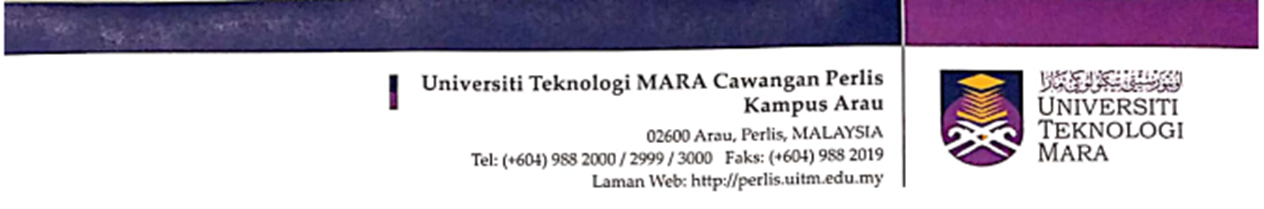
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**Date: 16 JANUARY 2024**

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Sir,

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2. On behalf of the corresponding author, I hereby submit the manuscript entitled “Spatial analysis of *Fimbristylis miliaceae* and soil properties for sustainable weed management in Harumanis mango cultivation to be considered for publication in IJAB which all the authors have agreed to. We confirm that we have removed any identifying content that could compromise blind review. We have read and believe to have understood as described in the instructions for authors.

3. This is the original submission that has not been published before and that is not currently under review at any other publication outlet. The current submission revealed that well-aligned with the scope of your journal and will be of interest to your readership.

4. Although we realise that other people may be selected; we would like to nominate the following reviewers for this submitted manuscripts as stated in the following table.

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Sincerely,



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**Running title**: Improving management of *Fimbristylis miliaceae* in Harumanis mango

# Spatial analysis of *Fimbristylis miliaceae* and soil properties for sustainable weed management in Harumanis mango cultivation

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# Novelty statement

# The novelty of this research involves the integrating data of *Fimbristylis miliacea* and soil properties such as exchangeable sodium and exchangeable calcium. The information provided is valuable for mango farmers to apply site specific management of *F. miliacea* based on weed mapping.

# Abstract

Understanding the spatial variation in soil properties and the distribution of weeds is essential for implementing sustainable weed management practices. This study aimed to investigate the spatial distribution of *Fimbristylis miliacea*, exploring the influence of soil properties on both their spatial distribution and density. Weed counts were conducted on a regular 20x20m grid, comprising 60 observation points covering a study area of 2.49 hectares. The physico-chemical soil properties, including pH, temperature, moisture, organic total carbon, electrical conductivity (EC), total nitrogen (TN), available phosphorus, exchangeable potassium (Ex-K), exchangeable magnesium (Ex-Mg), exchangeable calcium (Ex-Ca), and exchangeable sodium (Ex-Na), were determined. The density of *F.miliaceae* exhibited a positive correlation with Ex-Na and Ex-Ca. Geostatistical analysis revealed diverse distribution patterns for *F. miliaceae* and soil nutrients across the study plot. Generating weed distribution map can serve as a valuable tool for implementing localized mechanical and chemical control methods, thereby enhancing the efficiency, effectiveness, and cost-effectiveness of weed management. This knowledge is crucial for making well-informed decisions regarding the site-specific management of *F. miliaceae* in Harumanis mango cultivation.

**Keywords:** *Fimbristylis miliaceae*, Geostatistical analysis, Physico-chemical properties, Site-specific management, Spatial distribution

# Introduction

Mango, scientifically known as *Mangifera indica*, stands as a popular tropical fruit in South Asia, including Malaysia. Within the region, there exists a variety of mangoes, with 'Harumanis' emerging as the most favoured type in Perlis due to its distinctive aroma, texture, and sweetness. Over the years, the demand for Harumanis has steadily increased, resulting in a nearly tripled selling price per kilogram compared to other varieties. This trend has motivated local growers to expand their Harumanis cultivation, establishing it as a premium mango fruit prominently produced in Perlis (Azizan et al. 2019). The climatic conditions in Perlis play a crucial role in making the cultivation of the Harumanis variety feasible in the region. Specifically, the Harumanis mango tree requires a distinct dry period to initiate flowering. The flowering phase commences from January to February, with fruit-bearing occurring between March and April. Harvesting of the fruits takes place annually from May to June (Azizan et al. 2019).

