.0)^{1/2}$ ; $(X+0.5)^{1/2}$ ; $(X+0.05)^{1/2}$ (where X is value of an observation)	Weed data (population, dry weight, etc.)
Logarithmic methods	Log (X+1) (where X is value of an observation); Log X should not be adopted as Log 0 becomes infinitive	Weed data (population, dry weight etc.)
Angular/arcs in method	$\text{Sin}^{-1}X$ (where X is per cent value of an observation)	Insect population, fecundity, or any per cent data
Reciprocal method	1/X (where X is value of an observation)	Hardly used in weed research

Therefore, a hypothesis is made that the transformation of weed data through square-root or logarithmic methods is not an unavoidable one. It should not be followed indiscriminately except where the data required it. It is generally-held that the desired level of CV for field research data should not exceed 20%. But, most weed data, usually possess a larger variation than this, and at this level of variation, transformation found useless. Therefore, Finney (1989) viewed that the assumptions/pre-requisites for ANOVA of data are never certain and not so important to the general informativeness of the analysis. In those situations, where original and transformed data show similar test of significance, it would be better for several reasons that the original data analysis is highlighted (Das 1999).

## WEED SURVEY AND PHYTOSOCIOLOGY STUDIES

### Sampling of weeds in surveys

Generally, in a weed survey, the sampling area is 5-10% of the total surveyed area. Surveys identify and analyze weeds in order to formulate effective management approaches. Weed phytosociology (frequency, density, abundance, dominance, importance value index/IVI), similarity/ dissimilarity/ shift, mapping, management effectiveness, and insurgence of resistant weeds may be evaluated. Surveys encompass crops, orchards, agro-forestry systems, irrigated/ rainfed crops across villages, blocks, districts, agro-climatic regions based on the magnitude of problem of weed/ invasive weed and objective of survey. Sometimes, herbicide application in crop fields influences time of sampling. It should be decided whether to sample with or without herbicide treatment well before sampling. Sampling from no herbicide treated plots reflects the potential weed distribution and is useful to analyse site and management effects other than herbicides. Herbicide effects can superimpose all other influences in the current crop (Andreasen *et al.* 1991; Mehrtens *et al.* 2005).

Phyto-sociological studies may adopt destructive or non-destructive method, which has inherent advantages and disadvantages. In destructive

sampling, plants are pulled out/ cut at the base and their population count, fresh and dry weights recorded. In contrast, in a non-destructive sampling, the plants remain undisturbed and almost unhurt, which allow repeatability of observation. In plant ecological studies, the methods generally followed are: i) quadrat method, ii) transect method, iii) plot-less or point method, and iv) loop method (Das 2008). But, mostly, a quadrat is used for sampling in weed research. A quadrat of different sizes such as 20 cm x 20 cm, 50 cm x 50 cm, 100 cm x 100 cm (Rew and Cousens 2000; Salaudeen *et al.* 2022) may be used, depending on plants/ vegetation and magnitude of area of survey. A square quadrat may be useful in cropped lands, while a rectangular quadrat (100 cm x 50 cm) may be better in grasslands. For small plants like mosses, lichens and liverworts growing in patches, small quadrats of 20 cm x 20 cm; in grassland 50 cm x 50 cm quadrat if the stand is relatively pure, or 100 cm x 100 cm or more if greater diversity exists, may be quite useful. Generally, quadrats of 100 cm x 100 cm are used for studying herbaceous and weed vegetation in large areas like block/district. In forests the quadrat may be quite large from 10 m x 10 m to even one-fifth of an acre.

### Minimum size and number of quadrats

Using large quadrat for survey usually results in greater accuracy, but is cumbersome and time-consuming. Therefore, before conducting sampling, a representative “minimum size of quadrat”, and a representative “minimum number of quadrat” are to be determined judiciously by “species-area curve” method (Das 2008). This may lead to ensure that the total sampling area and weed flora distribution in the sampled area are quite representative to the whole area of survey.

### Sampling methods/techniques

The arrangement/placing of quadrats assumes enough significance in a survey. A definite method needs to be adopted for sampling based on types of vegetation and total area of vegetation. The methods could be representative method, random method, systematic method, restricted random sampling and stratified sampling (Das, 2008).

### Crops/sites/fields of surveys

Random method is employed to select the sites. In each site, representative areas like crop fields, fencerows, ditch banks, and wet spots may be considered for assessment. Surveyors may walk through fields in a random fashion to evaluate the severity level of weed infestation, which may be rated using 1 to 5 scale (1: light infestation; 5: heavy infestation), or through qualitative descriptors such as low, medium, and high.

### Time of sampling, data collection and analysis

A survey may have different purposes/objectives. It can be undertaken in crops seasonally (tropical climate), annually (temperate climate), or at certain intervals with specific objectives. The repetition of survey after a medium (5 years) or long (10 years and more) period may reveal weed succession/shift, similarity and dissimilarity of weed species over the years across the sites. The time of sampling is usually based on the chosen survey conditions. It could be at maximum ground cover of crop, completion of all management practices or maximum homogeneity of field conditions during flowering and seeding of the crop. Seasonal characteristics of weeds explain the variation more clearly even within same crop than by any other management or environmental parameter (Pinke *et al.* 2010).

Global positioning system (GPS) technology may give precise geographical location of weed infestations, facilitating spatial analysis and mapping. Digital data collection tools, such as mobile phones/smartphones allow for efficient recording and storage of field observations. Photography may serve as a visual record to document the extent and severity of weed infestations. Additionally, biomass sampling is conducted to quantify weed biomass, offering valuable insights into weed competition and the effectiveness of control measures.

Descriptive statistics (mean, median, mode, standard deviation, percentiles) are used to summarize data on weed density, frequency, and other attributes. Trend analysis for time-series data can assess weed species changes over time. Several linear and unimodal models (Table 6) may help to find

out relationships between weed populations, environmental factors, and management practices through indirect and direct gradient analysis (Hanzlik and Gerowitt 2016). Indirect gradient analysis using principal component analysis (PCA), correspondence analysis (CA), detrended correspondence analysis (DCA), and direct gradient analysis using redundancy analysis (RDA), canonical correspondence analysis (CCA), detrended canonical correspondence (DCCA) are being adopted by weed researchers for studying phytosociological aspects of weeds. Regression analysis can model and predict future weed infestation based on existing data. Further, spatial analysis allows for the mapping of weed distribution and identification of infested areas, supporting targeted management strategies (Tiwari *et al.* 2024).

### Phytosociological study and importance value index (IVI)

The importance value index (IVI) gives an overall ecological importance of a weed/plant species in a community (Phillips 1959). It is calculated (Eq. 16) by summing up relative frequency (Rf), relative density (Rdn), and relative dominance (Rdo) of a species (Das 2008). Frequency, density, abundance, and dominance/cover are quantitative estimates, but individually they can hardly reveal the true ecological importance of a species in any plant community, which is normally heterogeneous in nature. Thus, IVI is calculated as a value out of 300 for each species and the species are arranged in decreasing order of IVI. Generally higher the IVI of a species, greater is its importance ecologically at a given place at that point of time and *vice-versa*. Summed dominance ratio (SDR) is half the value of importance value index (IVI).

$$IVI = (R_f + R_{dn} + R_{do}) \quad (16)$$

### WEED DIVERSITY, RICHNESS, AND SIMILARITY/DISSIMILARITY STUDIES

A variety of methods are available for assessing weed diversity, each offering distinct advantages and limitations (Wilson *et al.* 1999; Yorks and Dabydeen 1998). Weed diversity can be evaluated at both the intra-community level [ $\alpha$  (alpha) diversity] and inter-community level [ $\beta$  (beta) diversity] using the following indices (Nkoa *et al.* 2015)

