Theoretical study of the effects of rainfall on the population abundance of Diamondback moth, *Plutella xylostella*

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Abstract

Change in Diamondback moth (DBM) *Plutella xylostella* (L.), number on head cabbage (*Brassica oleracea* var. capitata) was monitored for 15 months before the release of its natural enemies *Diadegma semiclausum* (Hellén) and three years after in Werugha, Wundanyi Division in Taita Taveta District, coast province of Kenya. It has been reported that during the rainy season, the DBM abundance on plants significantly decreased. The present work attempted to theoretical study of the effect of rainfall on the population abundance of DBM. The Pearson's correlation method was directly applied to the average rainfall and the DBM numbers in one hand and to the combined effect for the DBM population abundance reaction to rainfall added to the evapo-transpiration process and the DBM numbers on other hand. A multi layer perceptron artificial neural network (MLP-ANN) model was developed for nonlinear sensitivity analysis for measuring rainfall effects on DBM population abundance. The MLP-ANN was constructed using 68 data vectors divided as follows: 40 for training, 18 for validation and 10 for testing. Estimated Pearson's correlation coefficient values helped in deducing that the relationship between rainfall and DBM abundance was nonlinear. The MLP-ANN sensitivity analysis showed the specific contribution of the predictor variables (DBM population abundance) to the rainfall volumes. The study provided insight knowledge on the relative effect of rainfall on DBM population abundance and helped determining the time scale at which it operates for a vital and proper understanding of the basic ecology of the pest management.

Key words: Diamondback moth, population abundance, rainfall

Introduction

The Diamondback moth (DBM) *Plutella xylostella* (L.) (Lepidoptera: Plutellidae), adults are slender, very small, 1/3 inch (8mm) long, greyish-brown, with folded wings flaring outward and upward at their posterior ends. The DBM lay their eggs singly or in groups of two or three on the underside of lower leaves near the leaf veins or on the lower stalks. Egg hatch occurs in 5 to 10 days depending on the prevailing temperatures. Crop damage by DBM is caused by larval feeding. First instars mine leaf tissue, thereafter feeding occurs on the undersurface of the leaf, resulting in a windowpane from the remnants of the top leaf surface (Telekar and Shelton 1993).

Harcourt (1963) and Sivapragasam et al. (1988) reported that majority of DBM larvae were killed in immature stages due to rainfall. Annamalai et al. (1988) stated that 38% mortality of DBM was caused by the direct impact of rain which washed off the eggs. Further it has been stated that loss of eggs due to rain from the upper leaf surface of crop was greater (>50%) than from the lower surface. Study conducted by (Wakisaka et al. 1991) showed that DBM larvae mortality rate was lower in the experimental plots without rainfall and the direct impact of rainfall caused wash-off of eggs and larvae and the drowning of young larvae. Kobori and Amano (2003) carried out a study under artificial rainfall conditions and discovered that DBM eggs laid on the upper leaf surface of cabbage plant were washed off with precipitation of 17.3 mm in 1 hour with drops of 2.5 mm diameter. From these studies, it is obvious that rainfall has an effect on the DBM as well as other insect population abundance (Delobel 1984).

In contrast to numerous studies that illustrate temperature effects on insects (Worner 1992, Gilioli et al. 2005), the present study attempted to theoretically evaluate the level of dependency between rainfall and population abundance of DBM. Further, a sensitivity analysis was conducted to measure rainfall impact on the population abundance of DBM. The study main goal is in line with the following statement: ascertaining the relative effects of weather factors such as rainfall on insect population dynamics and determining the time scale on which it operates is vital to our understanding of the basic ecology of pest management (Aukema and Clayton 2005).

Materials and methods

Data source and collection methods

Experimental results were obtained from the pilot release area in Werugha location (03° 26’ 16’’ S; 38º 20’ 24’’ E) of Wundanyi Division in Taita Taveta District, coast province of Kenya. A detailed description of the pilot release area was provided in (Momanyi et al. 2006, Löhr et al. 2007). At this site, one single release of 125 pairs (male/female) of *D. semiclausum* was made on 26th July, 2002 for the biological control of DBM and the population dynamics of DBM and *D. semiclausum* were studied for 15 months before release and 36 months after release as described in detail in (Löhr et al. 2007, Tonnang et al. 2010).The rainfall records were obtained from the Kenya Meteorological Services. These yielded 4 years of rainfall data, from 2001 to 2005, with an overall annual average of 1182.6 mm.

Establishing the level of dependency between rainfall and population abundance

Expressing rainfall value before collection day, rainfall threshold (P) and rainfall sensitivity (S)

Under field conditions, different ways may exist in which rainfall volume influence changes on DBM population size. The present research has considered two possibilities:

1) heavy rainfall that leads to a decrease in number of egg/larva and later reduces the overall DBM number in the subsequent generations;

2) little rainfall volume that has no significant changes on the DBM population size.

With these considerations, an unknown threshold P was designated; if the value of rainfall volume is less that the threshold ($r < P$), rainfall has no influence on DBM population size; in contrary if $r > P$, the impact of rainfall on population abundance was accounted before analysis.