In addition to climatic considerations, effective weed control stands as a top priority for farmers seeking to optimize economic returns. Farmers often engage in multiple concurrent weed management practices, encompassing the reduction of the weed seedbank, elimination of competitive weeds, prevention of new invasions, and combatting herbicide resistance (Somerville et al., 2020). Weeds pose a significant threat to crop yield, accounting 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 present challenges in devising effective weed management strategies (Partel et al., 2019 & Somerville et al., 2019).

*Fimbristylis miliacea* (L.) Vahl, belonging to the Cyperaceae family, is an herbaceous plant with a grass-like appearance commonly found as a weed in rice fields. Its primary distribution encompasses tropical or subtropical regions in South and Southeast Asia, Central America, Northern Australia, and West Africa (Roy, 2019). *F. miliacea*, included in the Global Compendium of Weeds, is characterized as a tufted leafy annual or short-lived herb (sedge) and is identified as both an agricultural and environmental weed (Randall, 2012). In mango crop production, Stephen et al. (2013) reported a considerable diversity, with 33 weed species identified. Similarly, Rahim (2020) observed comparable diversity in both the mature mango canopy and inter-rows of both mature and immature mango trees, identifying 25, 22, and 24 species in mango, respectively. Among the prevalent weed species in mango, *Ageratum conyzoides*, *Mimosa pudica*, *Fimbristylis miliaceae*, *Euphorbia hirta*, and *Euphorbia heterophylla* were identified based on their highest relative abundance values.

Weed patches often remain in fixed locations over the years, as observed by various researchers (Gerhards and Christensen 2003; Kulkarni et al. 2017; Malmstrom et al. 2017). Numerous studies have highlighted associations between the patchy distribution of different weed species and the spatial heterogeneity of the soil. The presence of weeds is significantly influenced by soil organic carbon (SOC), soil texture, and nutrient status (Gaston et al. 2001; Nordmeyer and Häusler 2004; Korres et al. 2017). Kurniawati (2008) emphasized that weeds thrive in areas with good and fertile soil conditions that meet their living requirements.

Accurately assessing the spatial distribution of weeds is a crucial step for the effective implementation of weed management strategies at a given site. It is particularly pertinent for preventing the spread of weeds to clean areas, a concern that is highly relevant for new weed varieties, resistant strains, or emerging troublesome weeds. Employing site-specific weed management strategies based on mapping the patchy distribution of weeds can help control these unwanted plants (De Castro et al., 2012).

Numerous studies have employed geostatistical analysis to investigate the spatial variability of soil nutrients in mango crop cultivation across various locations (Mali et al., 2016; Shahidin et al., 2018; Azizan et al., 2019). Metcalfe et al. (2015) noted that the relationship between weeds and environmental factors can differ depending on the scale, emphasizing the importance of incorporating scale-specific considerations in the development of models. The ideal mapping approach is contingent upon factors such as crop type, weed management systems, and considerations like data quality, quantity, and the intended application of the map (Somerville et al., 2020). In line with the findings of Patzold et al. (2020), maps were generated for management purposes to exemplify the correlation between weeds and soil. Nevertheless, there is insufficient information regarding the correlation between the distribution of *F. miliaceae* and soil properties. Hence, the objective of this study was to outline the spatial distribution of *F. miliaceae* and evaluate the impact of soil properties on their spatial distribution in mango.

# Materials and Methods

**Experimental site:** This study was carried out on a mature *Mangifera indica* cv Harumanis plot (Plot B) at the Farm Unit of Universiti Teknologi MARA, Perlis Branch. Since 2010, 299 mango trees have been planted in a square planting technique with a 9-meter spacing between each tree on a total area of 2.49 hectares. The GPS coordinates are 6° 25' 46.9488" N and 100° 16' 11.4384" E, which correspond to Peninsular Malaysia's northern state at 53 meters above sea level.

