Comparison of Graphical Representation of Simple and Multiple Correspondence Analysis Results on the Category of Factors Related to Farmers Status in Using Reductant Herbicide

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Abstract. Reductants are used to reduce herbicide use on weed control. Based on the results of Simple Correspondence Analysis (SCA) in previous studies, factors that significantly influenced the use of reductants include farmer education, tree age, number of workers outside the family, length of harvest, frequency of herbicide use, frequency of the use of chemical fertilizer and organic fertilizer. Multiple correspondence analysis (MCA) can map both variables and individuals in complex visual map constructions, so that they can interpret the structures in data and patterns of relationship distinctively between variables. This study aims to graphically represent the factors associated with the status of farmers as users or non-users of reductant herbicides using MCA. The similarity of SCA and MCA results lies in coordinate points position for the user and the new user to all education categories points, and also to points of all tree age categories except for Age1. Meanwhile, on the coordinate points position of frequency of use of chemical fertilizers and organic fertilizers categories, there is no similarity in the results of the graphs of the two analyzes.

Keywords: Coffee production, graphical representation, Multiple Correspondence Analysis, reductant herbicide, coffee farmers.

1 Introduction

Coffee is one of the plantation commodities besides palm oil and rubber which has an important role in economic activities in Indonesia. The types of coffee that are mostly grown in Indonesia are Robusta and Arabica. South Sumatra is the largest Robusta coffee producing province in Indonesia [1]. South Sumatra is characterized by extensive land area and Robusta coffee production, and a high number of farmers [2]. Pagaralam is one of 11 coffee producing districts/municipalities in South Sumatra. Based on the Directorate General of Plantations and

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BPS data from 2018 to 2021, it showed that Pagaralam coffee production had experienced a relatively slow increase [3]. The low coffee production is influenced by several factors, one of which is farmers' lack of knowledge about proper land management and maintenance of coffee trees. Coffee plant care including inappropriate use of herbicides can cause the quality and quantity of coffee production to decrease [4]. Frequency of pesticide use is one of the factors that can influence land productivity [5], so it can also affect farmers' net income [6].

The use of herbicides is an alternative for controlling weeds, including on coffee plantations. In its application, the use of herbicides must be appropriate, so that the negative impacts of their use can be minimized [7–9]. The reductant herbicide "WS" is applied through education from a private company. For this reason, the use of reductants as herbicide mixing ingredients has a very positive impact on sustainable agriculture.

Based on socialization regarding the use of herbicides carried out by [10], it was found that farmers felt the importance of using reductants to reduce the impact of herbicide use. In the regression model of farmers' net income (as respondents), the qualitative variables of users and non-users of reductants have no significant effect [11]. By using group analysis, it was found that income determines the similarity of the two categories of farmers [12]. However, if the respondent categories are divided into 3, namely: users, non-users, and new users, then the frequency of herbicide use is related to the status of the reductant herbicide use [4].

Correspondence analysis (CA) is an exploratory technique in multivariate analysis on a set of categorical variables simultaneously from two-way contingency tables [13–16]. The results of CA are in the form of a graphical visualization of the representation ("map") of the relationship between pairs of row and column categorical variables in low-dimensional space. Mathematically, the degree of "clustering" or closeness of points on a map is related to their angle from the origin. Points in the same quadrant can be used as a guide to interpret the relationship between row and column variables. The farther the response category on a particular dimension is from the origin, the greater the importance of that dimension. CA is a versatile technique because it does not require fundamental distribution assumptions, so it accommodates all types of categorical variables whether binary, ordinal, or nominal. Some applications of CA can be seen in the exploration of the relationship between country of residence and the main language used [17], visualization of the relationship between soil physicochemical properties and the composition of soil litter arthropod families [18], and abundance data in ecology [19]. Meanwhile [20] apply Multiblock discriminant correspondence analysis (MUDICA) to psychological problems so that a combined picture of the relationship between observations and variables can be created based on information from large and complex data sets.

In previous research [4] regarding the relationship between factors that influence the use of reductant herbicide by using Simple Correspondence Analysis (SCA), it was found that 7 factors were related to the use of reductants. SCA was carried out to represent the relationship between each factor studied and the reductant usage factor graphically.

