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Research Article

Tailored Weed Management in Mango Farm: Insights from *Euphorbia heterophylla* and *Mimosa pudica* Spatial Distribution

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ABSTRACT

Understanding the spatial variation in soil properties and the distribution of weeds is crucial for implementing sustainable weed management practices. This study aimed to explore the spatial distribution of *Mimosa pudica* and *Euphorbia heterophylla*, examining the impact of soil properties on their spatial distribution and density. The emerged weeds were counted on a regular grid (20x20m) with 60 observation points covering a study area of 2.49 ha. The physico-chemical properties of soil such as pH, temperature, moisture, total carbon, electrical conductivity (EC), total nitrogen (TN), available phosphorus, exchangeable potassium, exchangeable magnesium (Ex-Mg), exchangeable calcium (Ex-Ca) determined. The density of *E. heterophylla* had a positive correlation with TN (r=0.339), Ex-Mg (r=0.367), and Ex-Ca (r=0.438). By contrast, *M. pudica* exhibited a negative correlation with EC (r=-0.449). The geostatistical analysis uncovered diverse distribution patterns for *E. heterophylla*, *M. pudica*, and soil nutrients across the study. The analysis revealed the Gaussian model is suitable for *E. heterophylla* and TN, the spherical model for *M. pudica*, EC, and Ex-Mg, and the exponential model for Ex-Ca. The creation of individual weed distribution maps can serve as a valuable tool for implementing localized mechanical and chemical control methods, enhancing the efficiency, effectiveness, and cost-effectiveness of weed management. The knowledge is essential for making well-informed decisions on the site-specific management of *E. heterophylla* and *M. pudica* in Harumanis mango cultivation.

Key words: Geostatistical analysis, site-specific, soil properties

INTRODUCTION

Mangifera indica cv. Harumanis has gained popularity and acclaim in Perlis. The cultivar stands out for its exquisite taste, delightful aroma, and premium price (Sani *et al*., 2018.). Consequently, weed control of Harumanis plantations is one of the priorities for farmers aiming to maximize economic returns. They often juggle multiple weed management approaches simultaneously, including reducing the weed seed bank, eliminating competitive weeds, preventing new invasions, and combating herbicide resistance (Somerville *et al*., 2020). Furthermore, weeds are the primary cause of crop yield reduction, responsible for up to 34% of losses in agricultural and horticultural crop production (Somerville *et al*., 2020). The diverse density and scattered distribution of weed populations pose challenges to effective weed management (Partel *et al*., 2019 & Somerville *et al*., 2019). Olorunmaiye *et al.* (2013) reported a significant diversity of 33 weed species in mango crop production. Meanwhile, Rahim (2020) observed a comparable diversity of weed species in both mature mango canopy and inter-rows of both mature and immature mango trees, identifying 25, 22, and 24 species in Harumanis mango, respectively. Among the prevalent weed species in Harumanis mango, broadleaf weeds like *Ageratum conyzoides*, *Mimosa pudica*, *Euphorbia hirta,* and *Euphorbia heterophylla* based on their highest relative abundance values.

Mimosa pudica, a perennial legume notorious for its resilience in crop fields, poses a challenge for manual eradication and has become an invasive weed in numerous tropical and subtropical countries (Tang *et al*., 2022). Often referred to as the sensitive plant or shy plant, it earned these names due to its protective response of shrinking upon touch (Baharuddin *et al*., 2021). Additionally, its seeds have a water-impermeable coating, leading to physical dormancy and allowing them to persist in the soil seed bank for extended periods, complicating effective control efforts (Tang *et al*., 2022).

Similarly, *E. heterophylla* also known as wild poinsettia, milkweed, and painted euphorbia, poses significant challenges in management, affecting crops across South America, Africa, Asia, and Australia (Novakoski *et al*., 2020). This plant infests both annual and perennial crops, and the occurrence of herbicide-resistant populations is widespread (Costa *et al*., 2018). *Euphorbia heterophylla* is highly adaptable, with seeds capable of surviving in the soil for years, competing fiercely with crops (Novakoski *et al*., 2020). Consequently, it directly impacts maize and soybean production in northwestern Paraná State, Brazil, leading to increased management costs and yield losses (Bianchini *et al*., 2019).

