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Spatial Evaluation of Bagworm (*Metisa plana*) Infestation in an Oil Palm Plantation Using GIS

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Abstract: This study investigates the spatial distribution of bagworm (*Metisa plana*) infestation in an oil palm plantation in Felda Besout 2, Malaysia, using Geographic Information System (GIS) technology. A total of 57 systematically selected oil palm trees were sampled, and parameters including larval stages, elevation, and coordinates were recorded. The spatial interpolation method, ordinary kriging, was used to construct distribution maps that revealed infestation intensity across the area. The results indicated a high concentration of *M. plana* larvae in the western section of the plantation, predominantly in their late instar stages (6th and 7th). There was no significant correlation between infestation density and elevation ($R^2 = 0.0144$). GIS proved to be an effective tool for visualizing and managing pest outbreaks in precision agriculture. This technology enhances pest monitoring strategies and supports site-specific decision-making for integrated pest management (IPM) in oil palm plantations.

Keywords: Bagworm, oil palm, Geographical Information System (GIS), spatial analysis, pest infestation, kriging, precision agriculture

1. Introduction

Malaysia plays a pivotal role in the global oil palm industry as one of the top producers and exporters of palm oil. As of 2022, the nation accounted for approximately 25% of global palm oil production, with over 5.7 million hectares under cultivation, contributing significantly to the national GDP and providing employment to nearly a million people (MPOB, 2023; Jalani et al., 2022). The *Elaeis guineensis* species, originally native to West Africa, is widely cultivated in Malaysia due to its high yield and multipurpose applications, including food production, biofuels, and oleochemicals (Corley & Tinker, 2016; Rival & Levang, 2014).

Despite its economic importance, the productivity of oil palm plantations is threatened by various biotic stressors, notably insect pests such as bagworms (*Metisa plana*), nettle caterpillars (*Setothosea asigna*), and rhinoceros beetles (*Oryctes rhinoceros*). Among these, *M. plana* has emerged as a major defoliator, especially in Peninsular Malaysia, capable of causing significant economic losses if left unmanaged (Basri et al., 2021; Chung et al., 2020; Halim et al., 2017). Infestation by *M. plana* can result in up to 43% yield reduction within two years of severe defoliation due to the larvae's continuous feeding on the photosynthetic leaf area (Kamarudin et al., 2012; Tuck et al., 2011). The insect's life cycle includes seven larval instars, and its mobility is enhanced through passive dispersal by wind, human movement, and vehicles (Cheong & Tey, 2012).

The conventional response to bagworm outbreaks involves aerial spraying with chemical insecticides or biological agents such as *Bacillus thuringiensis* (Bt). While Bt is effective and environmentally safer, overdependence on chemical methods has led to pesticide resistance, resurgence of secondary pests, and reduction in natural enemies and pollinators (Bakeri et al., 2008; Emmanuel et al., 2015). Moreover, blanket pesticide applications are costly, especially for smallholders, and often inefficient due to poor timing and lack of pest population data (Mazmiza et al., 2011).

To address these limitations, the adoption of precision agriculture (PA) and advanced spatial technologies such as Geographical Information Systems (GIS) has gained momentum. Precision agriculture focuses on site-specific management by optimizing input use, improving resource efficiency, and minimizing environmental impact (Mulla & Khosla, 2016; Khanal & Lal, 2016). GIS, as a decision-support tool, enables spatial mapping and analysis of field variables including pest density, topography, and soil attributes facilitating more accurate and efficient intervention strategies (Zhu, 2016; Esri, 2023).

In pest management, GIS offers the ability to visualize pest population distribution across landscapes, enabling targeted control measures rather than generalized spraying. It also supports predictive modelling when integrated with

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other datasets such as weather, vegetation indices, or pest phenology (Sciarretta & Trematerra, 2014; Liebhold et al., 2013). For instance, the use of kriging interpolation in GIS allows for the estimation of pest density in unsampled areas based on known sample points, improving spatial decision-making (Chung et al., 2019; Paramasivam & Venkatramanan, 2019).

