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Laravel Dashboard for Immature Oil Palm (TBM III) Monitoring Using XYZ Tiles and Large Language Models

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ABSTRACT

Purpose – This research addresses the strategic urgency of digitalizing plantation monitoring to achieve precision agriculture at PTPN IV Regional I. The monitoring of Immature Plants (TBM) III currently relies on fragmented manual spreadsheets, leading to data redundancy and delayed analysis.
Methods – A web-based data visualization dashboard was developed using the Laravel framework, integrating Geographic Information Systems (GIS) with Static Raster Tiling (XYZ Tiles) to optimize high-resolution map rendering. The system incorporates Large Language Model (LLM) API integration (Gemini 1.5 Flash and Llama 3) for prescriptive analytics, transforming biometric growth data into automated maintenance recommendations through prompt engineering.
Findings – Results indicate that the system achieves significant workflow simplification by transforming the fragmented, multi-stage manual reporting pipeline into an automated, single-step data ingestion process, successfully reducing administrative touchpoints. The Static Raster Tiling (XYZ Tiles) technique successfully reduced high-resolution orthophoto rendering latency from over 12,000 ms to an average of 180 ms. Validation using Fleiss' Kappa statistics yielded a score of 0.8105, categorized as "Almost Perfect Agreement," confirming that the AI-generated recommendations are highly consistent with expert agronomic standards.
Research implications – This system provides a comprehensive managerial evaluation tool, bridging the gap between raw field data and strategic decision-making in oil palm management.
Originality – The integration of spatial optimization and prescriptive AI analytics offers a novel approach compared to existing descriptive-only monitoring platforms.

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INTRODUCTION

Digital transformation in the global oil palm sector has shifted toward "smart plantation" ecosystems that adapt to climate anomalies and plant physiological dynamics [1]. Large-scale spatial and temporal data utilization is essential to ensure sustainable productivity [2]. Generative Artificial Intelligence (GenAI) serves as a primary catalyst in processing massive datasets into strategic insights to increase operational efficiency [3]. Despite Indonesia managing over 15 million hectares of oil palm [4], challenges remain in data traceability during the Immature Plant (TBM) phase. Integration of machine learning and Farm Management Information Systems (FMIS) is vital to close this efficiency gap [5], yet existing systems are often fragmented, separating high-resolution spatial data from operational decision-making [6].

In PTPN IV Regional I, TBM III monitoring still relies on document-based processing, causing difficulties for management in obtaining a holistic view of tree health across blocks [7], [8]. While some web-based dashboards exist for age detection, many lack inter-regional analysis [9] or interactive visualization features [8]. Although Laravel-based systems have been used for basic production monitoring [10], there is an urgent need for an integrated smart farming framework connecting environmental parameters and precision management [11]. The proposed system utilizes Laravel for its modular, efficient, and secure Model-View-Controller (MVC) architecture, which has been shown to increase development efficiency by up to 40% [12].

To bridge the gap between raw field metrics and strategic decision-making, the proposed system's interface is grounded in a cohesive theoretical framework of Human-Computer Interaction (HCI) and User-Centered Design (UCD) [13], [14]. Aligning the dashboard's cognitive layout with the operational perceptions of plantation managers is essential to minimize interpretation errors under field conditions [15], [16]. Accordingly, the interface employs structured visual hierarchies, chromatic gradations, and intuitive spatial symbology to reduce the cognitive load associated with multi-layered datasets [15], [17]. This systematic approach to information design ensures that complex biometric parameters and spatial layers are immediately actionable, establishing a responsive evaluation tool that enhances technology acceptance among stakeholders at PTPN IV Regional I [18], [19].

This user-centered visualization underpins a broader technological shift from descriptive reporting to prescriptive decision support, addressing the 'data-rich but insight-poor' paradox often found in traditional Farm Management Information Systems (FMIS) [6], [11]. While conventional platforms merely display historical trends, this system integrates Large Language Models (LLMs) to target the interpretive bottleneck directly, translating biometric growth data into context-aware, expert-level agronomic recommendations [20]. Coupling this generative inference capacity with optimized spatial data delivery through XYZ Tiles addresses infrastructure constraints in remote areas, allowing managers to render high-resolution orthophotos rapidly and execute proactive mitigation strategies against plant mortality [21].