Theoretically, it is difficult to estimate the day when rainfall will start to have an influence on the next DBM generation. For this reason the average rainfall values were calculated for 1 day, 2 days, 3 days … 14 days, before field data collections and were correlated to the number of DBM obtained during subsequent collections.

In addition, no prior information about the values of threshold P existed, leading to the following considerations: if $P=0$ the calculation will account for all rainfall values in between the time of population measurements. If P is sufficiently large, it means that rainfall has no influence on population abundance of DBM. Different values of rainfall threshold P were randomly chosen and for every value, the sum of rainfall (σ_1) above P was estimated; σ_1 described the reaction of DBM population to the rainfall based on the values of P.

Mathematically,

$$\sigma_1 = \sum_{k=1}^{n} r_k \,/\, r_k > P\,, \tag{1}$$

where r_k represents daily rainfall value within two collections and P the rainfall threshold values and n the number of collections. It was also assumed that the bigger the rainfall variation the stronger its effect on the population size. This was expressed by σ_2:

$$\sigma_2 = 1 + S\,(r_{max} - r_{min}), \tag{2}$$

where S is the population sensitivity; r_{max} and r_{min} are the maximum and minimum values of rainfall between two collections respectively; the difference (r_{max} - r_{min}) is the rainfall dispersal. σ_2 described the reaction of DBM population to the rainfall in relation to the dispersal.

Further the quantities σ_1 and σ_2 were multiplied to yield R representing two different processes with two unknown parameters S and P:

$$R = \sigma_1 \text{ x } \sigma_2. \tag{3}$$

Each value of R was subjected to the number of DBM abundance using Pearson's correlation test that showed a positively/negatively significance/nonsignificant reaction with the abiotic factor rainfall. The indirect confidence interval at 95% was estimated with the help of Fisher transformation. This approach was chosen because it is more informative than the simple results of hypothesis tests (where it usually decided to "reject H0" or "accept H0"). The method provides a range of plausible values for the unknown parameters. If confidence interval contains zero (0) point it was concluded that there is no linear influence of rainfall in the population size of DBM or a more complicated relationship may exist between these quantities.

Pearson's correlation coefficient

The Pearson's correlation coefficient was used to investigate and measure the degree to which the DBM population levels are related to rainfall volume. Sometimes called product-moment correlation, Pearson's r_p value varies from -1 to +1, with 0 indicating no relationship (random pairing of values) and 1 indicating perfect relationship, taking the form, "The more the rainfall, the more the DBM number, and vice versa." A value of -1 is a perfect negative relationship, taking the form "The more the rainfall, the less the DBM number, and vice versa" (Royden and Fitzpatrick, 2007). With more details, correlations from 0 to 0.25 (or -0.25) indicate little or no relationship, a value from 0.25 to 0.50 (or -0.25 to -0.50) reflect a fair degree of relationship; and a value from 0.50 to 0.75 (or -0.50 to -0.75) is a moderate degree of relationship, while value of correlation coefficient over 0.75 (or -0.75) reflects a strong relationship.

Evaluating the effects of rainfall on the population abundance of DBM

Multi-layer perceptron artificial neural networks modeling

The multi-layer perceptron feed forward artificial neural networks (MLP-ANN) is one of the most used artificial neural network (ANN) architectures. It has been intensively studied and widely applied in many fields (Gevrey et al. 2006, Park et al., 2007). The ANN is made-up of a collection of interconnecting simple processing elements, called neurons. The MLP-ANN consists of several layers which deal with the data input, internal calculation and outputs. In this study, a total of three layers (input, hidden and output) of MLP-ANN was constructed as shown in Figure 4. The back propagation algorithm was utilized to train the network and reduce the error calculation between the expected output (from the field) and the desired output (from the MLP-ANN). The neuron was activated by the sigmoid transfer function. The number of neuron for the input layer was function of the available input data vectors. Five neurons (rainfall, relative humidity, temperature, DBM and *Diadegma semiclausum* population density at time (t-1)) were considered as inputs for the developed MLP-ANN. The number of neurons in the hidden layers was determined through trial and error. When the network did not converge, more neurons were added to the hidden layers. The number of neuron in the output layer was function of the number of patterns to be recognized. One neuron was considered in this study, representing DBM population size at time t. The collected dataset contained 68 vectors. Datasets were randomly subdivided in three groups for training (40), validation (18) and testing (10).

Sensitivity analysis applied to rainfall using artificial neural networks

Sensitivity analysis is a technique used to determine how different values of an independent variable will impact a particular dependent variable under a given set of assumptions. If a small change in a parameter results in relatively large changes in the outcomes, the outcomes are said to be sensitive to that parameter (Gevrey et al. 2006, Park et al. 2007). In different terms, sensitivity analysis aims at establishing the relative importance of the input factors involved in the model, while answering questions such as:

1) Which of the uncertain input factors are more influential in determining the variability affecting the inference?

2) If the uncertainty of one of the inputs could be eliminated, which one should be chosen in order to reduce to minimum the variance of the output of interest?

