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RESEARCH ARTICLE

Assessing the persistent use of pesticides and adoption of climate-smart pest management practices among the vegetable growers in the Western zone of Tamil Nadu

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Abstract

Vegetable crops, vital to the global food chain, may be significantly impacted by climate change. Increased pests and diseases, low yields, crop failures and deteriorating quality issues under adverse climate make it unprofitable. Climate-Smart Pest Management (CSPM) practices combine with intensive surveillance to minimise the hazards of persistent use of pesticides to human health and the environment. Vegetable cultivation is predominant in the Western zone of Tamil Nadu as its topography and climatic factors favour year-round production. A sample of 120 farmers was selected from Dharmapuri, Namakkal and Coimbatore districts. The major pesticides used are organophosphates, carbamates, organochlorines, monocrotophos, methyl parathion, endosulfan etc. More than 70 % of the farmers are applying pesticides than the recommended level. Farmers don't know the ill effects of overuse due to a lack of awareness and apply it more frequently due to very high pest infestation in tomato, brinjal, bhendi, cauliflower and onion. About 15-20 times, the pesticides were sprayed from flowering to harvest, which may be a greater risk. Pesticide use intensity is on average 2-5 kg a.i./ha for tomato, brinjal and bhendi, cauliflower and onion. The relationship between farmers' perception of the adverse effects suggested that farmers who perceive higher risks of pesticides are more likely to adopt those practices and vice versa. The Ordinal logistic regression implied that the increased yield, reduced input cost, higher market prices and reduced health hazards demonstrate the high, medium and low levels of adoption and beneficial effects of the CSPM practices. Promotion of CSPM to the non-adopters requires massive sensitisation programmes and training, demonstrations, provision of subsidies, support price and financial assistance as strategies to be followed.

Keywords: adoption; climate; management; overuse; pesticides; vegetables

Introduction

Climatic fluctuations may have a significant impact on vegetable crops, which are essential to the world food chain. These crops are extremely vulnerable to the effects of climate change, especially rising temperatures, which can have an immediate effect on their productivity (1). Moreover, vegetable cultivation becomes unprofitable due to crop failures, low yields, an increase in pests and diseases and declining quality concerns under changing climatic conditions (2). A ferocious cycle between the need for pesticides to sustain vegetable production and their subsequent negative effects on the environment is generated by the adverse effects of climate change. Crop protection chemicals used improperly can become less effective and as climate change affects the environment, insect assaults become more intense, increasing the need for synthetic pesticides in agriculture (3, 4). This might lead to increased resistance to these crop-protection chemicals such as pesticides, fungicides and herbicides, which would be harmful to people, animals and the environment (5). However, anticipating the consequences of climate change on pests is difficult due to the numerous interacting influences of increasing temperature, changing pattern of precipitation and climatic regimes, increasing atmospheric CO_2 concentration and increased frequency of extreme weather events (6). If climate change-related variables create favourable circumstances for insect infestation and crop degradation, significant economic losses and a threat to human food security are likely to occur. Addressing this issue will require a proactive and scientific approach. As a result, developing adaptation and mitigation strategies such as updated Integrated Pest Management (IPM) approaches, using modelling tools and climate and pest monitoring is crucial. As one among the mitigating strategies to overcome this climate change scenario, Climate-Smart

Pest Management (CSPM), is a sustainable pest control technique that combines several practices viz. biological, cultural, physical and chemical methods along with early diagnosis, forecasting techniques and intensive surveillance which minimizes the hazards of human health, the environment and economy (7, 8). CSPM comprises pest control practices such as minimum tillage, mulching and establishing natural barriers, all of which promote organic carbon sequestration and hence increase resilience to particular pests (9, 10). Although previous studies have examined the factors influencing climate smart agriculture adoption and its impacts across various geographical contexts, they are often limited by certain methodological or contextual constraints. There remains a notable gap in research focusing on regions that are both socio-economically and physiologically vulnerable to climate change. In contrast, this study emphasises the types of pesticides in use, pesticide usage patterns, intensity and frequency of their application and adoption of various CSPM practices among the vegetable growers.