Temperature, soil type, pH, nutrients, and moisture can all vary within a field, influencing the location of weed patches (Robertson *et al*., 1994). Kurniawati (2008) stated that weeds growing in areas with good and fertile soil conditions that met the weed living requirements would grow vigorously. In addition, weed population spatial heterogeneity can thus be determined in part by the local distribution of sites with suitable abiotic conditions (Groenendael, 1988). A precise assessment of the spatial

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distribution of weeds is a key step for the success of weed management strategies at the site. The spread of weeds to clean areas, particularly relevant for new weeds and resistant or emerging troublesome weeds, and the implementation of site-specific weed management could be employed to control these weeds through patchy distribution mapping (De Castro *et al*., 2012).

The relationship between weeds and these environmental factors can vary based on the scale, as noted by Metcalfe *et al*. (2015), underscoring the need for scale-specific considerations in model development. The optimal mapping approach varies across crop and weeds management systems and depends on factors like data quality, quantity, and the intended use of the map (Somerville *et al*., 2020). However, there is limited information on the correlation between the distribution of *M. pudica* and *E. heterophylla* with soil properties. Therefore, this study aims to delineate the spatial distribution of *M. pudica* and *E. heterophylla* and assess the influence of soil properties on their spatial distribution and density.

MATERIALS AND METHODS

Experimental site

This study was conducted on a mature Harumanis mango farm located at Universiti Teknologi MARA, Perlis Branch (6°27′27"N, 100°17′01"E). The Harumanis mango trees have been grown on a total area of 2.49 hectares since 2010, with 299 trees planted in a square planting system with a 9-meter spacing between each tree. The mean annual temperature is 27.4°C and the mean annual precipitation amounts to 1993.7 mm from 1991-2021(MMD, 2022).

Weed sampling and soil sampling

The survey took place during the vegetative stage of Harumanis mango from November 2021 to January 2022. Sixty sampling points were selected by a systematic sampling technique. *Mimosa pudica*, *Euphorbia heterophylla*, and soil samples were collected within a 20-by-20 m grid layout one month after mechanical slashing. These samples were taken within a fixed square area of 1.0 m² at predetermined sample points. Several emerged *M. pudica* and *E. heterophylla* were counted and recorded. Soil samples were collected by extracting the top 15 cm of soil using an auger. GPS coordinates (easting and northing) of weed and soil sample locations were marked and recorded using a handheld Garmin GPS map receiver.

Physico-chemical properties of soil

Soil moisture and temperature were recorded using a soil and temperature probe at the time of soil sampling. The collected soil samples were left to air-dry at room temperature for 7 days. Following this, they were carefully crushed using a porcelain pestle and mortar. Then, the soil sample was sieved using a 2 mm mesh sieve for analysis of available phosphorus (Av-P), and exchangeable potassium (Ex-K), calcium (Ex-Ca), and magnesium (Ex-Mg). To determine total nitrogen (TN) and total carbon (TC), subsamples were then meticulously sieved and ground to a particle size of Ø = 250 μm. The resulting fine soil was separated from any organic matter, charcoal, shells, rocks, and plant seeds. These processed samples were utilized to determine TC and TN content, employing an Elemental Analysis CHNSO Analyzer as described in Naik *et al*. (2010). Soil pH was measured using a pH meter at a soil-water ratio of 1:2.5 while electrical conductivity (EC) was determined using an EC meter at a soil-water ratio 1:5. Furthermore, the levels of Av-P were analyzed using a spectrophotometer at 720 nm (Bray II method)(Craze 1995) and Ex-K, Ex-Ca, and Ex-Mg in the soil samples were extracted with 1 M ammonium acetate buffered at pH 7, and their concentrations were analyzed using ICP-OES as outlined in the method by Lavkulich (1981).

Statistical analysis

The statistical analysis was carried out using IBM SPSS Statistic version 25 software. The normality test was performed to determine the normality of the data set ($p \leq 0.05$). To identify outliers, all data sets had a non-normal distribution ($p \leq 0.05$) and were subjected to the Grubbs' Test (extreme studentized deviation test) using GraphPad software. To avoid increased sample variance and skewed semivariograms, outliers were eliminated from the data set before geostatistical analysis (Oliver and Webster 2014). Spearman correlation test was carried out due to all the data sets showing nonnormal distribution to determine the relationship between weed density (*M. pudica* & *E. heterophylla*) and soil properties at a 5% significance level.