Despite the availability of these technologies, the application of GIS in assessing *M. plana* infestations in Malaysian plantations remains limited. Understanding spatial distribution is critical to optimizing the timing, location, and method of pest control. This study therefore aims to evaluate the spatial variation of *Metisa plana* infestation in an oil palm plantation in Felda Besout 2 using GIS tools, with the objective of enhancing site-specific pest management strategies.

2. Materials and Methods

2.1 Study Area

The study was conducted in an oil palm plantation located at Lot Che Sara Binti Man, Felda Besout 2, Perak, Malaysia. The plantation spans approximately 1 hectare and comprises about 135 mature *Elaeis guineensis* trees planted in a triangular spacing pattern (9 m × 9 m × 9 m), which is commonly used in Malaysian oil palm estates to optimize land use and sunlight exposure. The geographical location was selected due to reports of recurring bagworm (*Metisa plana*) outbreaks and its accessibility for field monitoring and sampling.

2.2 Sampling Design and Data Collection

A systematic sampling method was employed to select sample trees for data collection. This approach was chosen due to the uniform planting pattern of oil palms in the study area, allowing equal spatial representation. Based on the total tree count, every second tree was selected along transects, resulting in 57 sampling points. Each selected tree was marked using colored spray paint for identification and consistency during the sampling process.

The field data were collected on January 10, 2019. At each sampling point, one frond was randomly selected and pruned from the tree using a sickle. The collected fronds were immediately bagged in transparent sealed plastic bags and transported to the laboratory for further analysis. In the laboratory, individual leaflets were separated from the frond, and the number of bagworm larvae was manually counted. The larvae were subsequently categorized into seven instar stages based on size and morphological features, following the standard instar classification developed by Mohd Basri and Kevan (1995). The bagworm instars were then grouped into three major developmental stages early (1st–3rd instar), middle (4th–5th instar), and late (6th–7th instar) to facilitate analysis of infestation severity.

In addition to biological data, spatial data were recorded using a Garmin GPSMAP 64s device. For each sampling point, the latitude, longitude, and elevation were measured in real time. This geospatial data formed the basis for spatial analysis and map generation using GIS software.

2.3 GIS-Based Spatial Analysis

The spatial data collected from the field were compiled and organized in Microsoft Excel to ensure compatibility with ArcGIS 10.5 software. Each row in the Excel file represented a sampling point and included fields for coordinates, elevation, total number of larvae, and larvae counts by instar stages. The data were then imported into ArcGIS and converted into shapefile (.shp) format for spatial interpolation and visualization.

To visualize spatial distribution of bagworm infestation, the kriging method a geostatistical interpolation technique—was applied using the Spatial Analyst extension in ArcGIS. Kriging was selected for its ability to account for spatial autocorrelation and provide unbiased predictions of infestation intensity across unsampled locations (Zhu, 2016; Paramasivam & Venkatramanan, 2019). The "ordinary kriging" algorithm was used, with the boundary of the study area manually digitized to confine the interpolation within the actual plantation limits. The coordinate reference system was set to WGS 1984 for consistency and global accuracy.

Separate spatial layers were generated to visualize: (1) total bagworm density, (2) elevation, and (3) population distribution of early, middle, and late instar stages. The resulting raster maps were formatted using classified color gradients (10-class scale), enabling interpretation of infestation hotspots. Each map included key cartographic elements such as legends, north arrows, and scale bars, and was exported in high-resolution image format for presentation and publication.

3. Results and Discussion

3.1 Bagworm Infestation Symptoms

Field observations revealed clear signs of bagworm infestation on the sampled oil palm trees (Figure 1). Affected fronds showed varying degrees of defoliation, with some trees exhibiting severe yellowing and drying of the canopy. At close range, visible holes and scrapes on the leaflet surfaces were consistent with feeding activity by *Metisa plana* larvae (Figure 2). These symptoms are indicative of both early and mature larval stages (Figure 3), corroborating findings by Ramlah et al. (2007) and Cheong and Tey (2012), who reported that early instars typically scrape leaf surfaces, while later stages consume entire leaflets, leading to tissue necrosis and leaf drop. Such damage ultimately impairs photosynthesis and reduces overall yield potential.