**Table 6. Common ordination methods with their properties and statistical assumptions (Hanzlik and Gerowitt 2016)**

	Indirect gradient analysis	Direct gradient analysis
Linear model	Principal component analysis (PCA)	Redundancy analysis (RDA)
Unimodal model	Correspondence analysis (CA)	Canonical correspondence analysis (CCA)
	Detrended correspondence analysis (DCA)	Detrended canonical correspondence Analysis (DCCA)

### Alpha ( $\alpha$ ) diversity (intra-community/within community)

Among the commonly used indices for measuring alpha diversity are Margalef's Diversity Index (DMg), Shannon–Weiner Diversity Index (H), and Simpson's Dominance Index (D). Margalef's Diversity Index provides a rapid estimate of species diversity based solely on species richness, though it is notably sensitive to sampling parameters such as unit, size, and design. In contrast, the Shannon–Weiner Diversity Index (H') incorporates both species richness and evenness in its calculation (Magnussen and Boyle 1995), and demonstrates moderate sensitivity to variations in sampling methodology (Eq. 17). Diversity index generally indicates richness (number) of weed species in an ecosystem.

$$\text{Shannon-Weiner index (H')} = [-\sum_{i=1}^S \{pi(\ln pi)\}] \quad (17)$$

Simpson's Dominance Index (D) is primarily employed to quantify species dominance. While it is relatively insensitive to sample size, it does not account for species richness. Nonetheless, it can be utilized to describe species evenness (Eq. 18), offering insight into the degree to which a single species dominates a community.

$$\text{Simpson index (D)} = [1 - (\sum_{i=1}^S pi^2)] \quad (18)$$

Species evenness can also be derived from the values of Shannon–Weiner Diversity Index (H2), which reflects the uniformity or disparity in the distribution of weed species within a given system (Eq. 19).

$$\text{Evenness index (E)} = \left( \frac{H'}{\ln S} \right) \quad (19)$$

Species richness refers to the total number of distinct groups of individuals that are genetically or functionally related within a community (Eq. 20).

$$\text{Richness index (R)} = \left( \frac{S-1}{\ln N} \right) \quad (20)$$

Ecological dominance (Eq. 21) serves as an alternative measure to Simpson's Index and similarly indicates the extent to which a single species exerts dominance within an ecological system.

$$\text{Ecological dominance (C)} = \left[ \sum_{i=1}^S \frac{ni(ni-1)}{N(N-1)} \right] \quad (21)$$

Where, S is the species richness i.e. the number of species presents in the quadrat, pi is the proportion of  $i^{\text{th}}$  species and  $pi = ni/N$ , ni is the density of  $i^{\text{th}}$  species, and N total number of individuals of all species in the treatment, “ is sum of all the factors.

### Beta ( $\beta$ ) diversity (inter-community/between the communities)

To compare differences or similarities between landscapes, two commonly used indices are Sørensen and Steinhaus Coefficients (Sørensen 1948). The Sørensen Coefficient/Similarity Index (Eq. 22) is a similarity measure based on species composition. It considers the number of species shared between communities relative to the total number of species present. In contrast, the Steinhaus Coefficient Index (Eq. 23) incorporates species abundance into its calculation. It estimates similarity by identifying the minimum abundance of each species shared between communities and expressing it as a proportion of the average total abundance across those communities.

$$\text{Sørensen coefficient index (Ss)} = \left[ \left( \frac{2J}{a+b} \right) \times 100 \right] \quad (22)$$

where, J=the number of species common to each community; and (a+b) = the sum of the total number of species in each community.

$$\text{Steinhaus coefficient index (SA)} = \left( \frac{2W}{A+B} \right) \quad (23)$$

where: W =the sum of the lower of the two abundances of each species in the community; A =total number of individuals in population A; and B=total number of individuals in population B.

### DETERMINATION OF WEED ECONOMIC THRESHOLD

The economic threshold (ET) is one of the major decision-making frameworks for rationalizing herbicides use for better weed management while reducing environmental impacts (Das *et al.* 2021). The ET is the density of a weed at which the cost of controlling it equals to the benefits obtained due to its control. It rejects complete eradication of weeds and advocates regulating weed populations at economically optimum levels. Several decision-making models on ET are available with high to low degree of precision (Cousens 1985a and 1985b; Kropff and Spitters 1991; Kropff and Lotz 1993). Several researchers have determined ET of single weed species having abundance in a crop (Moorthy and Das 1998; Hazra *et al.* 2011; Dodamani and Das 2013; Das *et al.* 2014; Raj *et al.* 2020; Das *et al.* 2021). However, the adoption of ET models as the major criterion for cost-effective herbicide use is low due to several reasons like seed bank build up by residual weeds, complexity in estimating ET density, patchy weed distribution, and limited validity in cropping systems with multiple weed species. From

the viewpoint of farmers, risk mitigation is more important than profit maximization, and the farmers are likely to take control actions at weed populations lower than the ET level (Coble and Mortensen 1992). But, the ET-based decision has great potential in designing weed management under single weed dominance in crops. Information on weeds population dynamics in cropping systems, biology, ecology and spatial heterogeneity would make ET more reliable, and managing weeds using integrated approach more successful. The density per unit area (Cousens 1985a and 1985b) and relative leaf area (Kropff and Spitters 1991; Kropff and Lotz 1993) of an individual weed are usually considered for working out its ET in certain crop. However, ET based on composite weed populations in crop fields hardly exists. The non-uniformity in weed species and their densities makes it difficult to determine whether the threshold reached or exceeded in crop field. There are a number of weed competition thresholds (Das 2008): i) period threshold, ii) quantity/ density threshold (damage threshold, economic threshold and action threshold). Kasasian and Seeyave (1969) have made a general assumption, such as, first 1/4<sup>th</sup> to 1/3<sup>rd</sup> period of the total growing duration/life cycle of a crop as its period threshold/critical period of weed interference. Another threshold, ecological threshold emphasizes on managing a composite culture of weeds to the level that maintains the existing plant species diversity and ecological harmony in a given area but hardly exists. In simpler terms, ecological threshold avoids the complete destruction/removal weeds or other vegetation from cropped or non-cropped situations.

### HERBICIDE BIO-EFFICACY, PHYTOTOXICITY, AND IMPACT STUDIES

#### Herbicide, nano herbicide, and bioherbicide/ organic herbicides

The population, fresh weight, and dry weight of weeds, and the phytotoxicity, growth and yield of crop are invariably studied for assessing the bio-efficacy of herbicides. Weed population varies largely in fields (Brar *et al.* 2000; Kurchania *et al.* 2000) due

to non-uniform/ patchy/ erratic distribution of weeds across the plots and even within a plot. Similar justification applies to uneven distribution of fresh weight and dry weight of weed samples across the plots/ treatments. Fresh weight is generally considered less reliable than dry weight (Das 2001b). Dry weight, on the contrary, gives a better estimate of the dry matter accumulation in plants over times. This holds most reliable where the samples are homogeneous and constituted of mostly alive/ green plants (e.g. crop plants). But, in case of weeds, different kinds/ species of weeds present at different densities and different stages of growth usually show differential tolerance/sensitivity to the applied herbicide, which leads to graded injury symptoms at different stages of mortality, such as, some weeds would be completely dried/dead, some started drying, some are yellow or burnt and some are still alive/ green. But, weeds are usually sampled, irrespective of these injury effects, and fresh weight and/or dry weight recorded, which overshadow the variation. The injury-level variation is much overlooked, if only one parameter (either fresh weight or dry weight) is recorded. Again, the variation in weed density distribution across the plots may magnify the sampling error. In such situation, lower the dry weight of weeds, greater is the bio-efficacy of treated herbicide – does not always hold true. Therefore, the reliability/ authenticity of weed fresh weight and/or dry weight data depicting herbicide bio-efficacy were evaluated by introducing two new parameters (Eq. 24, 25 & 26), such as, fresh weight (Fw): dry weight (Dw), and moisture content (%) of the weed samples fresh weight-basis or dry weight-basis (Das 2001b), and the bio-efficacy of herbicides, namely, post-emergent foliage-active glufosinate-ammonium and glyphosate each at 2.5 and 3.0 L/ha (product) was precisely estimated on *Cynodon dactylon* and *Cyperus rotundus* (Table 7). Similar analysis by Das and Yaduraju (2002) was also done on fixed area basis and fixed fresh weight basis. These two new parameters (Fw:Dw; moisture content) could separate out the usual variation of weeds across the plots and were quite reliable/ responsive and highly aligned to visual observations. They delivered the