Materials and Methods

Adoption of CSPM practices is essential for encouraging better vegetable production in terms of quality and quantity, guaranteeing farmers' financial gains and safeguarding the environment under the circumstances of persistent pesticide application. The Western zone of Tamil Nadu is characterised by diverse soil types, including red, black and laterite and a climate that varies from temperate in the hilly areas to tropical in the lower elevations, contributing to more vegetable cultivation under a larger area (11, 12). Tomato, brinjal, bhendi, cauliflower and onion were the major vegetables taken for this study. Because of the high insect occurrence in these crops, they are frequently treated with pesticides in larger amounts (13). Keeping these in view, a study was conducted in Dharmapuri, Namakkal and Coimbatore districts of Tamil Nadu to analyse the persistent pesticide usage pattern of vegetable farmers and assess the adoption level of CSPM practices followed among the vegetable growers. In the study area, farmers cultivating diverse vegetables have faced several pest-related problems for many years. Hence, four major vegetable cultivating blocks of Dharmapuri, Namakkal and Coimbatore districts were purposively selected for this study. From each block, 10 vegetable growers were selected to constitute a sample of 120 farmers (Table 1). The interview schedule was properly designed to capture all the possible components for assessing the frequency and intensity of pesticide use and adoption of CSPM practices among the vegetable farmers to mitigate climate change.

Table 1. Details of the samples in the study area

Sr. No.	District	Block	No of samples
I.	Dharmapuri	Palacode	10
		Pennagaram	10
		Dharmapuri	10
		Karimangalam	10
II.	Namakkal	Puduchatram	10
		Erumapatti	10
		Rasipuram	10
		Mohanur	10
III.	Coimbatore	Thondamuthur	10
		Karamadai	10
		Madhukkarai	10
		Annur	10
		Total	**120**

In 2022, overall pesticide usage in agriculture was 3.70 million tonnes of active ingredients, a 4 % increase over 2021, a 13 % rise in a decade and a doubling since 1990 (14). In the farm level, pesticide usage frequency is determined by how many times various pesticides are administered to a crop throughout its growth season, where a high frequency indicates that the pesticide is applied more frequently during the crop cycle (15, 16). Intensity of pesticide application is derived in terms of the active ingredient per hectare (unit area) of crop land. Typically computed by dividing the total amount of pesticide sprayed (in kg) by the cultivated land area (in ha), yielding a value of "kg of pesticide per ha."

Adoption index (AI)

An Adoption index is used to evaluate how widely the CSPM practices are being adopted by the vegetable growers. AI is referred to as the extent to which a farmer has adopted the full or a part (intensity of adoption) based on their score out of a specific number of induced technologies (17). This index can be used to compare the uptake of CSPM practices among the vegetable growers in the study area. Then the AI for each activity is computed by using the following formula:

$$\text{Adoption index (AI)} = \frac{(A_F \text{ X } 3) + (A_O \text{ X } 2) + (A_S \text{ X } 1) + (A_N \text{ x } 0)}{\text{Total no. of respondents x No. of statements}} \quad \text{(Eqn. 1)}$$

Where,

AI = Adoption Index for vegetable growers who adopt CSPM practices

A_F = Number of vegetable growers who adopt frequently

A_O = Number of vegetable growers who adopt occasionally

A_S = Number of vegetable growers who seldom adopt

A_N = Number of vegetable growers who never adopt

Based on the AI produced for the CSPM practices, the interval of the class was established by subtracting the lowest value from the highest value and dividing by the desired number of classes (18). The lower limit of the first class is set at the smallest value in the data set. The scores of the CSPM practices were calculated for each respondent to measure the status of vegetable growers' adoption. These practices include biological control, resistant plant varieties, crop diversification, crop rotation, cultural practices, mechanical and physical controls, deep summer ploughing, mulching, conservation agriculture, water management and monitoring of pests and diseases for forewarning (19). As a result, vegetable growers' levels of adoption have been found and classified as high, medium and low.

Ordinal logistic regression analysis

In this study, Ordinal Logistic Regression Analysis is employed to determine the relationship between a set of independent variables and an ordered dependent variable (20). The multiple choices made by farmers when measuring the adoption level of CSPM practices are intrinsically ordered. Consequently, any non-ordered model cannot effectively deduce the adoption of numerous CSPM techniques since the information provided by the ordered dependent variable is ignored (21). The dependent variable, adoption level of vegetable growers, viz. high, medium and low classes in CSPM practices, was derived by setting all those adoption indices. When the response variable comprises more than two ordinal categories, it is considered an extension of a binary logistic regression model (22). This model may also estimate the probability of being at or above a specific level of the response variable, because being below and above a particular category are just two complementary directions. This study used an AI to organise potential outcomes.