3) Are there factors whose effect on the outputs is so low that they can be confidently fixed anywhere in their ranges of variation without affecting the results (Cariboni et al., 2007)?

The MLP-ANN methodology was only applied on the data collected during three years period after the release of the DBM parasitoid *D. semiclausum* as the number of datasets before the release was too small for the training, validation and testing of the MLP-ANN. This technique was used here within specific boundaries that one or more input variables, such as changes in rainfall volume will have effect on DBM population abundance. The Rainfall parameter sensitivity was independently performed as a series of tests in which different parameter values of the MLP-ANN model were fixed to see how a change in the parameter rainfall causes a change in the DBM population abundance. The rainfall effect on the DBM population abundance was analyzed through a common approach, which consisted to perturb (increase or decrease) rainfall value and recording the response of the built model, whilst holding all other parameters constant at their most likely vector estimates.

Implementation and analysis of residuals for the MLP-ANN model

The Pearson's correlation coefficients estimates were carried out with the help of a computer program written in C programming language on UNIX platform. The program was linked to a MySQL data base containing the rainfall values, DBM numbers and date of collections. Another computer program written in object oriented C^{++} programming language was used in this research to implement the developed MLP-ANN model.

The Durbin - Watson test which is used for analysis of serial correlation was applied on the discrepancy between theoretical (obtained from the MLP-ANN model) and experimental trajectories (field datasets). Before its application, the residuals were subjected to Kolmogorov-Smirnov test for confirming their normal distribution (Draper and Smith, 1981). Durbin - Watson criterion (d) usually ranges in value from 0 to 4. A value near 2 indicates no-autocorrelation whereby a value toward 0 indicates positive autocorrelation and toward 4 indicates negative autocorrelation between residuals. The existence of positive or negative correlations of residuals indicates dependence between empirical and model trajectories, which lead to the rejection of the null hypothesis and the model validity. In case of non-autocorrelation, residuals independence is indicated and assertion could then be made that the model is good in mimicking the data.

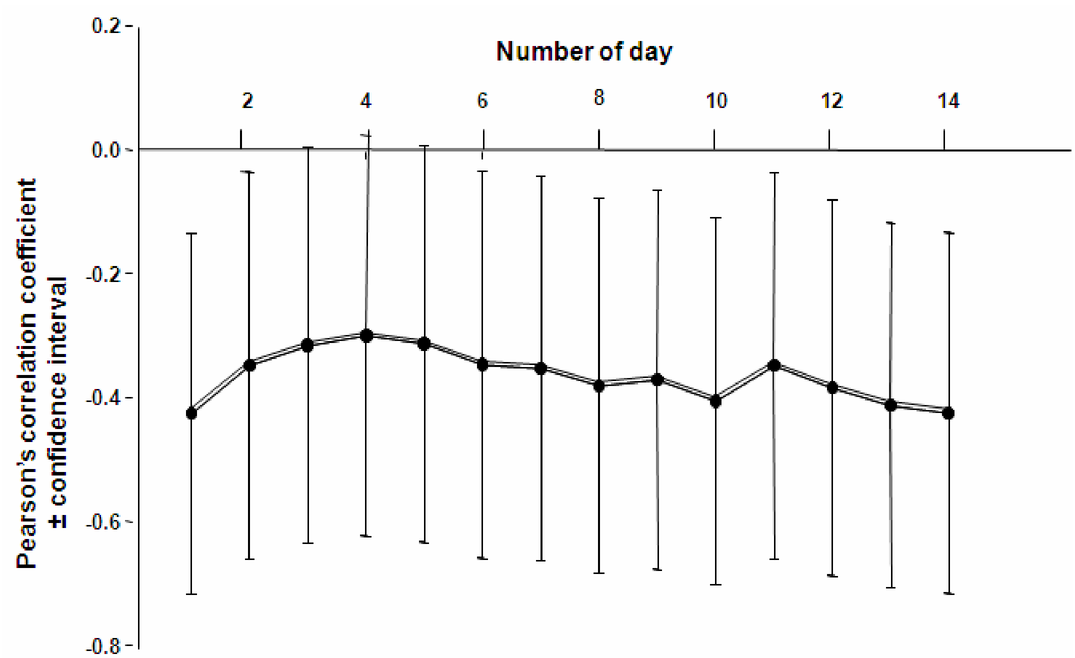
The Durbin-Watson criterion (d) was calculated using the following expression:

$$d = \frac{\sum_{i=2}^{n} (e_i - e_{i=1})^2}{\sum_{i=1}^{n} {e_i}^2}, \qquad (3)$$