**Table 7. Bio-efficacy of glufosinate-ammonium and glyphosate on *Cyperus rotundus* at 20 days after treatment (part of the table 1 of Das 2001b)**

Treatment	Product (L/ha)	<i>Cyperus rotundus</i>					
		Fresh weight (Fw) (g/m <sup>2</sup> )	Dry weight (Dw) (g/m <sup>2</sup> )	Fw-Dw (g/m <sup>2</sup> )	Fw:Dw	Moisture (%) (Fw basis) (%)	Moisture (%) (Dw basis) (%)
Glufosinate-AM	2.5	114.0	85.1	28.9	1.34	25.4	33.9
Glufosinate-AM	3.0	95.4	75.3	20.1	1.27	21.1	26.7
Glyphosate	2.5	112.4	78.7	33.7	1.43	29.9	42.8
Glyphosate	3.0	93.2	68.8	24.4	1.35	26.2	35.5
Unweeded control	--	320.0	116.4	203.6	2.75	63.6	174.9

truth when the result remained inconclusive based on fresh weight and dry weight of the weed sample. They, therefore, may be adopted along with fresh weight and dry weight for better appraisal of the bio-efficacy of herbicides, nano herbicide, and bioherbicide/organic herbicides.

$$\text{Fw: Dw} = \frac{\text{Fresh weight of weed sample}}{\text{Dry weight of weed sample}} \quad (24)$$

$$\text{Moisture (\%)} (\text{Fw basis}) = \frac{(\text{Weed fresh weight} - \text{weed dry weight})}{\text{Weed fresh weight}} \times 100 \quad (25)$$

$$\text{Moisture (\%)} (\text{Dw basis}) = \frac{(\text{Weed fresh weight} - \text{weed dry weight})}{\text{Weed dry weight}} \times 100 \quad (26)$$

Nano-herbicide formulations have higher ability for controlled release, lower decomposition rate, and improved bioavailability through targeted delivery. They have become exceedingly important in recent years towards achieving higher weed control efficiency with no or negligible residue and environmental footprints. The bio-efficacy of nano-herbicides/organic herbicides can be evaluated from crop fields in a similar way as mentioned above for herbicides. The weed control efficiency of conventional high molecular weight herbicides may be influenced tremendously under higher temperature and atmospheric carbon dioxide concentration, and the nano-herbicides may take their place in the coming years. The altered growth, physiology and tolerance levels of weeds may show lower susceptibility to herbicides with a consequent change in effectiveness and metabolism/degradation of herbicide in the environment. Many perennial weeds exhibit deep and persistent root system, high phenotypic plasticity, allowing them to adjust their growth and reproductive strategies in response to elevated atmospheric CO<sub>2</sub> levels and temperature. Such weeds allocate more resources to underground vegetative parts that acts as a food reserve to survive under unfavorable situations, while they have capability to regenerate abruptly once favorable conditions prevailed. Nano-formulated herbicides can be engineered for controlled release and improved mobility, allowing them to penetrate deeper into the soil profile and reach underground structures such as *Cyperus* spp tubers more effectively than conventional herbicides (Kah *et al.* 2012). This improves the bioavailability and persistence of active ingredients near critical target zones, enhancing control of regenerating propagules in perennial species. Nano herbicides have potential for integration into modern spraying tools like UAVs, especially in precision agriculture. Nano herbicides research may focus on nanoparticles characterization

and quantification, their uptake, translocation, persistence, and bio-safety evaluation.

The so-called organic herbicides need rigorous field testing for their selectivity to crops/ crop tolerance before they are recommended for organic production systems, although equally applicable for inorganic production system. These herbicides have environmental safety owing to low persistence, reduced resistance risk owing to non-selective contact action and can be incorporated to regenerative production systems.

### Assessment of crop phytotoxicity and weed control

Selective herbicide upon application at the recommended dose to a crop produces certain injury symptoms, mainly, on weeds, and in invisible, negligible, and undetectable scales on crop plants. The graded response of growth inhibition/reduction or death of crop plants due to herbicide is phytotoxicity. The level of phytotoxicity varies from plant to plant: weeds being most affected, whereas crop plants not affected or least/negligibly affected (particularly when herbicide is selective and applied at the recommended dose). Therefore, observations should be recorded separately for weeds and crop. Phytotoxicity to weeds indicates the degree of weed control (called bio-efficacy), whereas phytotoxicity to a crop indicates the degree of herbicide's selectivity to crop whether this herbicide can safely be used in that crop. The phytotoxic effects of herbicides can be assessed qualitatively by visual rating (**Table 8**) using a scale from 0 (zero) to 10 (where 0 equals to 0% and 10 equals to 100% phytotoxicity) or from 0 (zero) to 5 (where 0 equals to 0% and 5 equals to 100% phytotoxicity). Other phytotoxicity scales can be 1-5 or 1-10 as well. For recording phytotoxicity in the fields, first percent injury to crop compared to control is assessed visually and, then, rating is executed using these scales, such as, 0 for 0%, 1 for 10%, 2 for 20% injury and so on in the 0-10 scale. At least two persons, standing on either side of the herbicide-treated plot may be deputed for visual rating of phytotoxicity. These persons should be literate in weed science and have enough knowledge on the mode of action and usual injury symptoms of the specified herbicide. Per cent mean of phytotoxicity may be calculated simultaneously from the observations of both persons treatment-wise across replications in the field. A visual scoring of injury symptoms on crop due to herbicides was reported long back (Rao 1983). An exhaustive but convenient scoring of the phytotoxic effects on crops due to pre-emergence (PE) and post-emergence (PoE)

herbicides has been formulated here (**Table 8**). For PE herbicides, crop seed germination, seedlings emergence and population/stand may be considered as there is no direct contact/ exposure of herbicides with the crops. But, for PoE herbicides, crop seedlings death/mortality, chlorosis, necrosis, yellowing, bending, twisting and curling of leaves, growth stunting etc, which ultimately result in final plant stand may be considered. These symptoms are hardly uniform on all individual plants of the crop unless there is complete death of crop plants, rather they are graded/variable and difficult to quantify on individual plant-basis. Therefore, the phytotoxicity may be considered collectively on plant population-basis. For judging the phytotoxicity, the following steps may be followed:

- i) Wait for 5-10 days after application of herbicides for the injury symptom to be sufficiently visible for assessment depending on the chemical nature of the herbicides.
- ii) Two persons should stand on the middle of bund along the widths on either side of the treated plot and look at the whole plot along the length and assess the per cent of plot area or per cent plant population having injury from slight to severe scales.
- iii) Similarly, they should stand on the middle of bund along the length on either side of the same treated plot and look at the whole plot along the width and assess the per cent of plot area or per cent plant population having injury from slight to severe scales.
- iv) Count the injured plants row-wise or plot-wise arbitrarily and existing uninjured plant population to appraise the truth of visual rating.
- v) In a crop having similar biochemical/physiological mechanisms, the judging of phytotoxicity on area-basis may be as good as the single plant-basis phytotoxicity evaluation involving the injuries on leaves, stems, branches of crop plants.