**Weed sampling and soil sampling**: The survey was conducted from November 2022 to January 2023, during the vegetative stage of *M.indica*. A systematic sampling technique was used to choose sixty sampling points. One month following mechanical slashing, *Fimbristylis miliaceae* and soil samples were taken in a 20-by-20-m grid layout. These samples were collected within a fixed square area of 1.0 m2 at predetermined points. The count and recording of the number of emerged *F. miliaceae* were performed. Soil samples were acquired by extracting the top 15cm of soil using an auger. The GPS coordinates (easting and northing) for the locations of weed and soil samples were marked and recorded using a handheld Garmin GPS map receiver.

**Physico-chemical properties of soil**: Soil moisture and temperature were recognized using a soil moisture and temperature probe concurrent with the soil sampling process. Subsequently, the gathered soil samples were allowed to naturally air-dry at room temperature for a period of seven days. Following this drying period, the samples underwent careful crushing using a porcelain pestle and mortar. The crushed soil was then sieved through a 2 mm mesh sieve to facilitate the analysis of available phosphorus (Av-P), exchangeable potassium (Ex-K), calcium (Ex-Ca), sodium (Ex-Na) and magnesium (Ex-Mg). For the determination of total nitrogen (TN) and total carbon (TC), subsamples were meticulously sieved and ground to a particle size of ∅=250𝜇𝑚. This finely ground soil was separated from any organic matter, charcoal, shells, rocks, and plant seeds. The processed samples were subsequently employed to assess TC and TN content, utilizing an Elemental Analysis CHNSO Analyzer in accordance with the method outlined by Naik et al. (2010). Soil pH was determined by utilizing a pH meter with a soil-to-water ratio of 1:2.5, while electrical conductivity (EC) was assessed using an EC meter at a soil-to-water ratio of 1:5. In addition, the concentrations of available phosphorus (Av-P) were examined through spectrophotometry at 720nm, employing the Bray II method described by Craze (1995). Moreover, Ex-K, Ex-Ca, Ex-Na and Ex-Mg in the soil samples were extracted using 1 M ammonium acetate buffered at pH 7. The concentrations of these elements were then analyzed using ICP-OES, following the procedure described by Lavkulich (1981).

# Statistical analysis

The statistical analysis was conducted using IBM SPSS Statistics version 25 software. A normality test was executed to assess the normality of the data set (p≤ 0.05). For datasets exhibiting a non-normal distribution (p≤ 0.05), the Grubbs' Test (extreme studentized deviation test) was applied using GraphPad software to identify outliers. In order to prevent an increase in sample variance and skewed semivariograms, outliers were removed from the data set before performing geostatistical analysis, following the approach outlined by Oliver and Webster (2014). Given the non-normal distribution of all data sets, a Spearman correlation test was employed at a 5% significance level to determine the relationship between *F. miliaceae* density and soil properties. Weed density and soil nutrient data were analyzed with descriptive statistics, which included computing the mean, minimum, maximum, standard deviation and coefficient of variation.

# Geostatistical analysis

The semivariogram models were employed to map the densities of *Fimbristylis miliaceae*, Ex-Ca, and Ex-Na of the soil. The ArcGIS histogram tool was applied to scrutinize all data sets, considering their non-normal distribution. As per Environmental Systems Research Institute (ESRI) (2021c) guidelines, data were considered approximately normally distributed if the mean and median were similar, skewness was close to zero, and kurtosis was close to three (indicating a bell-shaped curve). Given the non-normal distribution of all data sets, log transformation was applied to stabilize their variance and approximate a normal distribution.

To evaluate the spatial variability of soil properties and weed density, a widely used and fundamental geostatistical semivariogram function was employed, as expressed in the following equation by Oliver and Webster (2014):

|  |  |
| --- | --- |
|  |  |

Where y ̂(h) = empirical semivariogram; z (x\_i) and z(x\_i+h) = the observed values of z at places x\_i and x\_i+h; and m(h) = number of pairs of experimental points separated by a distance h.