Fig 1: Oil palm infested by bagworm

Fig 2: Leaf defoliated by bagworm

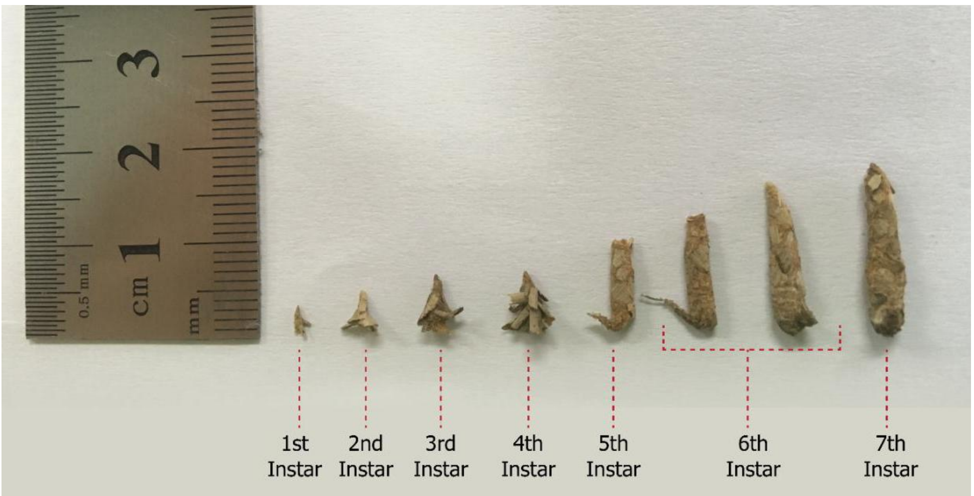

Fig. 3: Stages of *Metisa plana* instar

3.2 Distribution of Bagworm Instar Stages

The population analysis showed a non-uniform distribution of bagworm instars among the sampled fronds. The total number of larvae recorded across all 57 sampling points was 2,646. As shown in Figure 4, the sixth instar stage had the highest recorded number (n = 1,321), followed by the fifth (n = 416) and seventh (n = 256) instars. The lowest population was observed in the first instar stage (n = 26), indicating that the infestation was already at a mature stage during the sampling period.

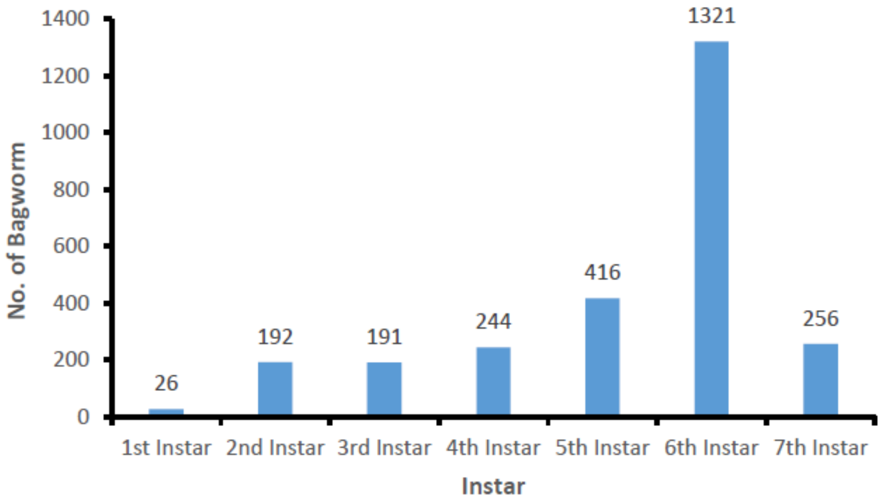

Fig. 4: Number of bagworm per frond for each instar stage

To facilitate analysis, the instar stages were grouped into three developmental categories: early (1st–3rd), middle (4th–5th), and late (6th–7th) instars. The overall population breakdown is summarized in Figure 5, showing that 60% of the bagworm population belonged to the late stage, 25% to the middle stage, and only 15% to the early stage. This stage distribution highlights a peak in larval maturity, suggesting that the infestation had persisted for some time and that intervention at this point may have limited efficacy. Similar results were reported by Halim et al. (2017), who emphasized that early detection is critical to minimize yield loss and improve pest control outcomes.