Multiple Correspondence Analysis (MCA) is a generalization of SCA [21–22] and a powerful technique for handling larger, more complex datasets, including the high-dimensional categorical data [23]. MCA is the specific application of CA to tables with individuals and their answers to a number of categorical variables [24]. The MCA output graph is a visual form of data that can result in the verbalization of the structures in data set [25]. MCA is based on a multidimensional contingency table of all two-way cross tabulations of all variables. That contingency table is called the Burt matrix. The Burt matrix has the number of rows equal to the number of individuals in the sample and the number of columns equal to the sum of the many categories of rows and columns variables. Some example of MCA application can be seen in the relationship between 6 frailty variables in the elderly [17], identification of segmentation of community preferences for regional head candidates [26], identification of factors related to the nutritional status of adolescents [27], and the associations between malaria Rapid Diagnosis Test (RDT) result and socio-economic, demographic and geographic variables [28].

MCA can map both variables and individuals in complex visual map constructions, so that they can interpret the structures in data and patterns of relationship distinctively between variables. This research aims to graphically represent the variables that are significantly related to the category of coffee farmers in the use of reductant herbicide using MCA. Apart from that, this research also aims to analyze the comparison of the interpretation of the results of the MCA graphical representation (or so-called plot) with the SCA plot from previous research. This research used secondary data based on [4], by exploring the simultaneous relationship between these significantly influencing variables and farmer status based on the use of reductant herbicide. The SCA plot being compared is an asymmetric column plot. The graphical representation of the plot of the MCA results obtained can show a decrease in the graphic suitability measure (total inertia) and a change in the position of the coordinate points of each factor category which is significantly related to the status category of farmers in the use of reductant herbicide. Differences in interpretation can be caused by changes in the goodness of fit of the MCA results. The results of the MCA graphic exploration can be used to classify the dominant variable categories that differentiate the characteristics of each category of farmer status in the use of reductant herbicide.

2 Research Methods

SCA and MCA are exploratory techniques whose each output is in the form of a plot which is a graphical representation of the relationship between row variables and column variables. The steps in MCA [13–16] use Minitab 19 software, starting from preparing a contingency table. For example, the row variable categories are denoted as X_1, X_2, …, X_a and the column variable categories are denoted as Y_1 (as Non-user), Y_2 (as New user), and Y_3 (as User). The cells of the contingency table are denoted as a matrix $N = (n_{ij})$; where n_{ij} is the frequency (number) of respondents who have the variable category row X_i and column category Y_j; for $i = 1, 2, \cdots, a$ and $j = 1, 2, 3$.

Next, each two-way contingency table is expanded into an indicator matrix Z which has size $K \times (a + 3)$; where K = 165 and the elements of each row of Z consist of two elements 1 and the other elements 0. The number of objects is as many as the total number of respondents. The number of columns is the sum of the number of row variable categories and column variable categories. Two kl-elements (where $k = 1, 2, \cdots, 165$ and $l = 1, 2, \cdots, a, a + 1, a + 2, a + 3$) which have a value of 1 in the matrix Z indicate that the k-th respondent has status $(a + j)$ and categorized variable i. The Burt matrix is obtained from $Z^T Z$. This Burt matrix consists of 4 submatrices, namely:

$$Z^T Z = \begin{bmatrix} Z_1 & Z_2 \\ Z_2^T & Z_3 \end{bmatrix} \quad (1)$$

with $Z_1 = diag\ (n_{i\cdot})$ where $n_{i.}$ is the number of respondents in the row variable category X_i; $Z_2 = N = (n_{ij})$; and submatrix $Z_3 = diag(n_{.j})$; where $n_{.j}$ is the number of respondents in the column variable category Y_j.

MCA outputs are in the form of a plot (graphical representation) which is used to represent variable categories, the measure of goodness of fit is in the form of total inertia from the first 2 largest inertia values, row profile i (i.e.: coordinate point of row variable category i), and profile column j (i.e.: coordinate point of column variable category j). Next, the final stage in this research is to compare the interpretation of the MCA results plot with the SCA results plot from [4].