The empirical semivariogram model was selected from a set of functions, including stable, circular, spherical, exponential, and gaussian, as outlined by Obroślak and Dorozhynskyy (2017). Parameters for the nugget (C0), baseline (C0 + C), and range (A) effects were determined based on the model that best depicted the relationship between experimental semivariance and the h distance. To validate the accuracy of the model estimator, cross-validation analysis was performed. This analysis included the examination of prediction errors such as mean error (ME), root-mean-square error (RMSE), average standard error (ASE), and root-mean-square standardized error (RMSSE). The equation for calculating prediction errors is provided below (Environmental Systems Research Institute (ESRI, 2021b):

1. Mean error

|  |  |
| --- | --- |
|  |  |

1. Root-mean-square error

|  |  |
| --- | --- |
|  |  |

1. Average error

|  |  |
| --- | --- |
|  |  |

1. Root-mean-square standardized error

|  |  |
| --- | --- |
|  |  |

Let Z ̂ (s\_i) be the predicted value from cross-validation, let z (s\_i) be the observed value, and let σ ̂ (s\_i) be the prediction standard error for location (s\_i).

The best fitted model selection criteria for soil each soil nutrient considered the mean error (ME) closest to zero, indicating an unbiased interpolation approach, the smallest root-mean-square error (RMSE), the average standard error (ASE) closest to the RMSE, and the root-mean-square standardized error (RMSSE) closest to one, as advocated by Panday et al. (2018) and Environmental Systems Research Institute (ESRI, 2021a). To evaluate the spatial dependence index, the nugget to sill ratio (%) was calculated and classified as high (<25%), moderate (25% - 75%), and weak (>75%) spatial dependence, following the classification by Cambardella et al. (1994).

Following cross-validation, the selected semivariogram models were utilized to generate prediction maps for weed and soil properties. Ordinary kriging was employed for map interpolation to obtain the best linear unbiased predictions. The construction of semivariogram model parameters and prediction maps was performed using ArcGIS software ArcMap version 10.8. The geostatistical analysis was executed using the Geographic Information System (GIS) program ArcGIS version 10.8, in accordance with the approach outlined by Monserrat et al. (2021).

# Results

Table 1 displays the descriptive statistics for *Fimbristylis miliacea*, Ex-Ca, and Ex-Na of soil in the mango plot at UiTM Perlis. The calculated coefficient of variation (CV) values indicate varying degrees of variability in the experimental area. Specifically, *Fimbristylis miliacea* exhibits a CV of 99.3%, Ex-Ca has a CV of 60%, and Ex-Na shows a CV of 30%.

Table 1: Descriptive statistics on density of *Fimbristylis miliaceae* and exchangeable calcium and sodium.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Mean | Minimun | Maximun | Standard deviation | | Coefficient of variation (%) |
|  | |  | *(n=60)* |  |  |  | |
| *Fimbristylis miliaceae* | | 5.98 | 0 | 24 | 5.94 | 99.3 | |
|  | |  | *(n=60)* |  |  |  | |
| Calcium | | 0.10 | 0.04 | 0.33 | 0.06 | 60.0 | |
| Sodium | | 0.002 | 0.0008 | 0.003 | 0.0006 | 30.0 | |

Table 2 displays the correlation between *F.miliacea* density and various soil properties. *F.miliaceae* showed a positive correlation with Ex-Ca (r=0.295\*) and Ex-Na (r=0.263\*), while no significant correlation was observed with other soil properties.