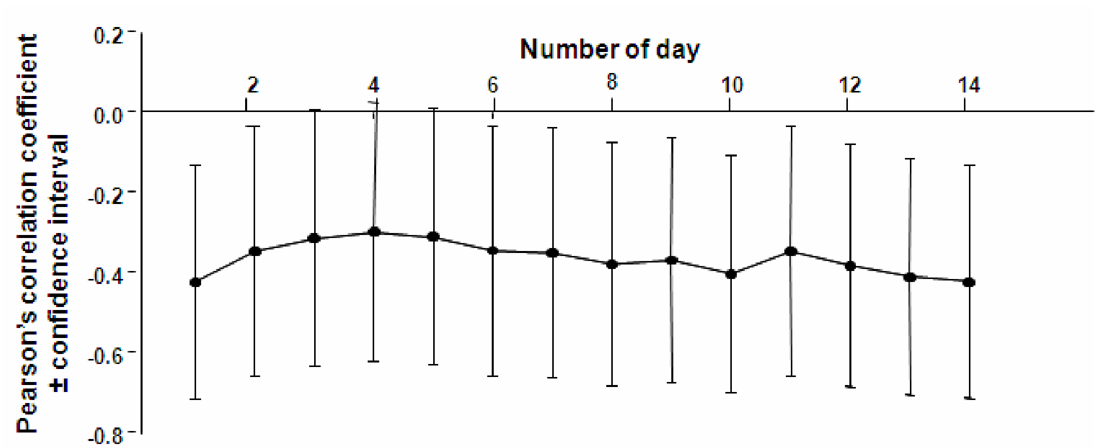
where n is the sample size and e_i the residual value at vector i (difference between empirical and model data)

Results

The graphs for Pearson's correlation coefficients ± confidence interval for the DBM population abundance obtained with the average rainfall (1 day, 2 days… 14 days) before and after the release of the parasitoid, *D. semiclausum* are shown in Figure 1. The values of the correlations for the DBM population abundance obtained with the average rainfall (1 day, 2 days… 14 days) before and after the release of the parasitoid, *D. semiclausum* varied from -0.25 to -05 which theoretically reflected a fair degree of relationship between the two quantities.



(a)



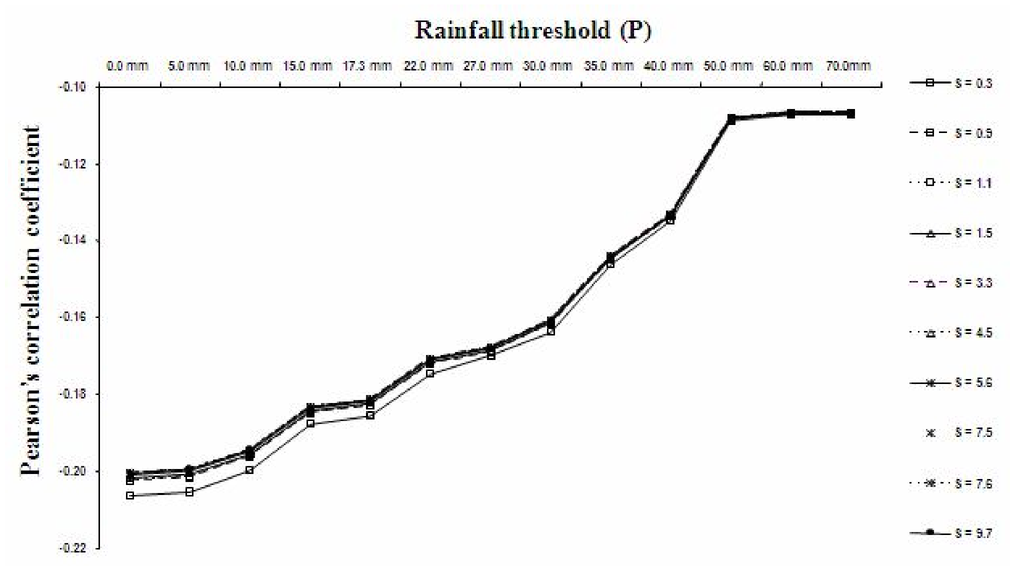
(b)

Fig. 1. Pearson's correlation coefficients ± confidence interval for the diamondback moth population abundance obtained with the average rainfall (1 day, 2 days,…, 14 days) before (a) and after (b) the release of the parasitoid, *Diadegma semiclausum* in Werugha, Wundanyi Division, Taita Taveta District of Kenya.