Geostatistical analysis

Densities of *M. pudica* and *E. heterophylla*, Ex-Ca and Ex-Mg, TN, and EC of soil were fitted into semivariogram models to create themed maps. The ArcGIS histogram tool was used to further examine all data sets (non-normal distribution) for data distribution. According to the Environmental Systems Research Institute (ESRI) (2021c), the mean and median were similar, the skewness was close to zero, and the kurtosis was close to three if the data were considered normally distributed (a bell-shaped curve). Therefore, the variance of all data sets (non-normally distribution) was stabilized using log transformation so that they would approximately have a normal distribution.

To assess the spatial variability of soil properties and weed density, the most common and fundamental geostatistical semivariogram function was utilized as shown by the following equation (Oliver & Webster 2014):

$$\hat{y}(\mathbf{h}) = \frac{1}{2m(\mathbf{h})} \sum_{i=1}^{m(\mathbf{h})} [z(\mathbf{x}_i) - z(\mathbf{x}_i + \mathbf{h})]^2$$

Where $\hat{y}(\mathbf{h})$ = empirical semivariogram; $z(x_i)$ and $z(x_i+\mathbf{h})$ = the observed values of z at places x_i and $x_i+\mathbf{h}$; and $m(\mathbf{h})$ = number of pairs of experimental points separated by a distance **h.**

The empirical semivariogram model was chosen from the following functions: stable, circular, spherical, exponential, and Gaussian (Obroślak & Dorozhynskyy 2017). The parameters for the nugget (C0), baseline (C0 + C), and range (A) effects were established using the model that best described the relationship between experimental semivariance and the h distance. The shortest sum of squares of the residue (RSS) and the highest coefficient of determination (r^2) were used to select the optimum adjustment model. The cross-validation analysis also was conducted to validate the accuracy of the model estimator and the following prediction errors were examined: mean error (ME), root-mean-square error (RMSE), average standard error (ASE), and root-mean-square standardized error (RMSSE). The equation for the prediction errors is shown below (Environmental Systems Research Institute (ESRI, 2021b):

i. Mean error

$$\frac{\sum_{i=1}^{n}\left(\hat{Z}(s_i)-z(s_i)\right)}{n}$$

ii. Root - mean - square error

$$\sqrt{\frac{\sum_{i=1}^{n}\left(\hat{Z}(s_i)-z(s_i)\right)^2}{n}}$$

iii. Average standard error

$$\frac{\sum_{i=1}^{n}\hat{\sigma}(s_i)}{n}$$

iv. Root-mean-square standardized error

$$\sqrt{\frac{\sum_{i=1}^{n}\left[\left(\hat{Z}(s_i)-z(s_i)\right)/\hat{\sigma}(s_i)\right]^2}{n}}$$

Let $Z(s_i)$ be the predicted value from cross-validation, let $z(s_i)$ be the observed value, and let $\hat{\sigma}(s_i)$ be the prediction standard error for location (s_i).

The ME that is closest to zero for which the interpolation approach is considered unbiased, the smallest RMSE, the ASE that is closest to the RMSE, and the RMSSE that is closest to one were chosen as the best-fitted models for each soil nutrient (Panday *et al*. 2018; Environmental Systems Research Institute (ESRI, 2021a). Based on the nugget-to-sill ratio (%), the spatial dependence index was calculated and classified as high (<25%), moderate (25% - 75%), and weak (>75%) spatial dependence (Cambardella *et al*. 1994).

After being cross-validated, the chosen semivariogram models were used to create prediction maps of weeds and soil properties. To obtain the best linear unbiased predictions, the maps were interpolated using ordinary kriging. ArcGIS software ArcMap version 10.8 was used to construct the semivariogram model parameters and prediction maps. The geostatistical analysis was performed using the Geographic Information System (GIS) program ArcGIS version 10.8 and GS+ version 9 (Monserrat *et al*., 2021).