3 Results and Discussion

In [4], there were 19 variables that were explored for their relationship to the use of reductant herbicide by respondents (Pagaralam coffee farmers) using SCA. Based on the use of reductant herbicide, respondents were divided into 3 categories, namely: Non users (not using), New users (only used for less than 2 years), and Users (as users). The results of the research show that there are 7 variables that have a significant influence on the use of reductants, namely: farmer education, tree age, number of workers outside the family, length of harvest period, frequency of herbicide use, frequency of chemical fertilizer use and frequency of organic fertilizer use.

Following MCA can explain the relationship between tree age and farmer status in the use of reductant herbicides. The initial step is to recapitulate the data in the form of a two-way contingency table as in Table 1. The data for the contingency table is based on the results of [4].

Table 1. Two-way contingency table on the relationship between tree age and farmer status

Categories of Tree ages	Notation	Categories of reductant herbicide			Total Row
		Non-User	New User	User	
≤ 10 years	Age1	1	24	7	32
(10, 20] years	Age2	6	33	27	66
(20, 25] years	Age3	4	3	14	21
> 25 years	Age4	4	9	33	46
Total column		15	69	81	165

Table 1 is used for the independence test and further representation process as a plot of SCA results, it is also used to compile the indicator matrix for MCA. Next, the SCA results plot is compared by the MCA results. Because there are 165 respondents, 4 categories of a row variable and 3 categories of a column variable, an indicator matrix Z can be arranged with a size of 165×7. The data for each respondent-k is represented by the row- k of the matrix Z. So, this matrix Z consists of column vectors **0** and **1**, as follows:

$$Z = \begin{bmatrix} \mathbf{1}_1 & \mathbf{0}_1 & \mathbf{0}_1 & \mathbf{0}_1 & \mathbf{1}_1 & \mathbf{0}_1 & \mathbf{0}_1 \\ \mathbf{1}_{24} & \mathbf{0}_{24} & \mathbf{0}_{24} & \mathbf{0}_{24} & \mathbf{0}_{24} & \mathbf{1}_{24} & \mathbf{0}_{24} \\ \mathbf{1}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{0}_7 & \mathbf{1}_7 \\ \mathbf{0}_6 & \mathbf{1}_6 & \mathbf{0}_6 & \mathbf{0}_6 & \mathbf{1}_6 & \mathbf{0}_6 & \mathbf{0}_6 \\ \mathbf{0}_{33} & \mathbf{1}_{33} & \mathbf{0}_{33} & \mathbf{0}_{33} & \mathbf{0}_{33} & \mathbf{1}_{33} & \mathbf{0}_{33} \\ \mathbf{0}_{27} & \mathbf{1}_{27} & \mathbf{0}_{27} & \mathbf{0}_{27} & \mathbf{0}_{27} & \mathbf{0}_{27} & \mathbf{1}_{27} \\ \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{1}_4 & \mathbf{0}_4 & \mathbf{1}_4 & \mathbf{0}_4 & \mathbf{0}_4 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{1}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{1}_3 & \mathbf{0}_3 \\ \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{1}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{0}_{14} & \mathbf{1}_{14} \\ \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{0}_4 & \mathbf{1}_4 & \mathbf{1}_4 & \mathbf{0}_4 & \mathbf{0}_4 \\ \mathbf{0}_9 & \mathbf{0}_9 & \mathbf{0}_9 & \mathbf{1}_9 & \mathbf{0}_9 & \mathbf{1}_9 & \mathbf{0}_9 \\ \mathbf{0}_{33} & \mathbf{0}_{33} & \mathbf{0}_{33} & \mathbf{1}_{33} & \mathbf{0}_{33} & \mathbf{0}_{33} & \mathbf{1}_{33} \end{bmatrix}$$

The Burt matrix is obtained from $Z^T Z$ which consists of 4 submatrices as in Equation (1). The entries of contingency table are the entries of matrix $N = (n_{ij}); i = 1, 2, 3, 4$ and $j = 1, 2, 3$. Based on Table 1, the entries of the submatrices are

$$Z^T Z = \begin{bmatrix} diag\ (32, 66, 21, 46) & (n_{ij}) \\ (n_{ij})^T & diag\ (15,\ 69, 81) \end{bmatrix}$$

Burt matrix entries on the relationship between Tree age and the use of reductant herbicide can be seen in Table 2.