Table 2: Correlation coefficients of *Fimbristylis miliaceae* densities in relation to soil properties

|  |  |
| --- | --- |
| Parameter | Fimbristylis miliaceae |
| Total nitrogen | .679 |
| Available phosphorus | -.170 |
| Exchangeable potassium | -.0.08 |
| Exchangeable calcium | .295\* |
| Exchangeable magnesium | .165 |
| Exchangeable sodium | .263\* |
| Total carbon | .103 |
| Soil temperature | .014 |
| Soil Moisture | -.049 |
| Electrical conductivity | -.082 |
| pH | .199 |

Significant correlation was noted at p≤ 0.05

Table 3 presents the adjusted semivariogram parameters for *F. miliaceae* density and soil characteristics, specifically exchangeable calcium and exchangeable sodium to the theoretical model to determine the spatial variability in the experimental plot. The selection of the best adjustment model was determined through cross-validation, a critical analysis in choosing the theoretical semivariance model that most accurately reflects the empirical semivariance of the data. The results indicate that the mean error (ME) ranged from -0.0001 to 0.0000, root-mean-square error (RMSE) ranged from 0.0060 to 6.3625, average standard error (ASE) ranged from 0.0006 to 6.1325, and root-mean-square standardized error (RMSSE) ranged from 0.989 to 1.0392. These findings suggest acceptable accuracies in predicting weed density for individual species and each soil property from the generated maps. The range value for *F. miliaceae* was determined to be 300.08m. The highest range for soil properties was 111.4m for Ex-Ca, followed by Ex-Na with a range of 88.91m. In this study, the most suitable models are the Gaussian and exponential models. The Gaussian model is applied to *F. miliaceae*, while the exponential model is employed for both soil properties (Ex-Ca and Ex-Na). The spatial dependence analysis categorizes *F. miliaceae* as having weak spatial dependence, whereas exchangeable calcium and exchangeable sodium, exhibited moderate spatial dependence.

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | Semivariogram parameters | | | | | | Cross-validation | | | |
| Model | (C₀)1/ | (C₀+C)2/ | 3/ | Range  (m) | SDI4/  (%) | \*Spatial class | ME5/ | RMSE6/ | ASE7/ | RMSSE8/ |
| *Fimbristylis miliaceae* | Gaussian | 35.237 | 35.237 | 1.0 | 300.08 | 100 | W | -0.1152 | 6.3625 | 6.1325 | 1.0374 |
| Calcium | Exponential | 0.0036 | 0.0044 | 0.8182 | 111.14 | 81.8 | W | -0.0001 | 0.0626 | 0.0602 | 1.0392 |
| Sodium | Exponential | 2.5760 | 4.1134 | 0.6262 | 88.91 | 62.6 | M | 0.0000 | 0.0060 | 0.0006 | 0.989 |

Table 3: Model parameters of the theoretical semivariograms and cross validation statistics for *F.miliaceae* and exchangeable calcium and sodium

\*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 illustrates the distribution map of *F. miliacea* in the mature mango plot. Different shades of green on the map represent varying density levels of *Fimbristylis miliacea* at different sampling sites. The darkest color corresponds to the highest density, while the brightest color indicates the lowest density. *Fimbristylis miliacea* infestations were identified in the study area, with range values of 0-10 plants/m², showing a higher prevalence in the northeast region.