### HERBICIDE RESIDUE AND ENVIRONMENTAL IMPACT ANALYSIS

#### Herbicide residue analysis in crop and soil

Herbicide residue studies focus on understanding its persistence, degradation, and environmental impact through field and lab experiments, using chromatography to measure residue levels in soil and crops. Degradation studies can analyze microbial and environmental factors, while predictive models assess risks like groundwater

**Table 8. Visual rating of crop phytotoxicity/injury and weed control due to pre-emergence (PE) and post-emergence (PoE) herbicides in a 0-10 scale at 7-10 days after herbicide application**

Crop phytotoxicity rating (compared to weed-free control)			Weed control rating (compared to weedy check control)		
Crop injury magnitude	Injury score	Injury symptoms on crops collectively plot-basis in the fields or whole plant-basis	Weed control magnitude	Weed control score	Injury symptoms on weeds collectively plot-basis in the fields or whole plant-basis
No injury	0	Normal; germination/seedlings emergence/crop plants stand completely unaffected (PE); Normal; no toxicity/injury to standing crop plants (PoE)	No weed control	0	No weed control; weed germination/emergence not at all affected (PE); No toxicity/injury to standing weeds (PoE)
Negligible	0.1-0.9	1-9% reduction in germination/seedlings emergence/crop plants stand (PE); 1-9% crop plants showing injury symptoms or 1-9% injury whole plant or whole plot basis (PoE)	Negligible/ less weed control	0.1-0.9	1-9% weed control considering reduction in weed germination/ emergence (PE); 1-9% weed control considering injury symptoms or 1-9% injury whole plant or whole plot basis (PoE)
Slight (perceptible injury)	1.0-3.9	10-39% reduction in germination/seedlings emergence/crop plants stand (PE); 10-39% crop plants showing injury symptoms or 10% injury whole plant or whole plot basis (PoE)	Moderate/ medium weed control	1.0-3.9	10-39% weed control considering reduction in weed germination/ emergence (PE); 10-39% weed control considering injury symptoms or 10-39% injury whole plant or whole plot basis (PoE)
Moderate (less chance of recovery)	4.0-6.9	40-69% reduction in germination/seedlings emergence/crop plants stand (PE); 40-69% crop plants showing injury symptoms or 40% injury whole plant or whole plot basis (PoE)	High weed control	4.0-6.9	40-69% weed control considering reduction in weed germination/ emergence (PE); 40-69% weed control considering injury symptoms or 40-69% injury whole plant or whole plot basis (PoE)
Severe (majority plant stand destroyed)	7.0-9.9	70-99% reduction in germination/seedlings emergence/crop plants stand (PE); 70-99% crop plants showing injury symptoms or 70% injury whole plant or whole plot basis (PoE)	Very high weed control	7.0-9.9	70-99% weed control considering reduction in weed germination/ emergence (PE); 70-99% weed control considering injury symptoms or 70-99% injury whole plant or whole plot basis (PoE)
Complete destruction	10.0	100% reduction in germination/seedlings emergence/crop plants stand (PE); 100% injury to crop plants, whole plant or whole plot basis (PoE)	Complete weed control	10.0	100% weed control considering reduction in weed germination/ emergence (PE); 100% weed control whole plant or whole plot basis (PoE)

contamination. Bioassay methods with sensitive indicator plants may be used for qualitative and quantitative estimation of herbicides residue, and GIS tools are used for spatial monitoring of residue patterns. These methodologies support safer and more sustainable herbicide use in weed management (Hasan *et al.* 2021; Parven *et al.* 2024). Gas chromatography (GC), often with capillary columns, is widely used (Tadeo and Sanchez 2000). Multi-residue methods (MRMs), which determine a wider range of multiclass pesticides are preferred over single residue methods because the products applied and the regularity of treatments are generally unknown and residues of more than one pesticide can be present in samples (Pico 2016). The complete procedure for determining pesticide residues in food, soil and environment is complex and consists of several stages, such as i) sample preparation, ii) extraction and clean up and iii) detection as per standard procedures (Raj *et al.* 2022). In the 2000's, several advanced methods were developed for detecting pesticides in food, focusing on rapid and simple pretreatment. Among them, the QuEChERS method (Quick, Easy, Cheap, Effective, Rugged, and Safe) became most popular (Pico 2016).

### Herbicide impacts on soil health

#### Soil physical properties

The important soil physical properties such as soil aggregation, bulk density, penetration resistance, infiltration, soil temperature, moisture content, and porosity are influenced by weed control practices/herbicides (Raj *et al.* 2023). It is crucial to record observation on soil physical parameters under weed control experiments, and such experiment may be conducted/continued for a longer period. The soil bulk density (BD) can be determined by the core sampler method (Lal 2010). For soil aggregation study, soil samples may be collected randomly from five places in each treatment plot and analysed using Yoder apparatus (Yoder 1936). The collected soil samples in sieves may be classified as large macroaggregates (aggregates size >2000  $\mu\text{m}$ ), small macroaggregates (aggregates size 250-2000  $\mu\text{m}$ ), and microaggregates (aggregates size 53-250  $\mu\text{m}$ ). Other parameters such as mean weight diameter (MWD), geometric mean diameter (GMD) (Kemper and Rosenau 1986), and aggregate ratios (AR) of soils (Choudhury *et al.* 2014) may be also analysed.

#### Soil chemical properties

##### Soil pH, EC, available N, P and K

Soil pH can be measured using digital glass electrode pH meter (Jackson 1973). Electrical

conductivity (EC) is measured in 1:2.5 soil: water suspension using conductivity meter (Piper 1950). The available N may be estimated by alkaline  $\text{KMnO}_4$  method (Subbiah and Asija 1956) in a Kjeldahl assembly, available P content by ascorbic acid method (Olsen *et al.* 1954) for alkaline soils and P-Bray 1 (0.03 M  $\text{NH}_4\text{F}$  and 0.025 M HCl) and P-Bray 2 method (0.03 M  $\text{NH}_4\text{F}$  + 0.1 M HCl) for acidic soils (FAO 2021). Available K may be determined using flame photometry after extraction with neutral normal ammonium acetate (Jackson 1973). Similarly, other macro-nutrients and micro-nutrients may be analysed.