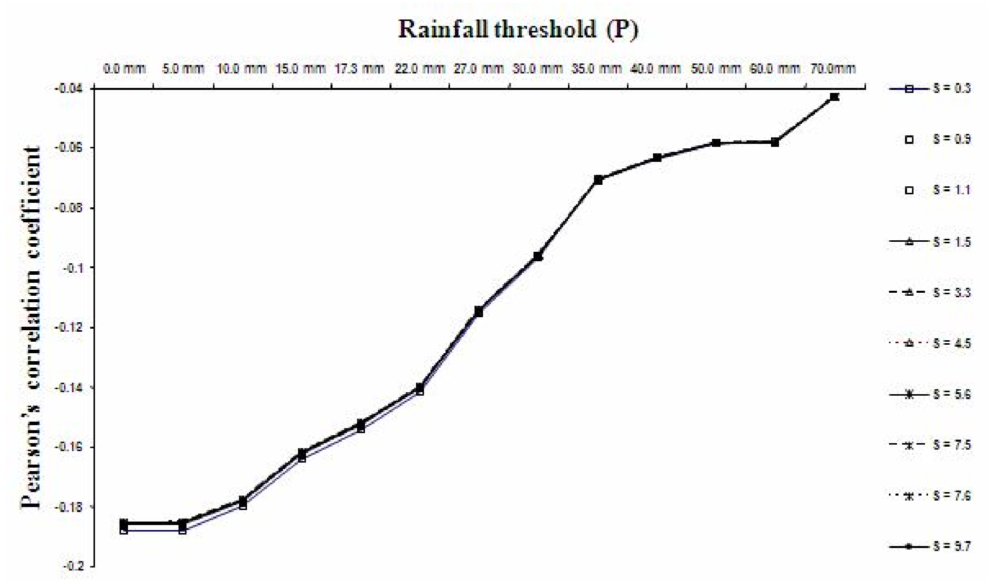
Figures 2 - 3 display the Pearson’s evaluation for the combined effects of the reaction of DBM population abundance to rainfall and the evapo-transpiration process ($R = \sigma_1 * \sigma_2$) correlation with the DBM numbers. These results showed very small numerical values for the Pearson’s correlation coefficients. Theoretically it indicated no linear relationship between the two quantities. On one hand, at varied rainfall threshold (P) and constant rainfall sensitivity (S) similar trajectory for Pearson’s correlation values was obtained. On another hand, at fixed volumes of rainfall threshold and varied volumes of rainfall sensibility (S) the Pearson’s correlation trajectories changed. The closest trajectory to 0 approximately (r = -0.045) was obtained with the highest value of rainfall threshold (P = 70mm). This value demonstrated that there no linear relationship between rainfall and DBM abundance. A negative relationship was expected in this case to translate that high rainfall value should have reduced the DBM population size. Since the correlation is nothing more than a quantitative estimate of the relationship, it is therefore not plausible to base in the negative numerical values obtained to conclude that the relationship between these variables is a negative one.

In the case of fitting a single straight line through the dots this should result in a negative slope or a line move down from left to right. The negative relationship in this context means that, higher values of rainfall tend to paired with lower DBM population abundance and vice versa. Although Pearson’s correlation method was capable of proving the absence of a strict linear relationship between rainfall and DBM population abundance, it was believed that nonlinear process are capable of producing more accurate and elaborate links between these quantities. The trial and error procedure to get the desired topology for the MLP-ANN models (fig. 4) begun by varying the rate of learning from 0.01 - 0.1 at step 0.01 and the number of hidden layers from 4 - 12. Several topologies were examined and the best result of the training phase was obtained with 0.085 as learning rate and 10 neurons in the hidden layer.

The evaluation of the quotients skewedness/standard error and kurtosis/standard error for residuals gave values < 3. In addition, the results of Kolmogorov-Smirnov tests showed that the residuals for the MLP-ANN model were normally distributed. This demonstrated the validity of the application of the Durbin - Watson criteria for analysis of the sequence of deviations. The value of 2.11 was obtained for Durbin - Watson (d) for DBM. This quantity being closed to 2 demonstrates complete independence of residuals and confirms the validity of the developed model for the analysis of rainfall effect on DBM abundance.

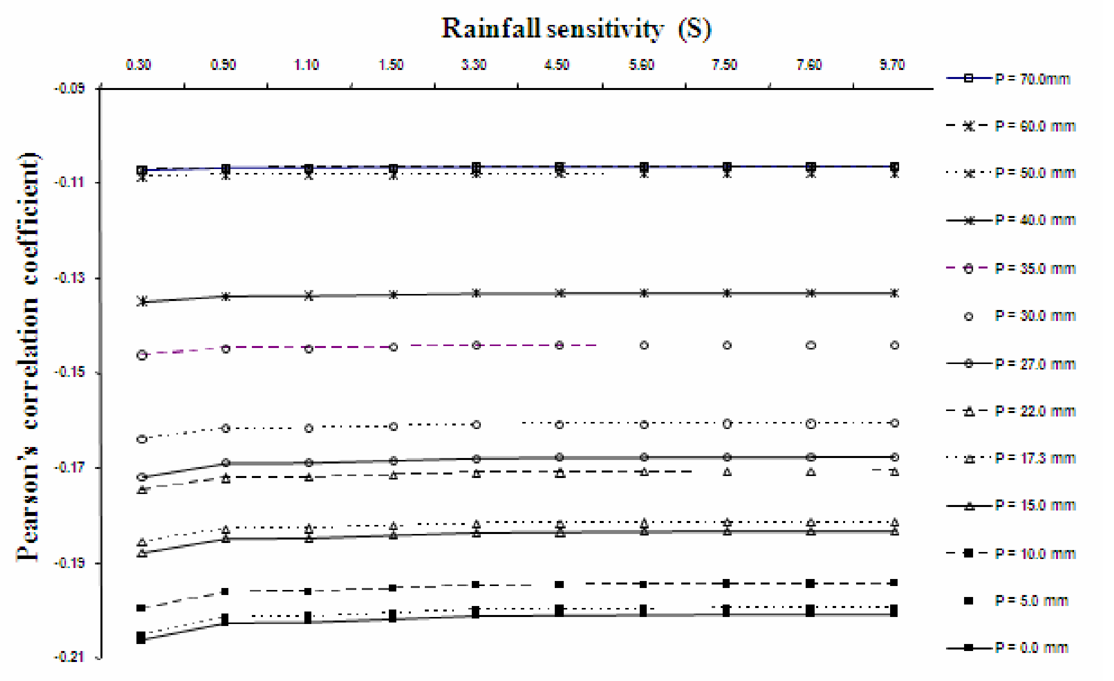


(a)