Table 2. Burt matrix $Z^T Z$ on the relationship between tree age and the use of reductant herbicide

Name	Age1	Age2	Age3	Age4	Non	New	User
Age1	32	0	0	0	1	24	7
Age2	0	66	0	0	6	33	27
Age3	0	0	21	0	4	3	14
Age4	0	0	0	46	4	9	33
Non	1	6	4	4	15	0	0
New	24	33	3	9	0	69	0
User	7	27	14	33	0	0	81

The inertia value obtained is a cumulative value which states the representative level of the MCA results plot. Analysis of Indicator Matrix in the form of inertia and cumulative values for the relationship between tree age and reductant use can be seen in Table 3.

Table 3. Inertia and cumulative values in the relationship between tree age and reductant use

Axis	Inertia	Proportion	Cumulative
1	0.7209	0.2884	0.2884
2	0.5542	0.2217	0.5100
3	0.5000	0.2000	0.7100
4	0.4458	0.1783	0.8884
5	0.2791	0.1116	1.0000
Total	2.5000		

Based on Table 3, the first two dimensions produce a total inertia of 0.51 (or 51%). The output from Minitab 19 is also in the form of coordinates points of categorical variable. The coordinate points (component 1, component 2) are represented in the MCA results plot which can be seen in Figure 1b. SCA results plot in [5] can be seen in Figure 1a. The total inertia on all SCA plots is 100%.

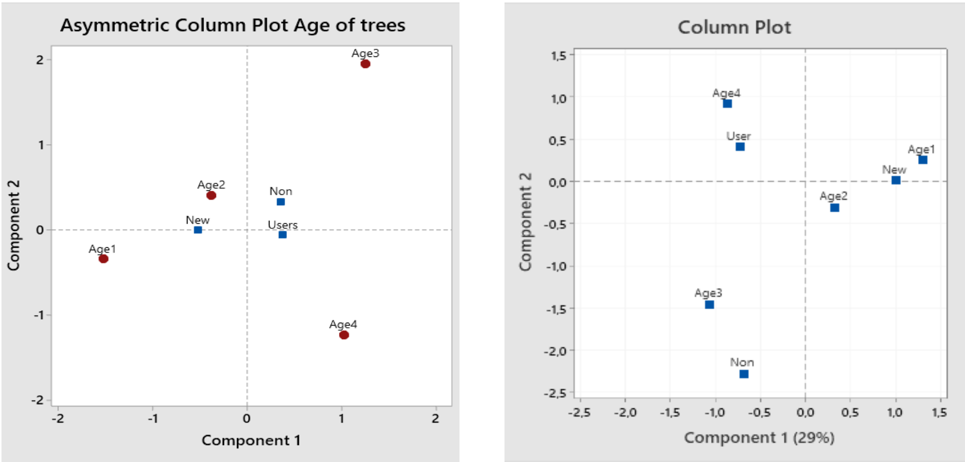

Fig. 1. Asymmetric column plot of SCA and column plot of MCA on Tree age

The MCA plot in Figure 1 represents a goodness of fit of 51%. In SCA plot, the tree age category less than equal 10 years (point Age1) is located far from point New user, and also the tree age category 20 till 25 years (point Age3) is located far from point Non user. But in MCA, the opposite applies. In the MCA results plot, point Age4 (>25 years) is close to point User, so it can be concluded that Users tend to have trees with an average age of more than 25 years. New users tend to have Tree age Age1 (≤10 years) and Age2 (10 till 20 years). Meanwhile, Non-users tend to have Tree age Age3 (20 till 25 years).

The comparisons on the other 6 factors were carried out in the same way, resulting in Figure 2 to Figure 7. The dominant variable categories characterizing the respondent's status in using reductant herbicides can be seen in Table 4.