RESULTS AND DISCUSSION

Table 1 presents the correlation coefficients of *M. pudica* and *E. heterophylla* densities about various soil properties. *M. pudica* exhibited a negative correlation with soil electrical conductivity (r=-0.449), whereas no significant correlation was found with other soil properties. This negative correlation with electrical conductivity aligns with findings reported by Gomaa (2012) for *Chenopodium murale* (r=-0.293) and *Echinochloa colona* (r=-0.285).

By contrast, *E. heterophylla* density showed positive correlations with soil nitrogen (r= 0.339), calcium (r= 0.438), and magnesium levels (r= 0.367). The positive correlation with soil nutrients corresponds to observations made by Walter *et al*. (2002) in *Alopecurus myosuroides* and *Viola arvensis*, where significant positive correlations were noted for magnesium content. Similarly, *Centella asiatica*, *Malva parviflora*, and *Cannabis sativa* exhibited positive correlations with calcium, as mentioned by Yousaf *et al*. (2022). However, certain weeds, such as *Poa annua*, demonstrated different patterns. Poa annua density exhibited an increase in areas characterized by lower levels of nitrogen, magnesium, potassium, organic carbon, and clay (Nordmedyer & Dunker,1999). However, in the current study, *E. heterophylla* density was higher in areas with elevated levels of magnesium.

Interestingly, higher nitrogen levels have been associated with increased competitive availability of nearby weeds over crops (Battles, 2020). This is in line with the observations of Carlson and Hill (1986), who found that wild oats efficiently utilized nitrogen compared to wheat. Weeds capable of effective nitrogen absorption tend to exhibit rapid growth, making them more competitive with host crops for nutrients (Zimdahl, 1993).

Shiratsuchi *et al*. (2005) reported that *Cyperus rotundus, Brachiaria plantaginea*, and *Commelina benghalensis* exhibited a negative correlation with calcium and magnesium levels. However, there were no significant correlations found between the density of *E. heterophylla* and soil properties including electrical conductivity, pH, organic carbon, phosphorus, potassium, soil moisture, and soil temperature. The strength of association between weeds and environmental properties can be scale-dependent (Metcalfe *et al*., 2015) and this should be taken into account when developing models. The best mapping strategy differs between crops and weed management systems. It is influenced by the quality and quantity of available data, as well as the map purpose (Somerville *et al*., 2020).

Table 2 displays the adjusted semivariogram parameters for weed density of *E. heterophylla* and *M. pudica*, as well as soil characteristics including total nitrogen, electrical conductivity, exchangeable magnesium, and exchangeable calcium. The best adjustment model was chosen using the shortest sum of squares of the residue (RSS) and the highest coefficient of determination (r^2). Besides, cross-validation analysis plays a crucial role in selecting the theoretical model of semivariance that best captures the empirical semivariance of the data. The outcomes indicate that the ME ranged from -0.0016 to 0.0352, RMSE ranged from 0.0671 to 3.5485, ASE ranged from 0.0747 to 3.728, and RMSSE ranged from 0.9058 to 1.2043. These results suggest acceptable accuracies in predicting weed density for individual species and each soil property from constructed maps. The range value of *E. heterophylla* indicates 44.5 m and *M. pudica* indicates 18.6 m. The highest range for soil properties was 124.3m for Ex-ca followed by EC (78.4 m), Ex-mg (31.5 m), and TN (16.8 m). According to Mali *et al*. (2016), higher range values for some soil parameters indicated that the soil chemical properties exhibited spatial dependency over greater distances, whereas low range values indicated that these values are influenced by neighboring values at a shorter distance than other variables.

In this study, the best-fitted models encompass spherical, exponential, and Gaussian models. Different best-fit models have also been reported for the spatial variability of soil parameters (Mali *et al*., 2016; Shahidin *et al*., 2018) and weed density has shown different weed spatial dependence, it is due to the differences in demography and dispersal characteristics for the weed species, interactions between coexisting species, edaphic factors, and cropping or control actions, among other processes that influence patchiness (Cousens & Croft, 2000) in mango. The spatial dependency of each weed species ranged from weak to moderate, with *E. heterophylla* classified as having moderate spatial dependence and *M. pudica* exhibiting weak spatial dependence. Additionally, the spatial dependency ratio revealed that soil parameters could be categorized as weak spatial dependency for total nitrogen, and moderate spatial dependency for soil electrical conductivity, while both exchangeable magnesium and exchangeable calcium displayed strong spatial dependency. Weak spatial dependency is attributed to extrinsic factors like agricultural techniques, strong spatial dependency to intrinsic factors such as soil characteristics and mineralogy, and moderate spatial dependency to a combination of internal and external variables (Cambardella *et al*., 1994; Mali *et al*., 2016).