In this study, the ordinal outcome variable is CSPM practices adoption, coded as 1, 2 or 3 (1 = low, 2 = medium and 3 = high) based on the levels of independent variables such as age, education level of the vegetable growers (in years), trainings attended by the vegetable growers, access to extension services, knowledge on CSPM practices, perceived negative effect on environment and human health.

The model to be estimated is shown below, based on the appropriate outcome description and variable specifications. Assuming the dependent variable,

$$\mathbf{Y^*} = x\beta + \varepsilon, \qquad \text{(Eqn. 2)}$$

where,

x is a row vector (1*k) with no constant,

β is a column vector (k*1) of structural coefficients and

ε is random error with a standard normal distribution (ε ~ N (0, 1)).

Let Y* be separated by cut points (thresholds): $\alpha_1, \alpha_2, \alpha_3, \ldots \alpha_j$, with $\alpha_1<\alpha_2<\alpha_3\ldots< \alpha_j$. To determine the level of adoption, consider the following:

$$Y = \begin{cases} 1 \text{ if } Y^* \leq a_1 \\ 2 \text{ if } a_1 < Y^* \leq a_2 \\ 3 \text{ if } a_2 < Y^* \leq \infty \end{cases}$$

As a result, the probability of CSPM practices adoption level may be calculated as follows.

$$P(y = 1) = P\,(y^* \leq \alpha_1)$$
$$= P(x\beta + \varepsilon \leq \alpha_1)$$
$$P(y = 2) = P\,(\alpha_1 < y^* \leq \alpha_2)$$
$$= F\,(\alpha_2 - x_\beta) - F\,(\alpha_1 - x_\beta);$$
$$P(y = 3) = P\,(\alpha_2 < y^* \leq \infty)$$
$$= 1 - F\,(\alpha_2 - x_\beta);$$

The cumulative probabilities can be derived as:

$$P(Y \leq j) = F\,(\alpha_j - x_\beta), \text{ where } j = 1, 2, \ldots J-1 \qquad \text{(Eqn. 3)}$$

The logistic regression model can be expressed as:

$$= \alpha + b_1x_1 + b_2x_2 + \ldots b_px_p \qquad \text{(Eqn. 4)}$$

The ordinal logistic regression model is expressed in logit form as follows:

$$\ln(Yj') = \text{logit}\,[\,\Pi(x)\,]$$
$$\text{logit}\,[\Pi(Y \leq j \mid x_1, x_2, \ldots x_p)]$$
$$= \ln 0\,\Pi(Y \leq j \mid x_1, x_2, \ldots x_p)$$
$$\Pi(Y > 9 \mid 1, 2, \ldots):$$
$$= \alpha j + (-b_1x_1 - b_2x_2 - \ldots - b_px_p) \qquad \text{(Eqn. 5)}$$

Thus, this model forecasts cumulative logits across J-1 response categories. Transforming the cumulative logit yields estimated cumulative odds and probabilities for being in or below the jth category. The proportional odds model was fitted to all eight independent variables. The Brant test was used to evaluate the assumption of proportionate odds in both models. Fit statistics, cut points, logit coefficients and cumulative odds for independent variables in the models were analysed and discussed. This analysis was done using R software version 4.4.1. The function computes the Brant test for the parallel regression assumption. Brant published the Brant test for ordinal logit models to test the parallel regression assumption (23). The method is compatible with models created using the polr() function from the 'MASS' package.

Results and Discussion

Pesticide usage is prevalent in the cultivation of all vegetables, with a particular emphasis on tomato, brinjal, bhendi, onion and chillies. Farmers rely heavily on local pesticide input dealers like Vishnu Agri Clinic and Rekha Traders for recommendations. Private company advisory services from Syngenta, Yara and Tata also play a crucial role in guiding farmers' decisions regarding the types and quantities of pesticides used. The major pesticides used by the vegetable farmers are organophosphates, carbamates, pyrethroids and organochlorines and are classified from grade I to grade III levels. It is observed that high-risk pesticides monocrotophos, methyl parathion, endosulfan, etc. were used due to their high pest control efficiency. Most farmers hire labourers to apply the pesticides, although a few carry out the task themselves. The common pesticides used by farmers are based on pest severity and their application is aimed at reducing pest infestation and safeguarding crops. The majority of the farmers (70 %) apply pesticides during the early morning hours, while the remaining 30 % prefer evening applications. The perception of high yields and pest control drives their decision to overuse pesticides. The research findings indicated that more than 70 % of the vegetable growers are applying pesticides than the recommended level to control pests, to increase production and to make a profit. Farmers applied pesticides more frequently due to the very high rate of pest infestation in the vegetable crops studied. A lack of adequate awareness prevents them from understanding the ill effects of excessive pesticide use. On an average 15-20 times the pesticides were sprayed from the initiation of flowering to the harvest which may turn to be a greater risk of pesticide residue on the produce (Table 2 & Fig. 1). Research indicates that the average frequency of application of the most used insecticide and fungicide products on the most intensively treated crops was between 10 and 20 times a year (15). The farmers felt that repeated pesticide application in vegetable crops is more important as the pest-free produce fetches a higher price in the market.