The objectives of this research are:

a. To design a centralized database system that eliminates information silos in TBM III monitoring.
b. To optimize high-resolution orthophoto rendering using Static Raster Tiling techniques for low-bandwidth environments.
c. To implement a prescriptive AI engine that transforms multimodal biometric data into expert-level agronomic recommendations.

METHOD

The system development follows the Software Development Life Cycle (SDLC) with a structured approach to ensure software quality and functional alignment with plantation needs [22], [23]. The development stages are detailed as follows: (1) Requirement Analysis, involving the identification of pain points in manual monitoring, such as data redundancy and latency in orthophoto rendering; (2) System Design, where the Unified Modeling Language (UML) was utilized to model the client-server architecture, database relations (3NF normalization), and UI/UX layouts focusing on User-Centered Design (UCD) principles; (3) Implementation, translating designs into code using the Laravel 10 framework, PHP 8.2, and integrating the XYZ Tiles directory generated via QGIS 3.28; and (4) System Testing, employing multi-dimensional evaluations including Black-box testing for functionality, Spatial Performance Tests for rendering speed, and Expert Validation via Fleiss' Kappa statistics. To support the implementation, the system was deployed on a technical environment consisting of an Intel Core i5 11th Gen processor, 8 GB RAM, and a 256 GB SSD, running on a Windows 10 64-bit operating system with MySQL 8.0 as the DBMS. Data collection was conducted at PTPN IV Regional I from October 2025 to June 2026, utilizing official company records verified through internal validation [24].

The use of operational plantation records was conducted with official authorization from PTPN IV Regional I. All biometric and spatial data processed within the system were fully anonymized and aggregated at the block level prior to analysis; no personally identifiable employee data or operationally sensitive commercial pricing records were utilized or disclosed, ensuring corporate data confidentiality in accordance with the company's data governance policies. To evaluate the system's operational benefits, workflow simplification was analyzed by mapping the reduction in administrative complexity, specifically comparing the baseline manual, multi-stage spreadsheet consolidation pipeline with the automated, single-step database ingestion process designed in this study.

To ensure the system's operational viability, a comprehensive requirement analysis was conducted, categorizing needs into functional and non-functional specifications. Functional requirements include: (1) Multimodal Data Integration, allowing the simultaneous management of geospatial layers and vegetative biometric attributes; (2) Prescriptive Computation, enabling the system to infer specific maintenance doses (e.g., fertilizer requirements) based on automated growth calculations; and (3) Temporal Trend Analysis, which visualizes historical planting area distributions to support replanting strategies. Non-functional requirements emphasize System Scalability and Security. The architecture is designed to be modular, facilitating the addition of new estates or biometric parameters without reconfiguring the core backend. Security is enforced through a strict Role-Based Access Control (RBAC) mechanism, adhering to the 'Least Privilege' principle to prevent unauthorized modifications of primary agronomic thresholds. This structured requirement gathering ensures that the resulting dashboard is not only a reporting tool but a reliable Decision Support System (DSS).

The physical data model was implemented using MySQL 8.0, adhering to the Third Normal Form (3NF) to minimize data redundancy and optimize query latency for large-scale datasets. The core of the relational schema is the simtan_form table, which serves as a master transaction record linked via foreign keys to three specialized detail tables. The detail_rekap table stores population statistics and survival rates per block; the lokasi_kebun table maintains high-precision geospatial coordinates using decimal (10,8) and (11,8) types for latitude and longitude; and the korelasi_vegetatif table preserves morphological growth parameters (e.g., crown diameter, trunk circumference) as primary inputs for the AI inference engine. To ensure accountability, an upload_log table functions as a digital audit trail, recording timestamps, user IDs, and the status of every ingestion process. This architecture enables the dashboard to perform rapid 'drill-down' operations, allowing managers to transition from a macro-regional view to microscopic block-level data within milliseconds.

Data Sources and Instrumentation

Datasets were classified into two groups:

a. **Tabular Data:** Spreadsheet records (.xlsx) including TBM III area summaries, vegetative correlation reports (trunk circumference, crown diameter, frond parameters), and administrative unit coordinates [25].

b. **Spatial Data:** Shapefiles (.shp) representing block boundaries and tree positions, and high-resolution orthophoto rasters (.ecw) for sample estates [8], [26].