Table 1. Correlation coefficients of *Euphorbia heterophylla* and *Mimosa pudica* densities about soil properties

Parameter	*Euphorbia heterophylla*	*Mimosa pudica*
Total nitrogen	.339*	.006
Available phosphorus	-.168	.017
Exchangeable potassium	.09	-.204
Exchangeable calcium	.438*	-.074
Exchangeable magnesium	.367*	.056
Total carbon	.197	.109
Soil temperature	.106	-.195
Soil Moisture	-.031	.070
Electrical conductivity	.014	-.449*
pH	.252	-.086

*Significant correlation was noted at $p \leq 0.05$

Table 2. Model parameters of the theoretical semivariograms and cross-validation statistics for weed species and soil properties

		Semivariogram parameters							Cross-validation			
		Model	(C_0)[1/]	(C_0+C)[2/]	$\left(\frac{C_0}{C_0+C}\right)$[3/]	Range (m)	SDI[4/] (%)	*Spatial class	ME[5/]	RMSE[6/]	ASE[7/]	RMSSE[8/]
Weed species	*Euphorbia heterophylla*	Gaussian	10.3122	17.4956	0.589	44.5	58.9	M	0.014	3.5485	3.728	0.9563
	Mimosa pudica	Spherical	2.3522	2.4166	0.973	18.6	97.3	W	-0.0481	1.6299	1.588	1.027
Soil nutrient	TN	Gaussian	0.0051	0.0067	0.761	16.8	76.1	W	-0.0016	0.0786	0.0748	1.047
	EC	Spherical	0.0006	0.0013	0.462	78.4	46.2	M	0.0352	0.7802	0.7759	1.0075
	Ex-Mg	Spherical	0.0023	0.0346	0.066	31.5	6.6	S	0.003	0.0671	0.0747	0.9058
	Ex-Ca	Exponential	0.1925	1.7635	0.109	124.3	10.9	S	0.0129	1.1337	0.9148	1.2043

*[1/] Nugget, [2/] Sill, [3/] Nugget/sill ratio, [4/] Spatial dependency index, [5/] Mean error, [6/] Root-mean-square error, [7/] Average standard error [8/] Root-mean-square standardized error. *S, strong spatial dependency; M, moderate spatial dependency; W, weak spatial dependency; -, no spatial dependency

Figure 1 shows the distribution map of *E. heterophylla* and *M. pudica* in Harumanis mango. The different green color shades shown on the map indicate the different density levels of *E. heterophylla and M. pudica* at the sampling sites. The highest density level corresponds to the darkest color tone, while the lowest density level corresponds to the brightest color. *Euphorbia heterophylla* infestations were found in the study area, with range values of 0-8 plant/m^2 which was more prevalent in the western areas compared to *M. pudica* more prevalent in the eastern part of the study area with a range of 0-5 plant/m^2.

Site-specific management of *E. heterophylla and M. pudica* can be done based on weed maps produced. Krahmer *et al*. (2020) stated that weeds are often spotlessly distributed within crops and suggested the application of chemical or physical weed control measures only when they are needed. The information from the weed maps is critical for crop-weed discriminating algorithms and decision-support models that estimate the risk presented by weeds in the fields (Kavhiza, 2020). Furthermore, combining prescription maps with herbicide application technologies like patch spraying or variable rate treatment has a lot of potential for weed control. It allows reliable decision-making related to weed management in agricultural fields by combining extremely modern sensor technologies with geographical information systems (GIS) (Zargar *et al*., 2018). Patch spraying, for example, can be carried out using either weed maps or real-time sensors. Weed detection and spraying occur simultaneously in real-time operations, whereas they are separate activities in map-based spraying (Castaldi *et al*., 2017).