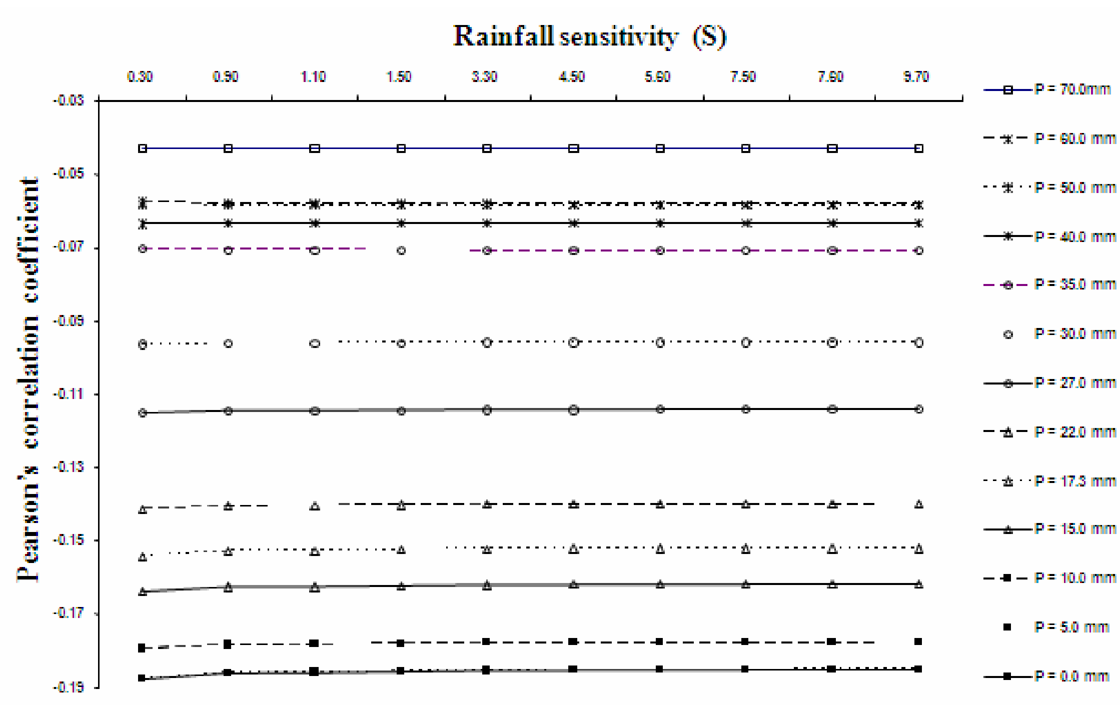


(b)

Fig. 2. Pearson,s correlation coefficient against rainfall threshold at different values of the rainfall sensibility (s) in Werugha, Wundanyi Division, Taita Taveta District of Kenya, before (a) and after (b) release of the *D. semiclausum* respectively.



(a)



(b)

Fig. 3. Pearson,s correlation coefficient against rainfall sensitivity at different values of the rainfall threshold (P) in Werugha, Wundanyi Division, Taita Taveta District of Kenya, before (a) and after (b) release of the *D. semiclausum* respectively.