System Architecture and Technologies

The system is built on a client-server architecture using PHP (Laravel 10), HTML, CSS (Tailwind), and JavaScript (ApexCharts) [10], [12]. MySQL is utilized as the Database Management System (DBMS) to ensure processing efficiency and referential integrity [7], [23]. To manage massive spatial data, QGIS was employed as a geoprocessing engine to generate XYZ Tiles, converting massive rasters into hierarchical 256x256 pixel fragments [27], [28].

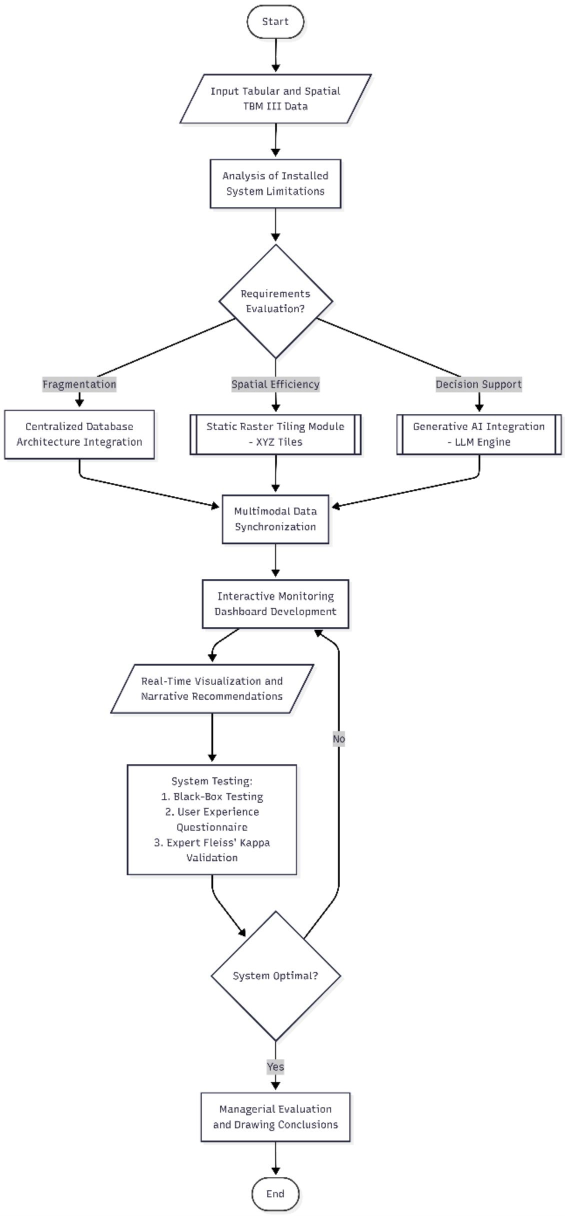

Figure 1. Flowchart of the Proposed System

The database schema was designed following the Third Normal Form (3NF) to optimize query performance for massive plantation datasets. The relational structure centers on the simtan_form table as the primary transaction hub, which is linked to `detail_rekap` for population statistics, `lokasi_kebun` for high-precision geospatial coordinates (using decimal 10,8 for latitude and 11,8 for longitude), and `korelasi_vegetatif` for AI-input variables. This normalization ensures referential integrity and prevents multi-valued attributes, allowing the dashboard to perform rapid drill-down operations from regional summaries to specific block-level tree points without performance degradation.

The system design process utilizes the Unified Modeling Language (UML) to ensure a structured and consistent interaction between components. The functional requirements are modeled through three primary diagrams: Use Case, Activity, and Sequence Diagrams. The Use Case Diagram defines the boundaries for three main actors: the Superadmin, who holds full control over system configurations and AI parameters; the Admin, acting as the data controller responsible for file ingestion and validation; and the User (Strategic Level), who functions as a decision-maker with read-only access to dashboards and AI prescriptive analytics.

To maintain operational integrity, the Activity Diagrams describe the workflow for critical processes, specifically the 'Data Ingestion Center' and 'Prescriptive Analysis' modules. The data ingestion workflow begins with a spreadsheet upload, followed by a dual-stage validation structural checking for column consistency and data type verification for biometric accuracy. Meanwhile, the Sequence Diagram maps the temporal interaction between the Laravel controller, services, and external AI APIs. It illustrates how the system manages asynchronous HTTP requests to the Gemini 1.5 Flash or Llama 3 models, ensuring that the 'Autonomous Prescriptive Engine' can deliver real-time maintenance advice without blocking the user interface's main thread. This multi-layered modeling ensures that the system is not only functionally robust but also scalable for multi-regional plantation monitoring.