Intensity of pesticide application

Different crops have varying pest pressures, farming practices, climatic factors and the type of pesticide determines the pesticide intensity (24). Hence, analysing the intensity of pesticide application involves examining how pesticide use varies across different crops, regions, farming practices and its potential environmental and health impacts (25). Concerning pesticide use intensity presented in Table 3, on average, 2-5 kg a.i./ha was used by the vegetable growers.

Table 2. Frequency of pesticide application

Sr. No	Crop	No. of applications/harvest	Percentage of farmers applying pesticides
1.	Tomato	12 to 15	85
2.	Brinjal	8 to 10	75
3.	Bhendi	7 to 9	68
4.	Cauliflower	14 to 18	92
5.	Onion	5 to 8	60

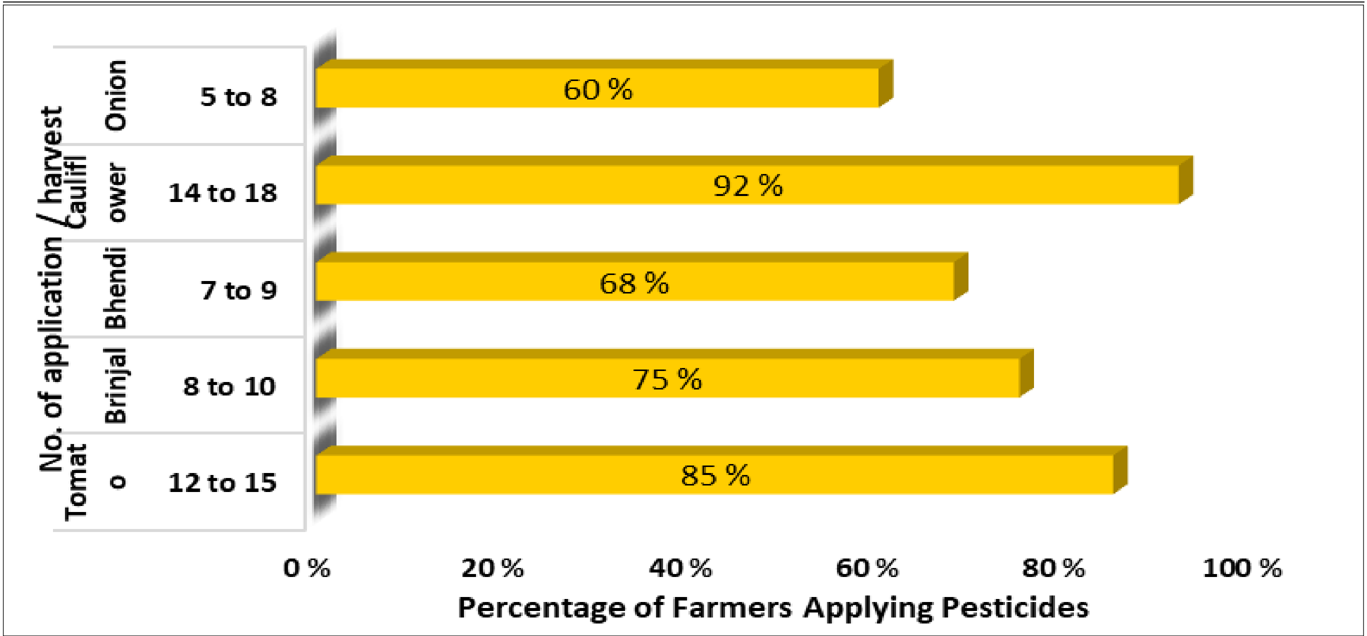

Fig. 1. Frequency of pesticide application.