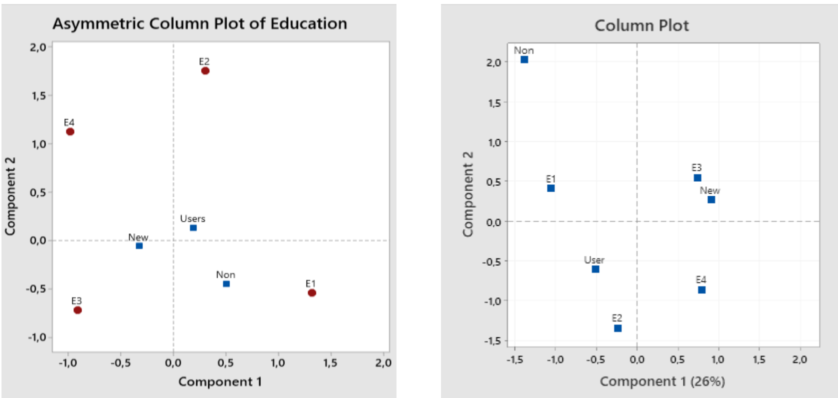

Fig. 2. Graphic representation of SCA (on the left side) and MCA (on the right side) results on the relationship between education and respondent status

The MCA plot in Figure 2 represents a goodness of fit of 49.23%. In SCA, the elementary education category (point E1) is closer to point Non user. But in MCA, E1 is not close to Non-users even though they are in the same quadrant. Point E2 (junior high school education level) is close to point User, so it can be concluded that the User category tends to have junior high school education. Point E3 (high school education level) is close to the New user category, which means that the New user category tends to have a high school education.

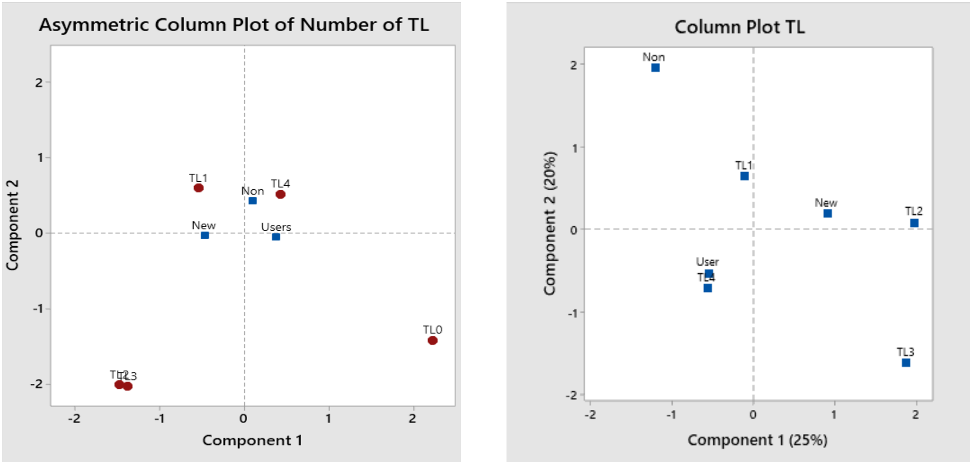

Fig. 3. Plot of SCA (on the left side) and MCA (on the right side) results on the relationship between number of workers outside the family and respondent status

The MCA plot in Figure 3 represents a goodness of fit of 45.41%. In SCA, the number of workers outside the family whose coordinate point states 1 person (point TL1) is close to point New user. But the opposite applies to MCA even though it is located in a different quadrant. In SCA, point TL4 (the number of workers outside the family is greater equals 4 people) is closer to point Non-user. But in MCA, TL4 and TL0 are actually very close to point User. So based on MCA, it can be concluded that reductant users tend to use greater equals 4 workers outside the family.