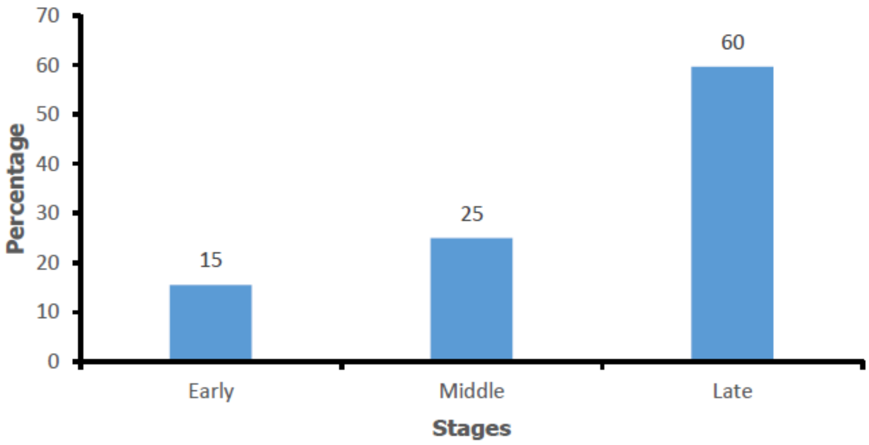

Fig. 5: Percentage of number of bagworm for each instar stage

3.3 Spatial Distribution Analysis

Spatial analysis using ArcGIS revealed that the highest concentration of *M. plana* larvae occurred in the western section of the study area, particularly in plots adjacent to plantation access roads (Figure 6). This spatial clustering supports the hypothesis that human and vehicular traffic act as passive dispersal agents for bagworm larvae, as previously suggested by Cheong and Tey (2012). The kriging-generated heat maps illustrated a maximum infestation intensity of 465 larvae per frond and a minimum of zero. This sharp gradient underscores the localized nature of pest outbreaks and reinforces the utility of spatial tools in guiding targeted interventions.

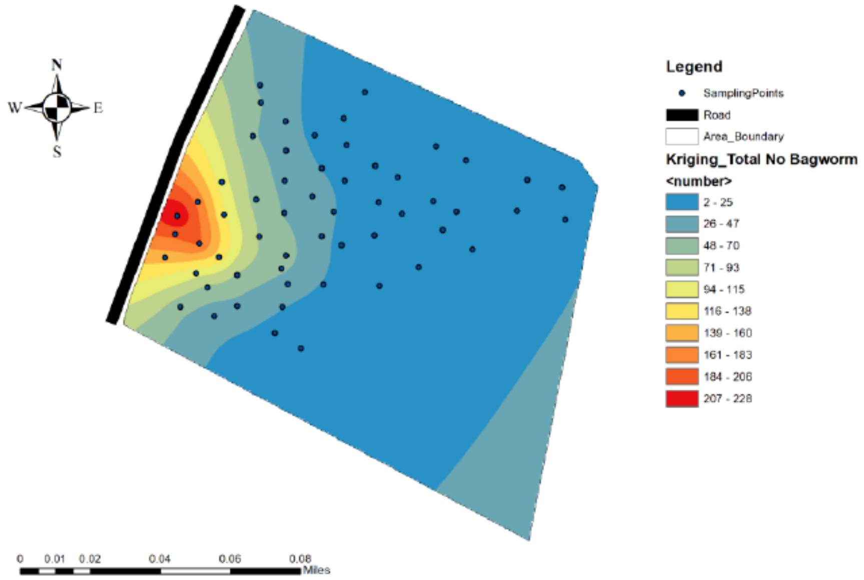

Fig. 6: Spatial variation number of bagworm per fronds

Furthermore, a separate spatial interpolation of elevation values was conducted to evaluate the influence of topography on larval distribution (Figure 7). The analysis yielded a poor correlation between elevation and bagworm density ($R^2 = 0.0144$), indicating that elevation within the relatively flat 1-hectare study site had minimal influence on infestation patterns. Similar conclusions were drawn by Sciarretta and Trematerra (2014), who noted that pest aggregation is often influenced more by human practices and vegetation structure than by elevation in smallholder plantations.