#### Organic carbon and carbon pools

For total organic carbon content, soil samples should be finely ground and sieved (250  $\mu\text{m}$ ) and analysed using TOC dry combustion analyser. Walkley and Black carbon (WBC) content in soil samples are determined by Walkley and Black (1934) method using  $\text{K}_2\text{Cr}_2\text{O}_7$  and conc.  $\text{H}_2\text{SO}_4$  and ferrous ammonium sulphate in the presence of phosphoric acid and diphenylamine indicator. Different fractions of soil organic carbon of varying lability may be estimated following Walkley and Black (1934) method as modified by (Chan *et al.* 2001) using separately 5, 10 and 20 mL of concentrated (36 N)  $\text{H}_2\text{SO}_4$  and 1 N  $\text{K}_2\text{Cr}_2\text{O}_7$  solution. This results in three acid-aqueous solution ratios of 0.5:1, 1:1, and 2:1 that corresponded to 12, 18 and 24 N  $\text{H}_2\text{SO}_4$  (WBC), respectively and produces different amounts of heat of reaction to bring about oxidation of SOC of different oxidizability. The amounts of C is determined allowed separation of total SOC into the following four fractions/pools of decreasing oxidizability (Chan *et al.* 2001):

Pool/fraction I (very labile): organic C oxidized with 12 N  $\text{H}_2\text{SO}_4$ ;

Pool/fraction II (labile): the difference in organic C oxidized under 18 N and 12 N  $\text{H}_2\text{SO}_4$ ;

Pool/fraction III (less labile): the difference in organic C oxidized under 24 N (WBC) and that under 18 N  $\text{H}_2\text{SO}_4$ ;

Pool/fraction IV (non-labile): the difference between TOC and organic C oxidizable under 24 N  $\text{H}_2\text{SO}_4$ .

Further, the four C fractions were classified under Active Pool ( $C_{\text{fraction I}} + C_{\text{fraction II}}$ ) and Passive Pool ( $C_{\text{fraction III}} + C_{\text{fraction IV}}$ )

#### Soil biological properties

Enumeration of soil fungi and bacteria under herbicide/weed control treatments may be done by serial dilution and agar/pour plate techniques using a 1 ml soil solution for plating (Das *et al.* 2010). Martin Rose Bengal agar medium (Martin 1950) for fungi and soil extract nutrient agar medium (Allen 1953) for bacteria are used. Nematode populations may be determined as per Southey (1986). Besides, microbial activity can be measured in terms of microbial biomass carbon (MBC), dehydrogenase activity (DHA) and alkaline/acid phosphatase activity from

different soil depth at flowering stages of crops. Soil samples are to be collected in small polythene bags by soil auger from each plot of the experimental field. Soil microbial biomass carbon is estimated as per Vance *et al.* (1987) and dehydrogenase activity as per Casida *et al.* (1964).

### Weed control treatments/ herbicides impact on greenhouse gases (GHGs) emission and C-footprints

Weed control treatments impact on GHGs emission and C-footprints need to be properly estimated for knowing the implication of agri-practices on climate change and global warming. Herbicide, hand weeding, inter-culture operations, hoeing etc. have impacts on GHGs emission (West and Marland 2002; Lal 2004) and environmental footprints (Table 9). The GHGs may be collected and sampled using a closed chamber technique and accordingly analysed (Bhatia *et al.* 2004, Gupta *et al.* 2016).

## WEED DETECTION, MAPPING, AND PRECISION CONTROL

Weed detection involves identifying and distinguishing weeds from crops or other vegetation using sensing technologies, image analysis, and pattern recognition algorithms to support efficient weed management in agricultural systems. It integrates optical, spectral, or thermal sensors with machine learning (ML) and computer vision techniques to capture and interpret spatial and temporal weed data, enabling targeted weed control in precision agriculture. Weed detection is challenging because weeds and crops often exhibit similar colour and texture characteristics. Traditional ML algorithms such as Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbour (k-NN) have been widely used for weed classification, achieving

about 90–97% accuracy (Hashemi-Beni *et al.* 2022). Recently, deep learning (DL) approaches, particularly Convolutional Neural Networks (CNNs), have gained prominence due to their ability to extract complex spatial features from images for improved weed identification (Wu *et al.* 2021).

### Steps for precision weed management using AI-based deep learning

#### Data acquisition

The weed detection pipeline begins with data acquisition, where image data are collected using unmanned aerial vehicles (UAVs), ground robots, handheld sensors, or satellite platforms (Figure 4). UAVs commonly capture RGB, multispectral, hyperspectral, or thermal imagery at 2–20 m altitude with resolutions around 3000 × 4000 pixels, while robots such as BoniRob collect multispectral imagery and satellites provide 4-band (RGB + NIR) data for large-scale monitoring. Two sensing approaches are commonly used: proximal sensing, where sensors mounted on tractors or robots collect high-resolution images using architectures such as GoogleNet, VGGNet, and DetectNet, and remote sensing, where UAVs or satellites collect imagery for large-area weed monitoring using CNN, DNN, or Fully Convolutional Network (FCN) models.

#### Dataset preparation and image pre-processing

It is performed through image resizing, colour model conversion, annotation, and augmentation techniques such as rotation, flipping, noise injection, and colour transformation, which increase dataset diversity and improve model training. This is followed by image preprocessing, which includes radiometric correction (illumination and sensor noise), geometric correction (spatial alignment), orthomosaic generation, and background removal. Vegetation

**Table 9. Weed management and ecological footprint (West and Marland 2002, Lal 2004)**

Weed management Practice	Carbon emissions (kg CO <sub>2</sub> e/ha)	Description	Advantages	Disadvantages
Manual weeding	5–20	Labor-intensive removal using hand tools	Low emissions, no chemicals	High labor cost, not feasible for large areas
Mechanical weeding	50–150	Use of tractor-drawn or power tiller implements	Reduces labor, efficient in row crops	Fuel use increases emissions, soil disturbance
Chemical weeding (herbicides)	150–300	Application of synthetic herbicides (e.g., glyphosate, atrazine)	Quick, cost-effective	High emissions from manufacture & application
Mulching (organic/plastic)	20–100	Weed suppression through cover materials	Reduces soil evaporation, moderate emissions	Plastic mulch adds disposal burden
Cover cropping	10–50	Use of dense-growing crops to outcompete weeds	Sequesters carbon, improves soil health	May require termination using herbicides or tillage
Flame weeding	300–600	Use of propane burners to kill weeds	Non-chemical, useful in organic systems	Very high fuel use and emissions
Integrated weed management	70–200	Combines cultural, mechanical, and chemical control	Balanced approach, moderate emissions	Requires knowledge & planning

indices such as NDVI, NDRE, and SAVI are commonly applied to separate vegetation from soil and enhance weed detection.

### Analysis using AI/ML

The processed imagery is then analysed using ML and DL classifiers to distinguish weeds from crops and background vegetation. CNN-based architectures such as ResNet, U-Net, and YOLO variants are widely used. For example, YOLOv7 (CSCW-YOLOv7) achieved 94.4–98% mean average precision for weed detection in wheat (Wang *et al.* 2024), while a dilated CNN achieved 94% accuracy using 15,000 soybean and broadleaf weed images (Tripathi *et al.* 2025). Detection approaches include bounding-box detection, semantic segmentation, and instance segmentation (Genze *et al.* 2022). Semantic segmentation models such as U-Net, SegNet, and DeepLabV3+ classify each pixel as weed, crop, or soil, whereas instance segmentation models such as Mask R-CNN, YOLACT, SOLO, and CenterMask identify individual weeds even under overlapping conditions, enabling weed density and biomass estimation.