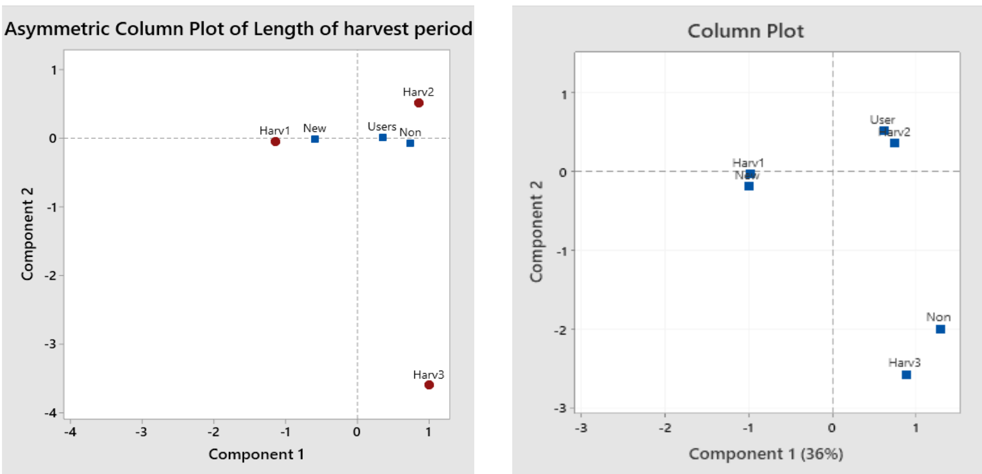

Fig. 4. Plot of SCA and MCA results on the relationship between harvest period and respondent status

The MCA plot in Figure 4 represents a goodness of fit of 63.22%. In SCA, the harvest period whose point states more than 4 months (point Harv3) located far from point Non users. In contrast, in MCA, Harv3 is adjacent to Non users. The similarity of the SCA and MCA plots can be seen at points Harv1 and Harv2. So, it can be concluded that New users tend to have a harvest period of less than 2 months (Harv1). Users tend to have a harvest period of 3 months (Harv3).

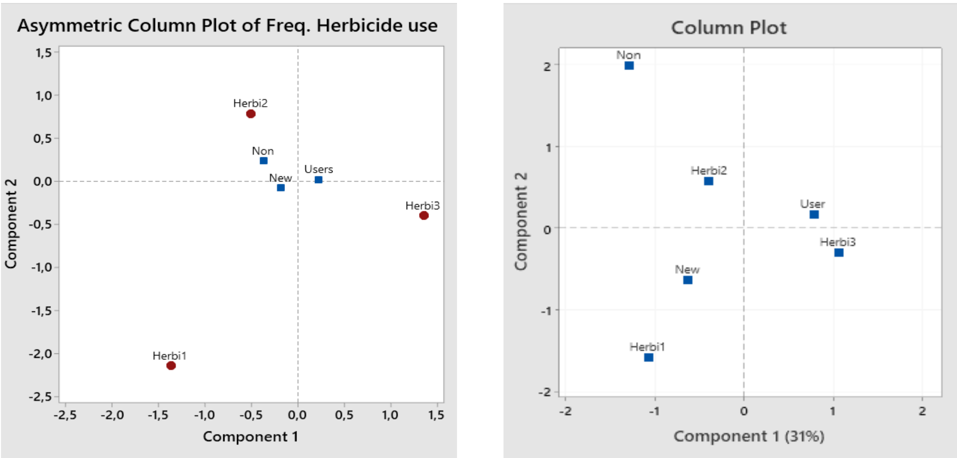

Fig. 5. Plot of SCA (on the left side) and MCA (on the right side) results on the relationship between Frequency of herbicide use and respondent status

The MCA plot in Figure 5 represents a goodness of fit of 57.86%. In SCA, herbicides are used once a year (point Herbi1) located far from the New users point. But on the other hand, in MCA, the Herbi1 point is located very close to the New user point. In SCA and MCA, the point that states herbicide used twice a year (point Herbi2) is close to and located in the same quadrant as point Non-users. So, it can be concluded that New users tend to use herbicides once a year. Meanwhile, Non-users tend to use herbicides twice a year.