Figures 2 and 3 display the spatial variability maps of soil properties in the Harumanis mango orchard that exhibit correlations with the distribution of *E. heterophylla* and *M. pudica*, respectively. Nutrient classifications based on the standards set by the Department of Agriculture (DOA) have been established (Azizan *et al*., 2019). It is noteworthy that the levels of tested soil properties were surprisingly below the optimum thresholds. In Figure 2a, the spatial variability map of TN in the study area ranged from 0.2% to 0.3%, indicating low levels of total nitrogen across almost all areas of the plot. Figure 2b illustrates the range of soil electrical conductivity, which varied from 0.08 to 0.15 mS/cm across all areas of the plot, staying below the optimum soil electrical conductivity level (<1.0 mS/cm). Likewise, the Ex-Mg level in the southwest area was considered low, ranging from 0.09 to 0.27 cmoL/kg, and other parts of the plot exhibited very low levels (ranging from 0.09 to 0.1 cmoL/kg) (Figure 3a). Similarly, the Ex-Ca showed a small area with low levels (2.1-4.8 cmoL/kg) in the western area of the plot (Figure 3b). The low soil nutrient levels in the research plot are likely attributed to the absence of compound or organic fertilizer application before the start of the research.

Table 1 indicates a negative correlation between the density of *M. pudica* and soil electrical conductivity. This finding is consistent with the distribution patterns observed in Figures 1b and 2b, where a higher density of *M. pudica* and an increased level of soil electrical conductivity were located in opposing areas of the plot. Conversely, the density of *E. heterophylla* showed positive correlations with soil nitrogen, calcium, and magnesium. The greater distribution of *E. heterophylla*, as illustrated in Figure 2a, corresponds to the areas displaying elevated levels of TN in Figure 2a, Ex-Mg in Figure 3a, and Ex-Ca in Figure 3b on the maps.

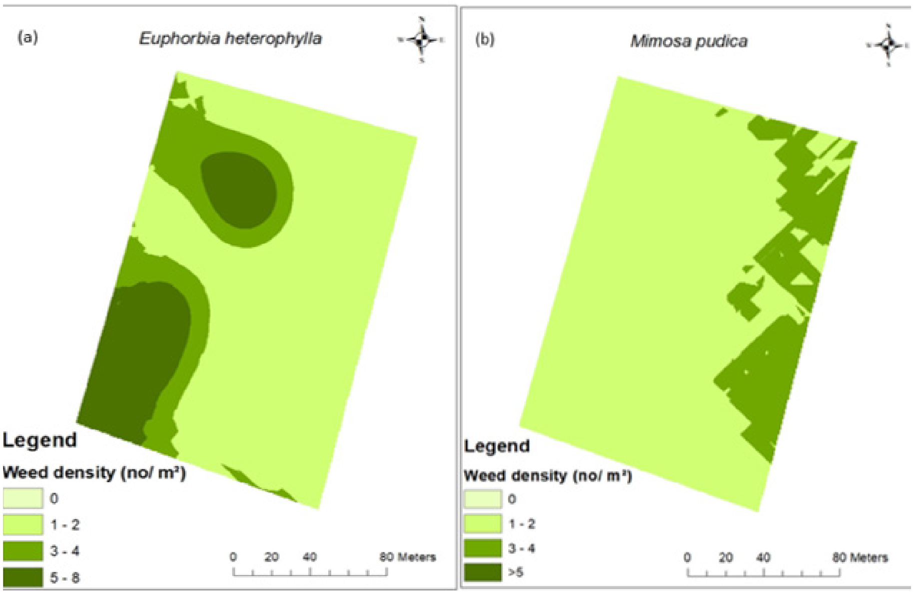

Fig. 1. Distribution map of *Euphorbia heterophylla* (a) and *Mimosa pudica* (b).