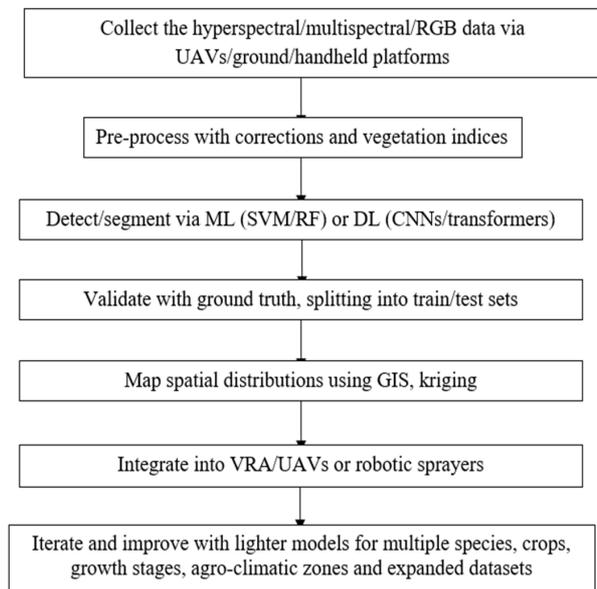
### Model evaluation

Model performance is evaluated using accuracy, F1-score, mean absolute error (MAE), and root mean square error (RMSE). Several architectures including DNN (You *et al.* 2020), DeepSolanum-Net (Wang *et al.* 2021), ERFNet-based Bonnet (Su *et al.* 2021), Modified U-Net (Zou *et al.* 2021a, 2021b), ResNet-34 (Zhang *et al.* 2022), DeepLabv3+ (Hashemi-Beni *et al.* 2022), and Mask R-CNN (Sapkota *et al.* 2022) have been widely applied, often using transfer learning to improve performance with limited datasets (Rai and Sun 2024).

### Weed mapping

After classification, weed mapping is performed to analyse spatial and temporal weed distribution, density, and species composition. The model outputs are converted into georeferenced raster or vector layers using GIS software such as QGIS or ArcGIS, and spatial interpolation methods such as kriging or inverse distance weighting (IDW) are used to identify weed hotspots (Wang *et al.* 2024). Repeated UAV flights enable temporal weed monitoring, helping evaluate weed emergence patterns and herbicide effectiveness. These maps are integrated into decision support systems to generate prescription maps for site-specific weed management. Ultra-high-resolution UAV imagery combined with object-based image analysis (OBIA) further enhances accurate in-season weed mapping. The steps in weed detection,

weed mapping, and site-specific herbicide sprays using UAVs/ robots or variable rate applicators (VRA), are orderly mentioned below (**Figure 4**):



**Figure 4. Steps in weed detection, mapping and precision weed management**

### Precision spraying technique

The final implementation phase i.e., precision weed control is implemented using AI-enabled UAVs, robotic weeders, and variable rate applicators (VRA) integrated with GPS and high-resolution sensors for targeted herbicide application. Common UAV platforms include DJI Matrice 100, DJI Agras MG-1, Sentra P.H.X., eBee SQ Fly, and AgEagle RX-60, which can cover approximately 400–600 acres within 40–55 minutes (Meesaragandla *et al.* 2024). Field trials in a 25 ha sugarcane field in Queensland, Australia, demonstrated that UAV-based spot spraying achieved about 97% weed control while reducing herbicide use by 35% compared with broadcast spraying (Azghadi *et al.* 2025). There are various factors that can affect the efficiency of this particular method of aerial spraying as follows:

- There should be definite altitude (1.5-3.0 m above canopy) and velocity (11-18 km/h) of the spraying operation.
- Suitable weather conditions like wind (1-3 m/s), temperature (15-28°C), humidity (>60%) at the time of application.
- Design and performance of the droplet-generating equipment, i.e., flat fan nozzle (150-250 µm drop size is suitable, lower size may drift and higher may bounce off).
- Application rate of the spray solution (15-25 liters/ha; 30-50 droplets/m<sup>2</sup>). The spray concentration is higher (70-80% water: 20-30% chemical) than traditional high-volume sprays (98% water:2% chemical).
- Physical and chemical properties of the spray formulation, i.e., size, polarity, anti-drift agents, anti-

evaporation agents, and surfactants etc. Suspension concentrate (SC), emulsion in water (EW), and oil dispersion (OD) are generally preferred formulation over wetttable powder (WP).

- Thickness of the crop: Grassy crops with erect leaves are easier to penetrate but broad-leaved crops require higher downwash or smaller droplets.

Therefore, UAVs-based weed detection using advanced sensing, image analysis, and DL enables accurate, site-specific weed monitoring and a data-driven management in precision agriculture. These innovations reduce input costs, labor, and environmental impact while improving overall crop health and productivity. Continued improvements in real-time processing, model generalization, and automated spraying systems will further enhance the scalability and effectiveness of precision weed control.

## Conclusions

Weed interference is a collective impact of different weed species. Weeds change continuously in crop field ecosystems, and more so under the changing climate. Therefore, the appraisal mechanisms of weed interference and dynamics, weed control efficiency, economic threshold, and herbicides bio-efficacy, selectivity and weed control spectrum need to be renewed/ reoriented to keep pace with the current changing scenarios with more scientific-bias. Weed science to become a distinct branch of biological sciences should have certain self-generated/ self-governed concepts, principles and hypotheses, defined/robust treatments, sound science-based methodologies, standard field plot and statistical techniques. Some theories/ principles/ advances of basic sciences (biology, ecology, physics, chemistry, mathematics) need to be put into use in weed science for developing inter-disciplinary linkage and widening the horizon of weed science. Finally, weed science should be developed as a basic science, an applied science, and more appropriately an interdisciplinary science with constant/ continuous research thrust towards improving methodologies.

## REFERENCES

- Allen ON. 1953. Experiments in soil bacteriology. 2nd ed. Minneapolis (MN): Burges Pub. Co. 127p.
- Andreasen C, Streibig JC and Haas H. 1991. Soil properties affecting the distribution of 37 weed species in Danish fields. *Weed Research* 31(4): 181–187.
- Azghadi MR, Olsen A, Wood J, Saleh A, Calvert B, Granshaw T, Fillols E and Philippa B. 2025. Precision robotic spot-spraying: reducing herbicide use and enhancing environmental outcomes in sugarcane. *Computers and Electronics in Agriculture* 235: 110365.
- Bhatia A, Pathak H and Aggarwal PK. 2004. Inventory of methane and nitrous oxide emissions from agricultural soils of India and their global warming potential. *Current Science* 87(3): 317–324.
- Brar LS, Walia SS and Walia US. 2000. Bio-efficacy of herbicides against weeds in Japanese mint (*Mentha arvensis* L.). *Indian Journal of Weed Science* 32(1&2): 77–79.
- Casida LE, Klein DA and Santoro T. 1964. Soil dehydrogenase activity. *Soil Science* 98: 371–376.
- Chan KY, Bowman A and Oates A. 2001. Oxidizable organic carbon fractions and soil quality changes in an oxipaleustalf under different pasture leys. *Soil Science* 166: 61–67.
- Choudhury SG, Srivastava S, Singh R, Chaudhari SK, Sharma DK, Singh SK and Sarkar D. 2014. Tillage and residue management effects on soil aggregation, organic carbon dynamics and yield attribute in rice–wheat cropping system under reclaimed sodic soil. *Soil and Tillage Research* 136: 76–83.
- Coble HD and Mortensen DA. 1992. The threshold concept and its application to weed science. *Weed Technology* 6(1): 191–195.
- Cousens R. 1985a. An empirical model relating crop yield to weed and crop density and a statistical comparison with other models. *The Journal of Agricultural Science* 105(3): 513–521. <https://doi.org/10.1017/S0021859600059396>.
- Cousens R. 1985b. A simple model relating yield loss to weed density. *Annals of Applied Biology* 107(2): 239–252. <https://doi.org/10.1111/j.1744-7348.1985.tb01567.x>
- Das TK, Paul AK and Yaduraju NT. 2014. Density–effect and economic threshold of purple nutsedge (*Cyperus rotundus*) in soybean. *Journal of Pest Science* 87(1): 211–220.
- Das TK, Sakhuja PK and Zelleke H. 2010. Herbicide efficacy and non–target toxicity in highland rainfed maize of Eastern Ethiopia. *International Journal of Pest Management*. 56(4): 315–325.
- Das TK, Sen S, Raj R, Ghosh S, Behera B and Roy A. 2021. Economic threshold concept for weed management in crops: Usefulness and limitation. *Indian Journal of Weed Science* 53(1): 1–13.
- Das TK. 1999. Is transformation of weed data always necessary? *Annals of Agricultural Research* 20(3): 35–41.
- Das TK. 2001a. Overview weed dynamics in crop field. *Pesticide Information* 27(3): 35–46.
- Das TK. 2001b. Towards better appraisal of herbicide bio-efficacy. *Indian Journal of Agricultural Sciences* 71(10): 676–678.
- Das TK. 2008. *Weed Science: Basics and Applications*. Jain Brothers Publishers, New Delhi. 936p
- Das TK. and Yaduraju NT. 2002. Bioefficacy of glufosinate–ammonium under zero tillage in mustard and on *Cynodon dactylon* L. Pers and *Cyperus rotundus* L. under non–crop situation. *Pesticide Research Journal* 14(1):16–21.
- Dodamani BM and Das TK. 2013. Density and nitrogen effects on interference and economic threshold of common lambsquarters in wheat. *Journal of Pest Science* 86: 611–619.
- FAO 2021. Standard operating procedure for soil available phosphorus Bray I and Bray II method. Food and Agriculture Organization of the United Nations, Rome, Italy.