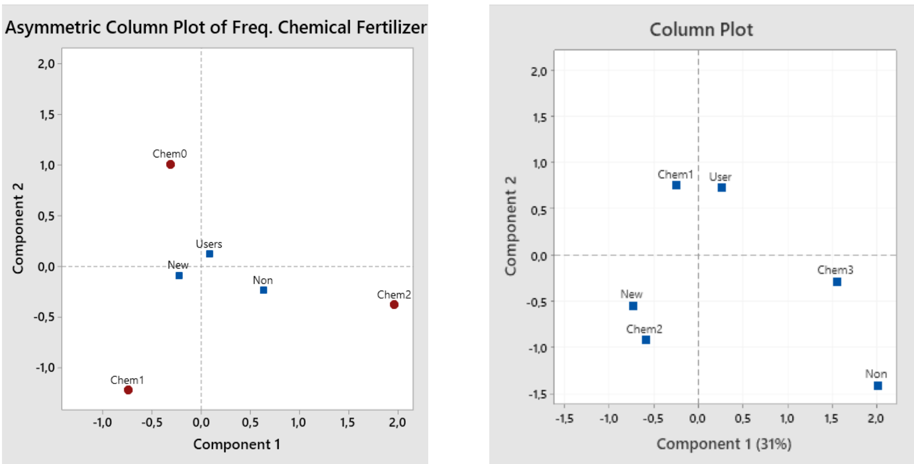

Fig. 6. Plot of SCA (on the left side) and MCA (on the right side) results on the relationship between Frequency of chemical fertilizers use and respondent status

The MCA plot in Figure 6 represents a goodness of fit of 58.96%. In SCA, chemical fertilizer is used once a year (point Chem1) close to point New users. But in MCA, the Chem1 point is located close to the User point in a different quadrant. In SCA, the use of chemical fertilizers in twice a year (Chem2 point) is close to Non-users. But in MCA, Chem2 is close to New users.

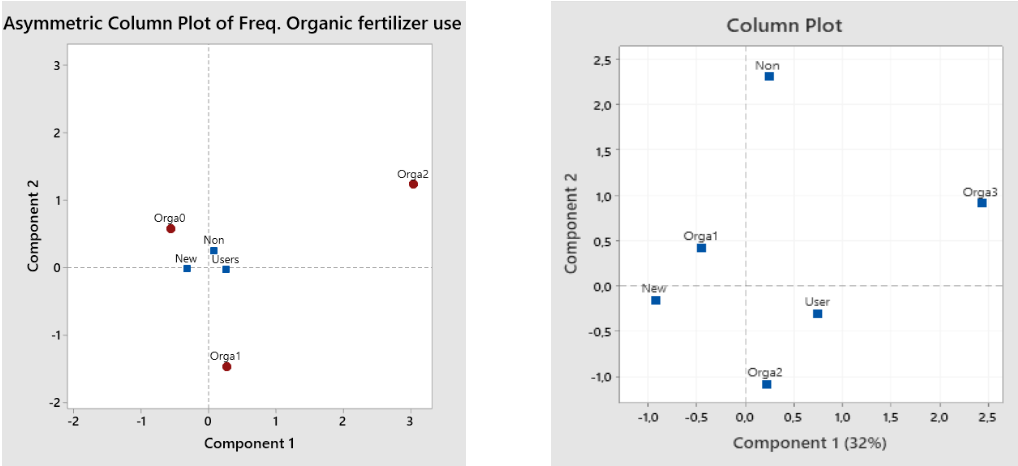

Fig. 7. Plot of SCA (on the left side) and MCA (on the right side) results on the relationship between use of organic fertilizer and respondent status

The MCA plot in Figure 7 represents a goodness of fit of 59.36%. In SCA, organic fertilizer is used once a year (point Orga1) close to New users. However, in MCA, point Orga1 is located close to the New user point but in a different quadrant. In SCA, the use of organic fertilizer in twice a year (point Orga2) is located far from Non-users and Users. But in MCA, Orga2 is close to the User. In SCA, point Orga3 (that states organic fertilizer used in 3 times a year) is close to point New users. But in MCA, Orga3 is not close to any category. Based on the MCA results plot, it can be concluded that Users tend to use organic fertilizer twice a year.