Table 3. Intensity of pesticide application

Sr. No	Crop	Pesticide use intensity (kg a.i./ha)
1.	Tomato	2.0 - 3.5
2.	Brinjal	1.8 - 2.5
3.	Bhendi	1.2 - 2.0
4.	Cauliflower	3.0 - 4.5
5.	Onion	1.0 - 1.8

Adoption Index (AI)

The sample of 120 vegetable growers surveyed was categorised into high, medium and low adopters, each embracing 39 (32.50 %), 34 (28.33 %) and 47 (39.17 %), respectively. The categorisation was done based on score value and the score value was changed into the AI (26, 27). The Table 4 depicted that the number of vegetable growers fall under the extent of adopting each CSPM practices and percentage of vegetable growers for the same also showed in Fig. 2. The practice of cultivating resistant plant varieties stands first based on the index derived for all the CSPM practices and followed by crop diversification, crop rotation cultural practices, water management and so on (Fig. 3).

Adoption of CSPM practices - Ordinal logistic regression model

The Ordinal logistic regression model was employed to estimate the determinants of farmers' adoption level of CSPM practices, particularly in vegetable cultivation in the study area. To identify the factors influencing their adoption level, explanatory variables age, education level of the vegetable growers (in years), trainings attended by the vegetable growers, access to extension services, knowledge on CSPM practices, perceived negative effect on the environment and human health were entered into the regression ordinal model. Vegetable growers can be classified as high adopters, medium adopters and low adopters of CSPM practices based on the explanatory variables (28).

Overall, the likelihood ratio chi-square of 46.271 with a p-value of 0.000 indicated that our model is statistically significant. The estimates of p show that the likelihood ratios for all explanatory variables are different from zero and the model fits the data very well (29). It determines the significance of the independent variables (xi). It rejects the null hypothesis that the associated coefficient is zero. The coefficients are not found to be

Table 4. Adoption of climate smart pest management practices (n = 120)

Sr. No.	Practices	Frequently (3)	Occasionally (2)	Seldom (1)	Never (0)	AI	Order
1	Biological control	27	44	37	12	0.172	7
2	Resistant plant varieties	93	24	3	0	0.275	1
3	Crop diversification	76	33	11	0	0.254	2
4	Crop rotation Cultural practices	82	17	21	0	0.251	3
5	Mechanical and physical controls	47	69	4	0	0.236	5
6	Deep summer ploughing	28	39	48	5	0.175	6
7	Mulching	17	26	32	45	0.113	9
8	Conservation agriculture	22	28	58	12	0.150	8
9	Water management	65	36	19	0	0.238	4
10	Monitoring of pests and diseases for forewarning	0	4	20	96	0.023	10