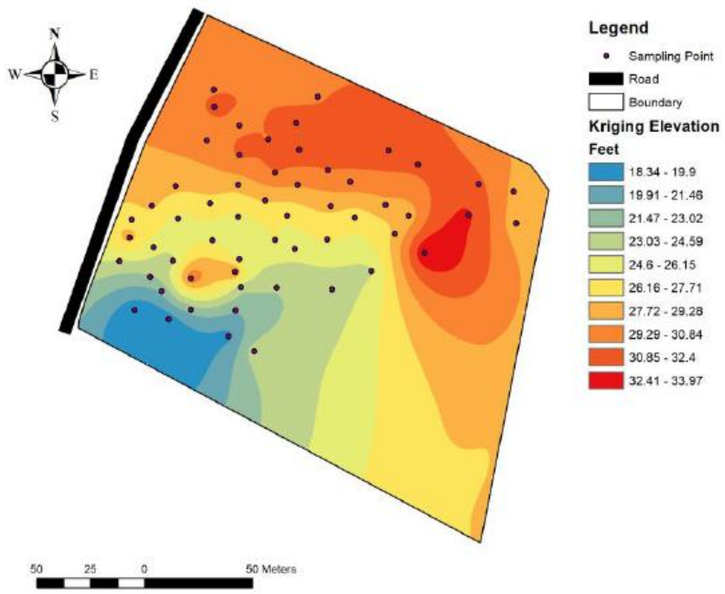

Fig. 7: Spatial variation elevation in the study area

The kriging maps for each developmental stage further demonstrated that mature larvae were predominantly clustered in high-density zones, particularly near frequently accessed paths. This information is crucial for implementing site-specific integrated pest management (IPM), allowing estate managers to prioritize treatment zones and avoid unnecessary pesticide application in unaffected areas. Overall, the integration of GIS and field survey data proved valuable in understanding pest distribution and lifecycle dynamics in an oil palm ecosystem.

5. Conclusion

This study successfully demonstrated the application of Geographic Information System (GIS) technology in evaluating the spatial distribution of *Metisa plana* infestation in an oil palm plantation. The findings revealed that the majority of the bagworm population was concentrated in the western part of the plantation, with 60% of the larvae found in their late developmental stages. This spatial clustering near roads and access paths suggests that human and vehicular activities may facilitate the pest's dispersal within the plantation. The kriging-based spatial interpolation provided an effective visual representation of infestation intensity, confirming the utility of GIS in precision agriculture for pest surveillance and targeted control.

Importantly, the analysis showed no significant correlation between elevation and pest density, suggesting that topography had a negligible influence on the infestation within the relatively uniform landscape of the study area. The predominance of late instar larvae indicates that by the time of detection, the infestation had reached an advanced stage, thus limiting the effectiveness of chemical or biological intervention. These results highlight the importance of early detection and frequent monitoring in the integrated pest management (IPM) of oil palm pests.

Based on the findings, it is recommended that estate managers incorporate GIS-based surveillance systems into routine plantation monitoring. Such systems can help identify infestation hotspots early, enabling more efficient resource allocation and timely application of control measures. Future studies should consider integrating GIS data with environmental variables such as temperature, humidity, and vegetation indices to improve the predictive capability of pest outbreaks. Moreover, training field personnel in spatial data collection and GIS interpretation will be essential to realizing the full potential of precision agriculture tools in pest management.

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Conflict of Interest

The authors declare no conflicts of interest.

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