- Genze N, Ajekwe R, Güreli Z, Haselbeck F, Grieb M and Grimm DG. 2022. Deep learning-based early weed segmentation using motion blurred UAV images of sorghum fields. *Computers and Electronics in Agriculture* **202**: 107388.
- Fazil Karamatullah, Das TK, Nath CP, Nazir R and Samim M. 2022. Nitrogen and weed management effects on weeds and yield of barley in Kandahar, Afghanistan. *Indian Journal of Weed Science* **54**(3): 309–313.
- Finney DJ. 1989. Was this in your statistics textbook? V. Transformation of data. *Experimental Agriculture* **25**: 165–175.
- Ghosh S, Das TK, Shivay YS, Bandyopadhyay KK, Sudhishri S, Bhatia A, Biswas DR, Yeasin Md and Ghosh S. 2022. Weeds response and control efficiency, greengram productivity and resource-use efficiency under a conservation agriculture-based maize wheat-greengram system. *Indian Journal of Weed Science* **54**(2): 157–164.
- Gill GS and Vijayakumar A. 1969. Weed index: A new approach for comparing weed control treatments. *Indian Journal of Agronomy* **14**(1): 96–98.
- Gupta DK, Bhatia A, Kumar A, Das TK, Jain N, Tomer R, Malyan SK, Fagodiyi RK, Dubey R and Pathak H. 2016. Mitigation of greenhouse gas emission from rice-wheat system of the Indo-Gangetic plains: Through tillage, irrigation and fertilizer management. *Agriculture, Ecosystems and Environment* **230**: 1–9.
- Hanzlik K and Gerowitt B. 2016. Methods to conduct and analyze weed surveys in arable farming: a review. *Agronomy for sustainable development* **36**: 1–18.
- Hasan MM, Zhang Y and Liu C. 2021. Herbicide residue analysis: Techniques, challenges, and applications in sustainable agriculture. *Environmental Pollution* **274**: 116569. <https://doi.org/10.1016/j.envpol.2021.116569>
- Hashemi-Beni L, Gebrehiwot A, Karimodini A, Shahbazi A and Dorbu F. 2022. Deep convolutional neural networks for weeds and crops discrimination from UAS imagery. *Frontiers in Remote Sensing* **3**(1): 755939.
- Hazra D, Das TK and Yaduraju NT. 2011. Interference and economic threshold of horse purslane (*Trianthema portulacastrum* L.) in soybean cultivation in northern India. *Weed Biology and Management* **11**(2): 72–82.
- Jackson ML. 1973. *Soil Chemical Analysis*. Prentice Hall of India Ltd. New Delhi 219–221.
- Kah M, Beulke S, Tiede K and Hofmann T. 2012. Nanopesticides: state of knowledge, environmental fate, and exposure modeling. *Critical Reviews in Environmental Science and Technology* **43**. 10.1080/10643389.2012.671750.
- Kasasian L and Seeyave C. 1969. Weed control in the tropics. *PANS* **15**(4): 508–517. <https://doi.org/10.1080/09670876909411898>
- Kemper WD and Rosenau RC. 1986. Aggregate stability and size distribution. In: *Methods of Soil Analysis: Part 1–Physical and Mineralogical Methods*. A. Klute (ed.). pp 425–442. Agronomy Monograph **9**. American Society of Agronomy, Madison, Wisconsin.
- Krishnamurthy K, Ayyappan S and Doraiswamy S. 1975. Evaluation of herbicides in rice and their comparative performance through herbicide efficiency index. *Pesticides* **9**(10): 13–15
- Kropff MJ and Lotz LAP. 1993. Modeling the effects of weeds on crop production. *Weed Technology* **7**(1): 216–219
- Kropff MJ and Spitters CJT. 1991. A simple model of crop loss by weed competition from early observations of relative leaf area of the weeds. *Weed Research* **31**(2): 97–105.
- Kumar M, Das TK and Yaduraju NT. 2012. An integrated approach for management of *Cyperus rotundus* (purple nutsedge) in soybean-wheat cropping system. *Crop Protection* **33**: 74–81.
- Kurchania SP, Bhalla C S and Paradkar NR. 2000. Bio-efficacy of metsulfuron-methyl and 2,4-D combinations for broadleaf weed control in wheat. *Indian Journal of Weed Science* **32**(1 & 2): 67–98.
- Lal R. 2004. Carbon emission from farm operations. *Environment International* **30**(7): 981–990.
- Lal R. 2010. Laboratory Manual of Environmental Soil Physics, School of Environment and Natural Resources, The Ohio State University, Columbus, USA.
- Magnussen S. and Boyle TJB. 1995. Estimating sample size for inference about the Shannon-Weaver and the Simpson indices of species diversity. *Forest Ecology and Management* **78**(1–3): 71–84
- Mani VS, Mala ML, Gautam KC and Bhagwandas. 1973. Weed killing chemicals in potato cultivation. *Indian Farming* **23**(1): 17–18.
- Martin JP. 1950. Use of acid, rose bengal, and streptomycin in the plate method for measuring soil fungi. *Soil Science* **69**: 215.
- Meesaragandla S, Jagtap MP, Khatri N, Madan H and Vadduri AA. 2024. Herbicide spraying and weed identification using drone technology in modern farms: A comprehensive review. *Results in Engineering* **21**: 101870.
- Mehrtens B, Lüemann U and Hurlle K. 2005. Environmental variables affecting weed seedling emergence patterns and dynamics in a maize-winter wheat rotation. *Weed Research* **45**(6): 501–512.
- Mishra M and Misra A. 1997. Estimation of integrated pest management index in jute-A new approach. *Indian Journal of Weed Science* **29**: 39–42.
- Misra M and Tosh GC. 1979. Weed control index – A new approach to weed control evaluation. *PANS* **25**: 132–133.
- Moorthy BTS and Das TK. 1998. Threshold level of weed umbrella sedge (*Cyperus iria*) in upland rice (*Oryza sativa*) under rainfed direct-seeded condition. *Indian Journal of Agricultural Sciences* **68**(1): 7–8.
- Nkoa R, Owen MD and Swanton CJ. 2015. Weed abundance, distribution, diversity, and community analyses. *Weed Science* **63**: 64–90.
- Odum EP. 1975. *Ecology*. Oxford and IBH Publishing Co. Pvt. Ltd., New Delhi, 244p
- Olsen SR, Cole CV, Watanabe FS and Dean LA. 1954. Estimation of available phosphorus by extraction with sodium carbonate, Circular **939**: 1–19. USDA, Washington, D.C.
- Parven A, Roy B and Sultana N. 2024. Integrated approaches to monitor and mitigate herbicide residues in agroecosystems: A review. *Journal of Environmental Management* **345**: 119013.
- Phillips EA. 1959. *Methods of Vegetation Study*. New York: Henry Holt and Co.