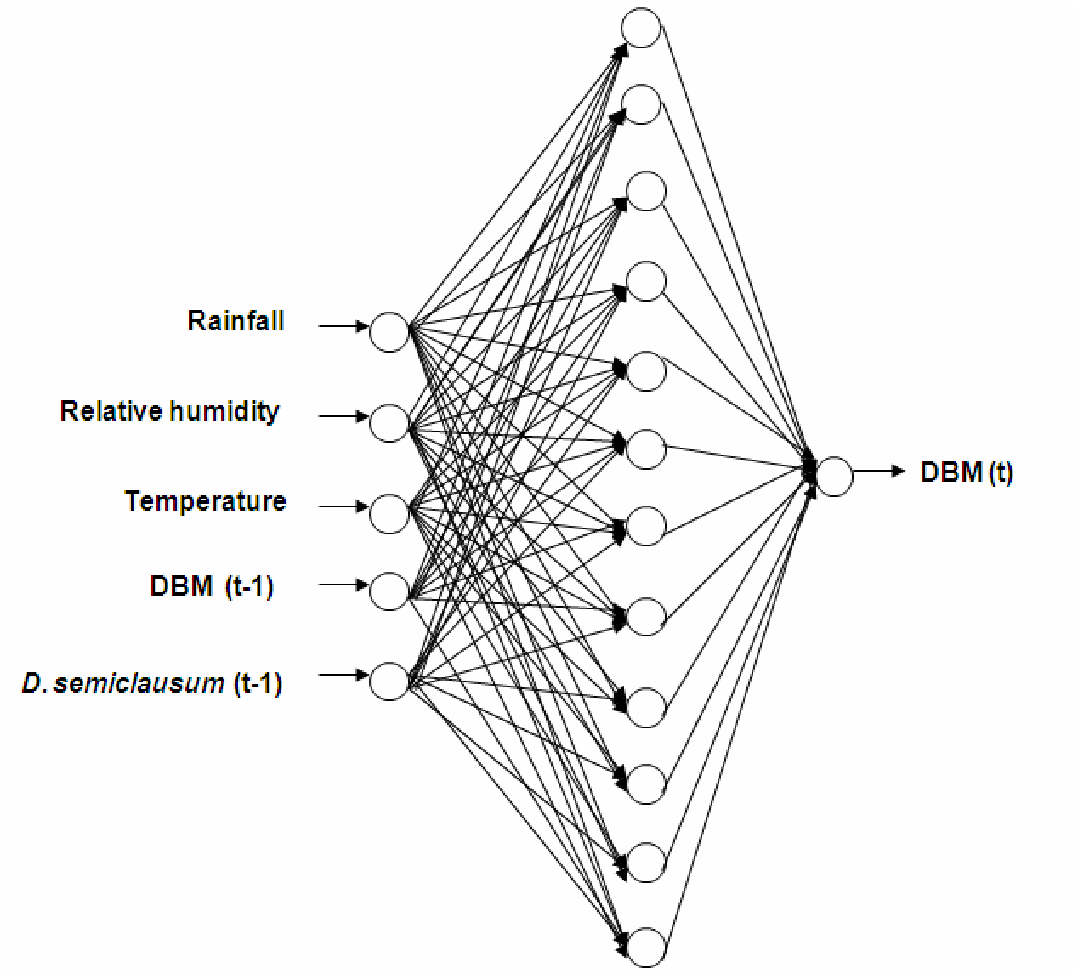


Fig. 4. Develop MLP - ANN model for the diamondback moth population sensitivity analysis at Werugha, Wundanyi Division, Taita Taveta District, Coast Province of Kenya after the release of the *D. semiclausum.*

Figure 5 displays the contribution of rainfall on the DBM population abundance. The figure shows that DBM population keeps increasing at very low rainfall volume and drastically drops when the volume of rainfall became important. Although there appeared to be a general trend toward increasing rainfall rate with decrease in DBM population abundance, the DBM population reached a level where, increasing rainfall did not have any effect.

Discussion

There are some common pitfalls in using correlation. Correlation is symmetrical, not providing evidence of which way causation flows. Within the living environment of the DBM, if other variables also cause the dependent variable to change, then any covariance they share with the given independent variable in a correlation may be falsely attributed to that independent variable. This may prolong to the extent that there is a nonlinear relationship between the two variables; applying correlation analysis will understate the relationship.

Correlation can be attenuated to the level that, there is measurement error, including use of sub-interval data or artificial truncation of the range of the data. Correlation can also be a misleading average if the relationship varies depending on the value of the independent variable. Failure of obtaining high correlation values between studied variables; rainfall and DBM abundance may simply signify that the relationship between quantities is nonlinear.