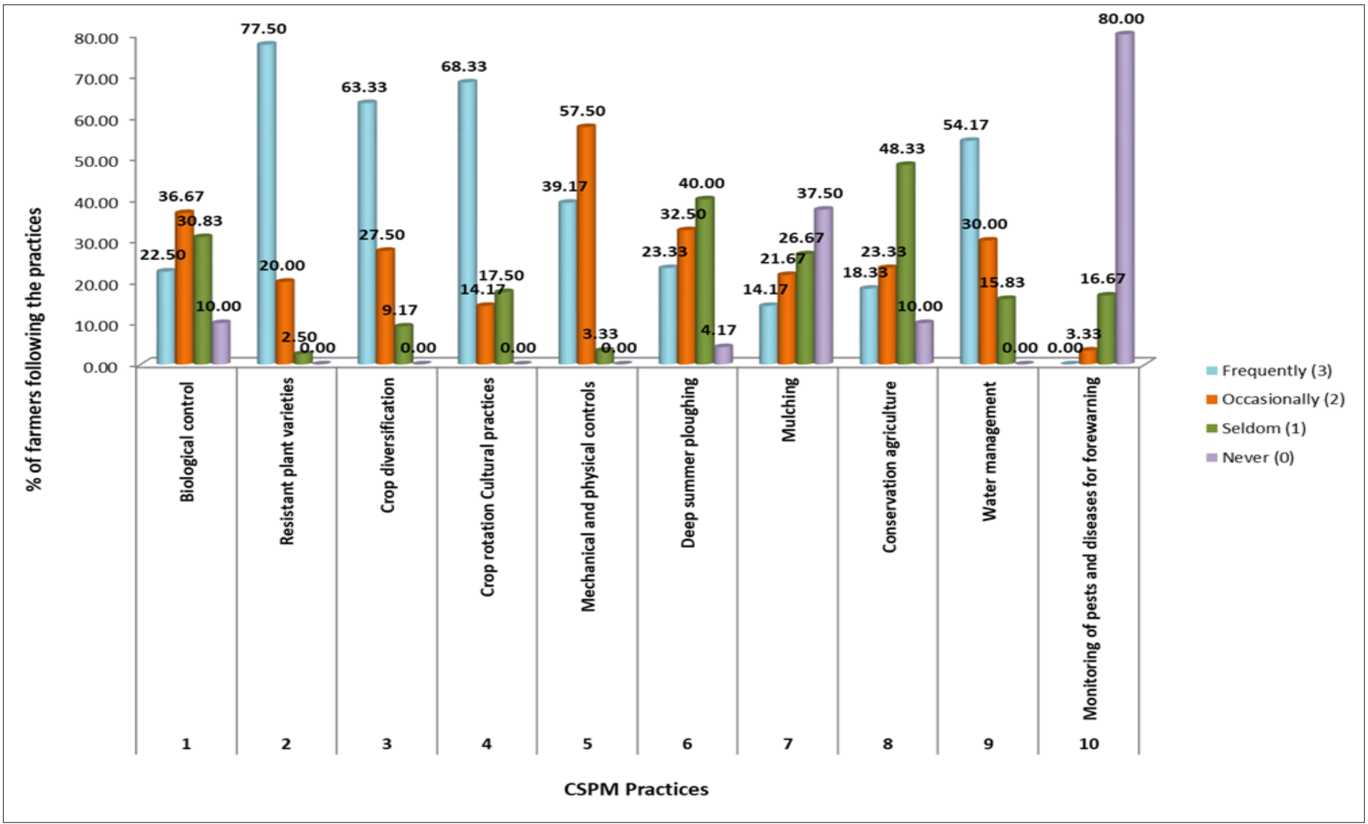

Fig. 2. Adoption of various CSPM Practices by the vegetable growers.

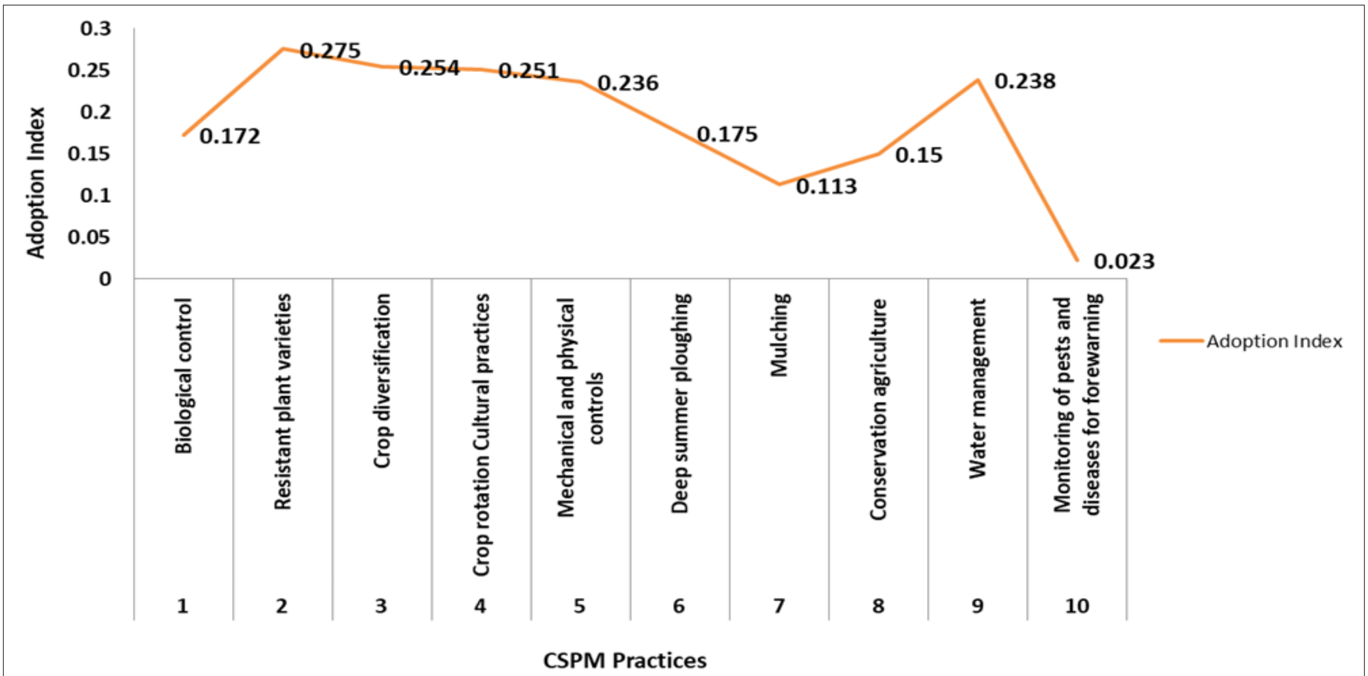

Fig. 3. Adoption of various CSPM practices by the vegetable growers.