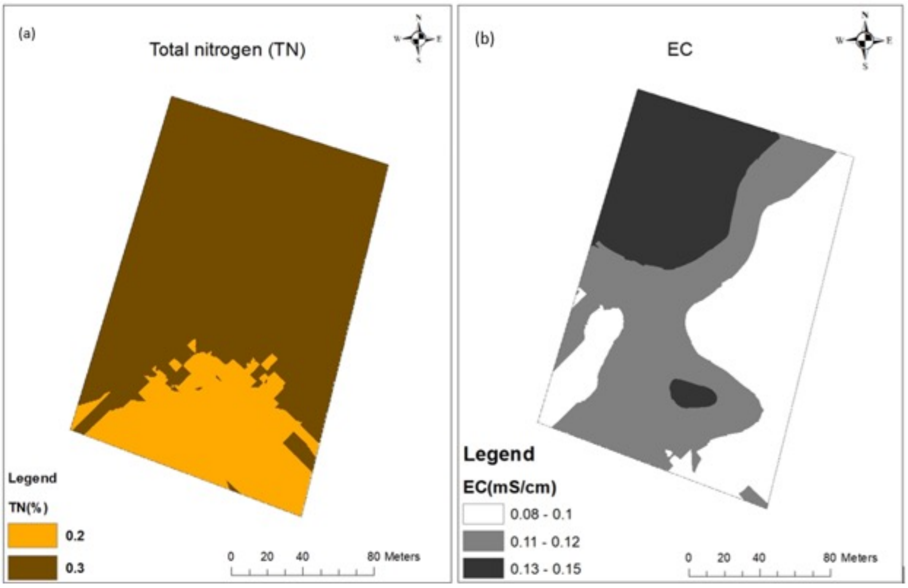

Fig. 2. Distribution maps of total nitrogen (a) and soil electrical conductivity (b).

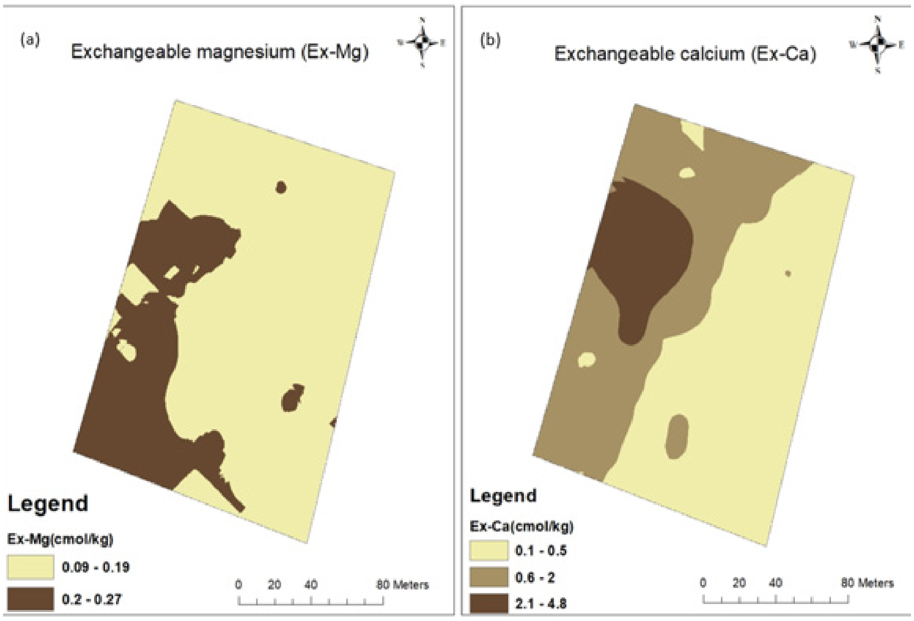

Fig. 3. Distribution maps of soil exchangeable magnesium (a) and soil exchangeable calcium (b)

CONCLUSION

In summary, *E. heterophylla* plants were predominantly found in the western area of the Harumanis mango plot, attributed to specific soil physico-chemical properties such as total nitrogen, exchangeable magnesium, and exchangeable calcium in these areas. On the other hand, *M. pudica* was distributed in the eastern area of the plot, correlating with soil electrical conductivity levels. The creation of individual weed distribution maps for each species proves valuable, serving as a practical tool for localized mechanical and chemical control methods. This approach enhances the efficiency, effectiveness, and cost-effectiveness of weed management. Such information is crucial for making informed decisions on the site-specific management of *E. heterophylla* and *M. pudica* in Harumanis mango cultivation.

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ETHICAL STATEMENT

Not applicable.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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