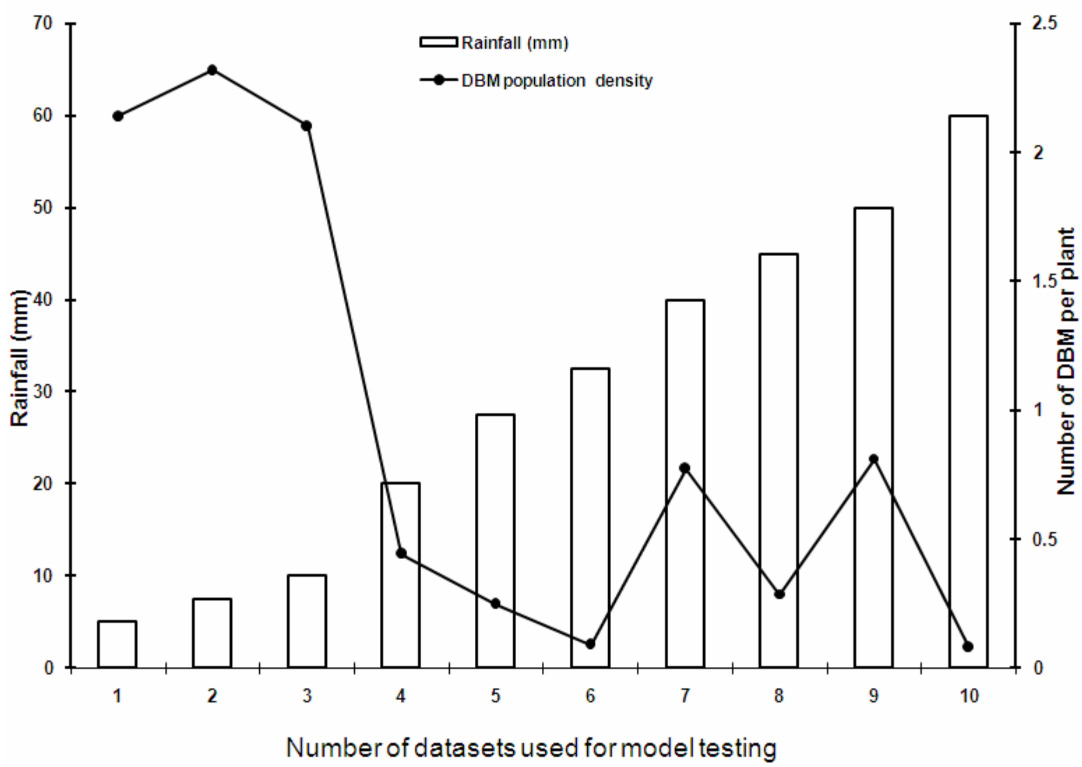


Fig. 5. Contribution of rainfall on DBM population abundance at Werugha, Wundanyi Division, Taita Taveta District, Coast Province of Kenya after the release of the *D. semiclausum.*

A key thing to remember when working with correlations is never to assume a correlation means that a change in one variable causes a change in another. In this context, rainfall and DBM abundance may have been strongly correlated but we cannot assume that a drastic change on DBM population abundance causes the rain to increase its falling (or vice versa). In some situations DBM population abundance may vary due to other external factors such as natural enemies or application of insecticides. The second caveat is that the Pearson's correlation technique works best with linear relationships meaning that, as the rainfall gets larger, the DBM population abundance is expected to get larger (or smaller) in direct proportion. It does not work well with curvilinear relationships (in which the relationship does not follow a straight line). Therefore, using a single variable sensitivity analysis as Pearson's correlation may lead to misleading interpretation. Owing to the fact that, the environment in which the DBM are found is composed of many characteristics acting together, and it is evident that we must consider variable interactions, this justified the application of MLP-ANN which can account for majority of variables interacting with DBM.

The MLP-ANN sensitivity analysis was able to show the specific contribution of the predictor variable (DBM population abundance) to the rainfall values, while the Pearson correlation values only estimated the coefficient values. Harcourt (1963), Sivapragasam et al. (1988) and Wakisaka et al. (1991) conducted studies on the effect of rainfall on DBM population. Their results only mentioned that rainfall affects the DBM population without precision on the volume and how? The present work makes allusion of the rainfall impact on DBM population without any emphasis on which stage the population of the insect is affected. An elaborate study was conducted by Kobori and Amano (2003). The work vectored that DBM eggs laid on the upper leaf surface were washed off with precipitation of 17.3 mm in 1 hour with 2.5 mm diameter rain drop while few eggs on the lower surface were washed off. The results illustrated that under same conditions as for the eggs, the falling rate of larvae decreased with advancing larval stadium except for the first larval stage. The rate of falling larvae increased with increasing treatment time. Kobori and Amano (2003) worked with artificial rain, whereas the present study was done under field conditions with real rainfall volumes. These results showed that after a certain threshold (around 20 mm), the rainfall volume does not have any effect on the DBM population. Increase in rainfall volume at this level does not lead to a reduction in DBM population number. This is in agreement with Kobori and Amano (2003), who reported that even a rainfall of one hour duration with volume greater than 30 mm does not lead to a complete removal of the larvae. However, lack of precise duration and drop size of the precipitations limited the full understanding of rainfall effects on the DBM population under field conditions.

These results indicated that a significant relationship exists between DBM population abundance and the rainfall, but fail to demonstrate the existence and duration of the time lag between rainfall and the DBM numerical response. While no direct mathematical equation was obtained for clear explanation of the type of relationship existing between the rainfall and the DBM abundance, information from the literature (Tanaka and Tanaka 1982; Sivapragasam et al. 1998; Haseeb et al. 2001) suggested rainfall could operate through a variety of pathways to affect the DBM population. For example, after rainfall there is an increase in the levels of humidity, which in consequence provides excellent conditions for the parasitic fungi that can infect and kill the DBM larvae and therefore, impacting on the overall DBM population abundance.

This study has theoretically investigated the effect of rainfall abundance in the real field situation, and it was suggested that advanced research should be conducted on this subject. Because understanding of the rainfall importance in DBM abundance could lead to an effectiveness of integrated methods to control the DBM by artificial rain or water through water sprinkling. Such method was investigated in Hawaii, and the results showed that the pest was effectively and economically controlled through the implementation of an integrated overhead sprinkler system operating between 08:00h and 22:00h, combined with weekly release of braconid *C. plutellae* (Nakahara et al. 1986). The same study also suggested that intermittent application of water in the field during the early hours could disrupt the mating and oviposition activities which is an additional effect on decreasing the pest population size.

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