0, indicating that the calculated values are valid. Therefore, the regression model is fit to evaluate the contribution of the hypothesised explanatory factors.

Out of seven independent variables considered in this model, four variables were found to be highly influential on the adoption level of CSPM practices at 1 % level of significance. These variables include education, training, extension, knowledge and perception of negative environmental effects. The result of the econometric model indicated that the independent variable, education, increased the likelihood of farmers adopting the CSPM practices, which was statistically significant at 1 % (Table 5). The direction of the relation is to the positive side, implying that as the education increases, the adoption level also increases. One unit increase in the education of the farmers leads to an increase in the log odds of being in a higher level of adoption by 0.128, given that all other variables in the model are maintained constant. Technical training is an essential channel for farmers to understand and adopt risk avoidance measures and it can efficiently transmit information and increase the adoption of CSPM practices (30). Significant influence of training on the adoption level indicated that the farmers' participation in the training was statistically and significantly related in a positive direction towards adoption at the probability of 0.443.

Table 5. Results of ordinal logistic regression

Sr. No	Variables	Co-efficient Value	Std. Error	z	p- value
1.	age	0.011	0.005	2.243	0.004**
2.	education	0.128	0.027	4.741	0.000***
3.	training	0.443	0.086	5.151	0.000***
4.	extension	0.287	0.064	4.483	0.000***
5.	knowledge	0.926	0.409	2.263	0.009**
6.	pernegenv	0.773	0.119	6.496	0.000***
7.	pernegheal	-0.255	0.093	-2.742	0.051*
	H|L	-1.319	0.237		
	L|M	0.806	0.252		
		LR Chi-square		92.16	
		Prob > Chi square		0.000	
		Log likelihood		-46.271	
		n		120	

*, **, *** Significant at 10 %, 5 % and 1 %, respectively. pernegenv - perception of a negative effect on the environment, pernegheal - perception of a negative effect on human health.

Specifically, participation in training helps farmers update their knowledge and raise concerns about following the practices. Hence, knowledge influences their adoption by 0.926. Farmers who can access the extension services, show a higher adoption level of CSPM practices. Here, availing extension services by farmers are likely to adopt the practices with the probability of 0.287. Farmers' perception of negative environmental effects tends to lead the farmers to follow CSPM practices. Similarly, there was a positive relationship between the dependent variable and their negative perception induced their adoption level with a probability of 0.773. In reality, farmers' perception of negative health effects tends to lead farmers to follow CSPM practices, but in this case, there was a negative relationship between the dependent variable (-0.255) and their negative perception because of ignorance of the effects on health aspects. The cut points H|L and L|M depicted that the latent variable is cut to form the three groups observed in our data.

The results of ordered logistic regression in terms of proportional odds ratios are presented in Table 6. For a one unit increase in the education of the farmers, there is the odds of high adoption versus the combined medium and low adoption levels are 1.030 greater, given that all of the other variables in the model are held constant. Likewise, the odds of the combined medium and high adoption levels versus low adoption are 1.030 times greater, while keeping all other variables held constant. For a one unit increase in technical training, the odds of the high category of adoption versus the medium and low levels of adoption are 1.538 times greater, while other variables are being held constant. Because of the proportional odds assumption, the same increase by 1.538 times is found between the low adoption level and the combined medium and high adoption level. For extension services, for a one unit increase in pared, i.e. going from 0 to 1, the odds of high adoption level with the combined medium and low level adoption categories are 0.374 greater, keeping all of the other variables are held constant whereas the odds of the combined medium and high adoption level categories versus low adoption are 0.374 times greater, keeping all other variables held constant. For the independent variable perception of negative effect on environment (pernegenv), if there is a one unit increase in pared, the odds of high adoption level versus the combined medium and low adoption level categories are 1.892 times greater, keeping all of the other variables constant. Similarly, the odds of the combined medium and high adoption levels versus low adoption are 1.892 times greater, keeping all other variables held constant.