Based on the plot interpretation of Figure 1 to Figure 7, it can be summarized the relationship between the row variable categories and farmer status in the use of reductant herbicides. Table 4 presents a comparison of the SCA and MCA results plots. The row variable categories displayed in the table are categories that are closely related to the respondent's status.

Based on Table 4, all variable categories that dominantly characterize New users in the results of both plots are the same, except for the frequency of chemical fertilizers use and the frequency of organic fertilizers use categories. Likewise, the variable categories that characterize Users in the results of both plots are the same except for the Frequency of herbicides, chemical fertilizers and organic fertilizers uses. In the results of the two plots, there is no category in the Frequency of chemical fertilizer use variable that tends to characterize Users.

In the SCA results plot, there are variable categories that characterize User and Non-user respondents, but on the other hand, this is not the case in the MCA results plot. The variable categories that characterize Non users are E1, TL4, Chem2, and Orga2. Meanwhile for User, the variable category is only Herbi3. The variable category Orga2 in the MCA results plot characterizes Users, but in SCA, Orga2 actually characterizes Non-users. Likewise, the category Chem2 in MCA characterizes New users, but in SCA it characterizes Non users. If we look at the total inertia, the MCA results are less representative, ranging from 45.41% to 63.22%, so the missing information is quite large.

Table 4. Recapitulation of interpretation comparison of SCA and MCA results plots

Row Variable	Plot	The row variable categories correspond to the category of		
		Non-user	New User	User
Education	SCA	E1	**E3**	**E2**
	MCA		**E3**	**E2**
Tree age	SCA	Age3	Age2	**Age4**
	MCA	Age3	**Age1** Age2	Age4
Number of workers outside the Family	SCA	TL4	**TL2** TL3	**TL4**
	MCA		**TL2**	**TL4**
Harvest periods	SCA		**Harv1**	**Harv2**
	MCA	Harv3	**Harv1**	**Harv2**
Frequency of herbicide use	SCA	**Herbi2**	**Herb1**	Herbi3
	MCA	Herbi2	**Herbi1**	
Frequency of chemical fertilizers use	SCA	Chem2	**Chem1**	
	MCA		**Chem2**	
Frequency of organic Fertilizer use	SCA	Orga2	**Orga1**	**Orga0**
	MCA			Orga2

In Table 4, The bolded notation is the row variable category that is very close to the column category. The blueprinted notations are row variable categories that tend to characterize respondent status in the SCA results plot, but not in the MCA results. Meanwhile, the notation printed in red applies the opposite. The notation printed in green is a row variable category that characterizes the respondent's status in the MCA results, which is different from the results in the SCA.

In general, the similarity of the graphical representation of the SCA and MCA results shows that Non-users are dominantly characterized by tree ages of 20 to 25 years. New users are dominantly characterized by their education level being high school, the age of the trees being 10 to 20 years, employing an average of 2 workers from outside the family, length of harvest period in less than equal 2 months, and frequency of herbicide use in once a year. Meanwhile, the reductant Users are dominantly characterized by their education level being junior high school, the age of the tree more than equal 25 years, employing more than 4 workers from outside the family, and the harvest period along 3 months.

3. Conclusion

The similarity of SCA and MCA results lies in coordinate points position for the User and the New user to the points of education categories, also to points of all tree age categories except for Age1, number of workers outside the family, and harvest period. In the SCA results plot, there are variable categories that characterize the status of User and Non-user respondents, but on the other hand, this is not the case in the MCA results plot. Likewise, the frequency of chemical fertilizer use category which characterizes New users and the frequency of organic fertilizer use category which characterizes Users in the SCA results are different from the MCA results. So, at the position of the coordinate points for the categories of frequency of use of chemical fertilizers and organic fertilizers, there are no similarities in the graphic results of the two analyses.

The points configuration representation of the two SCA and MCA output graphs is located in different quadrants, and also the total inertia (measure of goodness of fit) is different, so adjustments need to be made through translation, rotation and dilation. For further research, it is necessary to carry out a Procrustes analysis to compare the configuration of the two graphs.

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