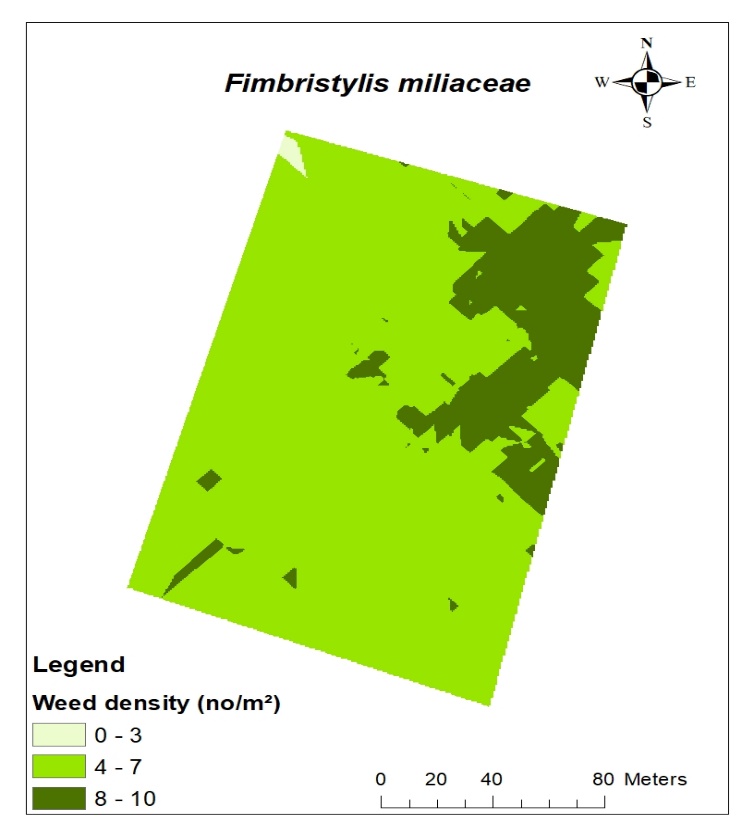


Figure 1: Distribution map of *Fimbristylis miliaceae*

In Figure 2a, the spatial variability map of Ex-Ca in the study area ranged from 0.06 to 0.14 cmol/kg, indicating consistently low levels of Ex-Ca across almost all areas of the plot. Similarly, Figure 2b illustrates the range of soil Ex-Na, which varied from 0.0011 to 0.002 cmol/kg across all areas of the plot, exhibiting very low levels. The northeast region in both Figure 1 and Figure 2 displays the dark color, consistent with the correlation observed between *F. miliaceae* and Ex-Ca and Ex-Na in Table 2.

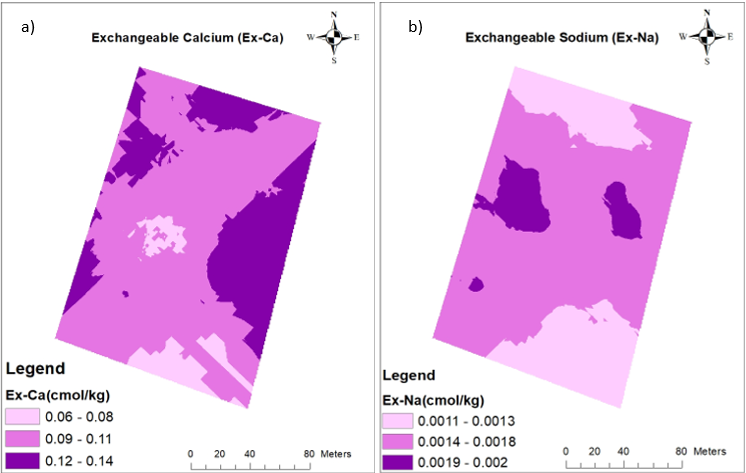
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Figure 2: Distribution maps of exchangeable calcium (a) and exchangeable sodium(b).

# Discussion

The classification for coefficient of variation (CV) values suggested by Vasu et al. (2017) indicates that CV <15% is considered low, 15% ≤ CV ≥ 35% is moderate, and CV > 35% is high for soil nutrient variability. Furthermore, the coefficient of variation classification proposed by Warrick (1980) for weed density considers CV <12% as low, 12% ≤ CV ≥ 60% as a, and CV > 60% as high. The experimental area exhibited high variability in *Fimbristylis miliaceae*, as indicated by a calculated coefficient of variation (CV) exceeding 60%. Similarly, Ex-Ca also demonstrated high variability, with coefficient of variation values surpassing 35%, in contrast to Ex-Na, which showed moderate variability with a coefficient of variation value above 15% ≤ CV ≥ 35%.

# The correlation coefficients between *Fimbristylis miliaceae* densities and soil properties in Table 2 are comparable to the findings of Yousaf et al. (2022), who identified positive correlations between Centella asiatica, Malva parviflora, and Cannabis sativa with calcium.Additionally, Gibbons et al. (2017) reported positive correlations between leafy spurge and spotted knapweed cover with calcium. By contrast, Shiratsuchi et al. (2005) observed a negative correlation between *Cyperus rotundus*, *Brachiaria plantaginea*, and *Commelina benghalensis* with calcium. Gibbons et al. (2017) also found that cheatgrass had a negative correlation with calcium. According to Gibbons et al. (2017) noted that spotted knapweed cover has a negative correlation with sodium, which contradicts the present study's result indicating a positive correlation between *F. miliaceae* and sodium.