- Pico Y. 2016. *Chemical Analysis of Food: Techniques and Applications*. Elsevier, Amsterdam, 757p.
- Pinke G, Karácsony P, Czúcz B, Botta–Dukát Z and Lengyel A. 2010. The influence of environment, management and site context on species composition of summer arable weed vegetation in Hungary. *Applied Vegetation Science* **13**(3): 405–414.
- Piper CS. 1950. *Soil and Plant Analysis*. The University of Adelaide, Australia: 286–287.
- Rai N and Sun X. 2024. Weed Vision: A single–stage deep learning architecture to perform weed detection and segmentation using drone–acquired images. *Computers and Electronics in Agriculture* **219**:108792.
- Raj R, Das TK, Chakraborty D, Bhattacharyya R, Babu S, Govindasamy P, Kumar V, Ekka U, Sen S, Ghosh S, Roy A and Sharma T. 2023. Soil physical environment and active carbon pool in rice–wheat system of South Asia: Impact of long–term conservation agriculture practices. *Environmental Technology and Innovation* **29**: 102966.
- Raj R, Das TK, Kaur R, Shekhawat K, Singh R and Singh VK. 2020. Effects of nitrogen and densities on interference and economic threshold of *Phalaris minor* in wheat. *Crop Protection* **135**: 105215.
- Raj R, Das TK, Pankaj Banerjee T, Ghosh A, Bhattacharyya R, Chakraborty D, Prasad S, Babu S, Kumar V, Sen S and Ghosh S. 2022. Co–implementation of conservation tillage and herbicides reduces weed and nematode infestation and enhances the productivity of direct–seeded rice in North–western Indo–Gangetic Plains. *Frontiers in Sustainable Food Systems* **6**:1017013. doi:10.3389/fufs.2022.1017013.
- Rao VS. 1983. Principles of Weed Science. Chapter 19. pp 438–458. Oxford and IBH Publishing Co. Pvt. Ltd., New Delhi.
- Rew LJ and Cousens RD. 2001. Spatial distribution of weeds in arable crops: are current sampling and analytical methods appropriate? *Weed Research* **41**(1): 1–18.
- Salaudeen MT, Daniya E, Olaniyi OM, Folorunso TA, Bala JA, Abdullahi IM, Nuhu BK, Adedigba AP, Oluwole BI, Bankole AO and Macarthy OM. 2022. Phytosociological survey of weeds in irrigated maize fields in a Southern Guinea Savanna of Nigeria. *Frontiers in Agronomy* **4**: 985067.
- Sapkota BB, Popescu S, Rajan N, Leon RG, Reberg–Horton C, Mirsky S and Bagavathiannan MV. 2022. Use of synthetic images for training a deep learning model for weed detection and biomass estimation in cotton. *Scientific Reports* **12**: 19580.
- Sørensen T. 1948. A method of establishing groups of equal amplitude in plant sociology based on similarity of species content and its application to analysis of the vegetation on Danish Commons. *K Dan Vidensk Selsk Biol Skr* **5**: 1–34.
- Southey JF. 1986. Laboratory methods for work with plant and soil nematodes. Reference Book 402. Her Majesty's Stationery Office (HMSO), London (UK): Ministry of Agriculture, Fisheries and Food.
- Su T, Zhang C, Wu Y and Chen Q. 2021. Real–time weed detection using improved ERFNet for precision agriculture. *Computers and Electronics in Agriculture* **191**: 106556. <https://doi.org/10.1016/j.compag.2021.106556>
- Subbiah BV and Asija GL. 1956. A rapid method for the estimation of nitrogen in soil. *Current Science* **26**: 259–260.
- Susha VS, Das TK and Sharma AR. 2014. Weed management in maize (*Zea mays*) in western Indo–Gangetic Plains through tank–mix herbicide application. *Indian Journal of Agricultural Sciences* **84**(11): 1363–1368.
- Tadeo JL and Sanchez–Brunete C. 2000. Herbicides: gas chromatography. In: *Encyclopedia of Analytical Science*: 2984–2991. Academic Press. <https://doi.org/10.1016/B0122267702063614>
- Tiwari M, Gupta PK, Tiwari N and Chitale S. 2024. Potential of temporal satellite data analysis for detection of weed infestation in rice crop. *Egyptian Journal of Remote Sensing and Space Sciences* **27**(4): 734–742.
- Tripathi SK, Singh SP, Sharma D and Pateka HU. 2025. Weed detection using convolutional neural network. *Computer Vision and Pattern Recognition*, <https://doi.org/10.48550/arXiv.2502.14360>
- Vance ED, Brookes PC and Jenkinson DS. 1987. An extraction method for measuring soil microbial biomass C. *Soil biology and Biochemistry* **19**(6): 703–707.
- Walkley AJ and Black CA. 1934. Estimation of soil organic carbon by the chromic acid titration method. *Soil Science* **37**(1): 29–38.
- Wang K, Hu X, Zheng H, Lan M, Liu C, Liu Y, Zhong L, Li H and Tan S. 2024. Weed detection and recognition in complex wheat fields based on an improved YOLOv7. *Frontiers in Plant Science* **15**: 1372237.
- Wang Q, Cheng M, Xiao X, Yuan H, Zhu J, Fan C and Zhang J. 2021. An image segmentation method based on deep learning for damage assessment of the invasive weed *Solanum rostratum* Dunal. *Computers and Electronics in Agriculture* **188**: 106320.
- West TO and Marland G. 2002. A synthesis of carbon sequestration, carbon emissions, and net carbon flux in agriculture. *Tellus B: Chemical and Physical Meteorology* **54**(4): 585–597.
- Wilson SD, Shay JM and Armott JT. 1999. *Measuring plant diversity: Lessons from the grasslands of North America. Ecological Applications* **9**(2): 497–508.
- Wu Z, Chen Y, Zhao B, Kang X and Ding Y. 2021. Review of weed detection methods based on computer vision. *Sensors* **21**:3647. <https://doi.org/10.3390/s21113647>.
- Yoder RE. 1936. A direct method of aggregate analysis of soils and a study of the physical nature of erosion losses. *Agronomy Journal* **28**: 337–351.
- Yorks TE and Dabydeen S. 1998. Modification of the Whittaker sampling technique to assess plant diversity in forested natural areas. *Natural Areas Journal* **18**:185–189.
- You J, Liu W and Lee J. 2020. A DNN–based semantic segmentation for detecting weed and crop. *Computers and Electronics in Agriculture* **178**: 105750.
- Zhang Y, Li D, Wang X and Liu Y. 2022. Comparative study of conventional machine learning classifiers for weed identification in precision agriculture. *Agricultural Systems* **196**: 103321.
- Zou K, Chen X, Wang Y, Zhang C and Zhang F. 2021a. A modified U–net with a specific data augmentation method for semantic segmentation of weed images in the field. *Computers and Electronics in Agriculture* **187**: 106242.
- Zou K, Chen X, Zhang F, Zhou H and Zhang C. 2021b. A field weed density evaluation method based on UAV imaging and modified U–Net. *Remote Sensing* **13**(3): 310.