Proportional odds assumption

Ordered logistic regression posits that the coefficients describing the relationship between a response variables' lowest and highest categories are the same as those describing the relationship between the next lowest and highest adoption levels and so on. This is termed the proportionate odds assumption or parallel regression assumption. Since all group pairings have the same connection, there is only one set of coefficients, where, in the case of the relationship between each pair of result groups, several models would be required to characterise (31, 32). A significant test statistic indicates that the parallel regression assumption has

Table 6. Results of ordinal logistic regression - odds ratio

Sr. No	Variables	Co-efficient value	Std. error	z	p- value
1.	age	0.056	0.025	2.243	0.004**
2.	education	1.030	0.217	4.741	0.000***
3.	training	1.538	0.299	5.151	0.000***
4.	extension	0.374	0.083	4.504	0.000***
5.	knowledge	1.228	0.541	2.263	0.009**
6.	pernegenv	1.892	0.291	6.496	0.000***
7.	pernegheal	-1.259	0.459	-2.742	0.051*
	H|L	-1.319	0.237		
	L|M	0.806	0.252		
		LR Chi-square		92.16	
		Prob > Chi square		0.000	
		Log likelihood		-46.271	
		n		120	

*, **, *** Significant at 10 %, 5 % and 1 % respectively. pernegenv - perception of a negative effect on the environment, pernegheal - perception of a negative effect on human health.

Table 7. Brant test of parallel regression assumption

Sl. No.	Variable	Chi square	Prob > Chi square	df
1.	age	0.149	0.854	1
2.	education	0.357	0.730	1
3.	training	2.624	0.158	1
4.	extension	3.495	0.012	1
5.	knowledge	0.718	0.422	1
6.	pernegenv	0.163	0.649	1
7.	pernegheal	0.276	0.703	1
	All	13.452	0.416	7

pernegenv - perception of negative effect on environment, pernegheal - perception of negative effect on human health.

been broken. Here, the Brant test can be used to determine if the proportionate odds assumption is correct (Table 7). The aforementioned tests indicate that the proportional odds assumption was not violated.

Conclusion

Pesticide usage is prevalent in the cultivation of major vegetables. The major pesticides used by the vegetable growers are organophosphates, carbamates, pyrethroids, organochlorines, monocrotophos, methyl parathion, endosulfan, etc. due to their high pest control efficiency. The perception of high yields and pest control drives their decision to overuse pesticides. More than 70 % of the vegetable growers are applying pesticides than the recommended level. On average, 15-20 times the pesticides were sprayed, which may pose a greater risk of pesticide residue on the produce. In the context of pesticide use intensity, on average, 2-5 kg a.i./ha was used by the vegetable growers. Adoption of CSPM practices is essential for protecting the environment in the face of persistent pesticide use. The practice of cultivating resistant plant varieties stands first based on the AI derived for all the CSPM practices and followed by crop diversification, crop rotation, cultural practices and so on. The independent variables include education, training, extension, knowledge and perception of negative environmental effects were found to significantly influence the adoption of CSPM practices. There was a negative relationship between the dependent variable (-0.255) and their negative perception because of ignorance of the effects on health aspects. The proportional odds ratios expressed that for a one unit increase in the significant independent variables, there is the odds of high adoption versus the combined medium and low adoption levels are greater and the odds of the combined medium and high adoption levels versus low adoption are greater while keeping all other variables held constant. The increased yield, reduced input cost, higher market prices for environmentally friendly products and reduced health hazards for the vegetable farmers demonstrate the beneficial effects of the CSPM practices. Hence, it is important to disseminate the CSP practices to the non-adopters because of sustainable pest control, environmental and health protection. It requires massive sensitisation programmes, training and demonstrations as strategies to be followed. Ensuring the provision of sizable funds in the form of subsidies on purchase cost, short and medium term loans and crop insurance scheme and encouraging premium pricing for crops produced for following CSPM practices, such as buying organic inputs, promoting on-farm biomass recycling and certification is also suggested. To mitigate the health and environmental risks associated with pesticide usage, there is a need for targeted awareness campaigns, stricter regulations and better access to health services.

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Authors' contributions

AJR conceptualised and formulated the research manuscript. BK helped in the statistical analysis of data. SA helped in tabulation and editing the manuscript. NN helped in collecting the data. PPM helped in summarising and revising the manuscript. ES helped in editing the manuscript. KSB helped in reviewing the manuscript. RM helped in summarising the manuscript. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: The Authors do not have any conflicts of interest to declare.

Ethical issues: None

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