# In addition, the outcomes obtained for model parameters of the theoretical semivariograms and cross-validation statistics concerning *F.miliaceae*, exchangeable calcium, and sodium align with Mali et al.'s (2016) observations (Table 3). Higher range values for specific soil parameters imply spatial dependency over extended distances, while lower range values indicate influences from neighboring values at shorter distances, distinguishing them from other variables. The Gaussian function employs a normal probability distribution curve, proving effective when phenomena exhibit similarity at short distances due to its gradual rise in semivariance (GISGeography, 2022). Extrinsic factors such as agricultural techniques are associated with weak spatial dependency, strong spatial dependency is linked to intrinsic factors like soil characteristics and mineralogy, and moderate spatial dependency results from a combination of internal and external variables (Cambardella et al., 1994; Mali et al., 2016).

On the other hand, site-specific management strategies for *F. miliacea* can be developed based on the weed maps generated in figure 1. According to Krahmer et al. (2020), weeds are often unevenly distributed within crops, suggesting that chemical or physical weed control measures should be applied only when necessary. Weed maps play a crucial role in crop-weed discriminating algorithms and decision support models assessing the weed risk in fields (Kavhiza et al., 2020). Integrating prescription maps with herbicide application technologies, such as patch spraying or variable rate treatment, holds significant potential for effective weed control. This approach enables informed decision-making in agricultural fields by combining advanced sensor technologies with geographical information systems (GIS) (Zargar et al., 2018). Patch spraying, for instance, can be implemented using either weed maps or real-time sensors, with weed detection and spraying occurring simultaneously during real-time operations, unlike the separate activities involved in map-based spraying (Castaldi et al., 2017).

Figures 2 present spatial variability maps of soil properties within the mango plot, demonstrating correlations with the distribution of *F.miliaceae*. The study focuses on mango trees grown in lateritic soils, characterized as highly weathered tropical red soils with inherent low fertility, commonly classified as Ultisols in the U.S. Soil Taxonomy. The lack of information on nutrient composition in lateritic soil, considered problematic, could result in nutrient deficits if not managed appropriately (Nasron et al., 2021). Laterite soils typically exhibit moderate acidity in soil reaction and are associated with acidic parent materials and leaching of bases such as calcium (Ca), magnesium (Mg), potassium (K), and sodium (Na) from the soil (Nayak et al., 2002). Calcium tends to be less available in acidic soils and more available in alkaline soils (Bhindhu & Sureshkumar, 2021). The dark color observed in the northeast region in both Figure 1 and Figure 2 aligns with the correlations between *F. miliaceae* and soil properties. This consistent spatial pattern emphasizes the influence of weed distribution on soil characteristics. Overall, these spatial variability maps serve as valuable tools for understanding the distribution of crucial soil nutrients and their potential impact on weed presence, aiding in the development of targeted and effective weed management strategies within the mango plot.

# Conclusion

# In summary, the successful creation of maps provides a valuable tool for assessing *Fimbristylis miliaceae* distribution and identifying its correlation with Ex-Ca and Ex-Na. These maps contribute to site-specific weed management on the mango farm. Utilizing weed maps derived from spatially resolved soil data has the potential to enhance weed management planning by facilitating well-informed decisions tailored to specific site conditions.

# .

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# Author Contributions

# Nurul Aiza Mohd Fauzi conducted the experimental work and drafted the manuscript, under the guidance of Chuah Tse Seng and Khairunnisa Kamarudin. Chuah Tse Seng provided assistance in interpreting the results and preparing the manuscript.

# Conflict of Interest

All authors declare no conflict of interest

# Data Availability

Data presented in this study will be available on a fair request to the corresponding author

**Ethics Approval**

No approval is needed

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