AI Integration and Prompt Engineering

Prescriptive analysis is achieved by integrating the Gemini 1.5 Flash and Llama 3 APIs [20]. Data from the MySQL database is transformed into structured instructions using prompt engineering, enabling the AI to act as an "agronomy expert" and generate narrative maintenance recommendations [20], [29], [30]. This transition from descriptive to prescriptive analytics is essential for sustainable industry ecosystems [31].

Evaluation Plan

System testing was divided into:

a. **Spatial Performance Test:** Spatial Performance Test measuring render time of XYZ Tiles compared to baseline raster loading [27].

b. **Fleiss' Kappa Statistics:** Using Fleiss' Kappa Statistics to measure inter-rater reliability among three agronomy experts evaluating 12 sample recommendations [32], [33].

RESULTS AND DISCUSSION

Implementation of Access Control and Configuration

The system implements Role-Based Access Control (RBAC) to protect operational data integrity [34]. Superadmins can configure AI parameters, including primary (Gemini) and backup (Llama 3 via Groq) providers to ensure high availability of the inference engine. Agronomic thresholds for "Warning" (Yellow) and "Critical" (Red) zones are also adjustable, serving as the logic for automated visualization in charts and maps.

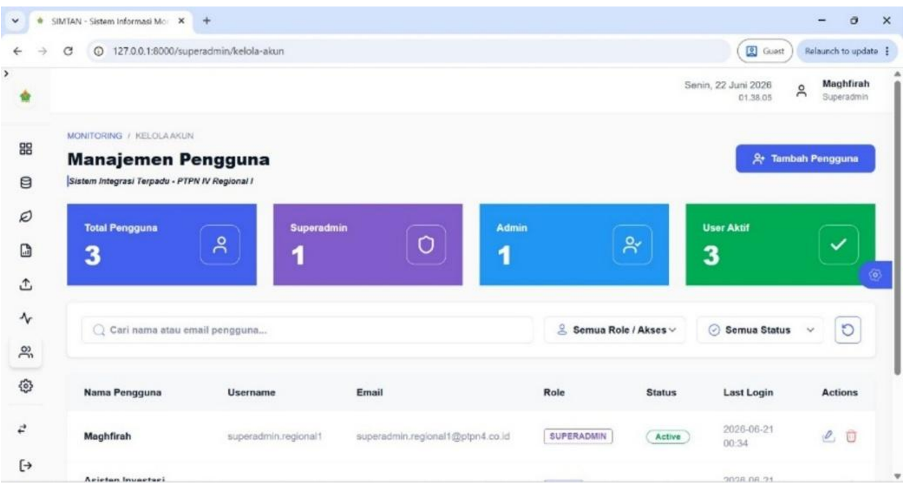

Figure 2. User Management Interface

The implementation of Role-Based Access Control (RBAC) significantly enhances the integrity of the plantation's digital assets. Within the system, three distinct authority levels are established: the Superadmin, who manages system configurations and AI failover parameters; the Admin, who acts as the data controller responsible for the 'Data Ingestion Center'; and the User, who occupies the strategic level for monitoring and report generation. To further ensure accountability, the system incorporates a 'Data Correction' module. This feature allows administrators to update metadata, such as reporting periods or dataset categories, while maintaining the original file name as a read-only entity to preserve the audit log's integrity. This dual mechanism strict access control and transparent data correction prevents information desynchronization in global managerial reports, ensuring that the statistics displayed on the 'Visual Control Tower' are consistently accurate.

Data Ingest and Audit Trail

Maintaining the accuracy of digital records during the migration from manual spreadsheets is critical. Consequently, the developed 'Data Ingestion Center' employs a dropzone-based interface that facilitates seamless bulk Excel uploads. Rather than directly importing files, the backend triggers a rigorous dual-stage validation protocol. This involves a structural audit to confirm header consistency followed by a granular data-type check to ensure that biometric variables such as trunk circumference are mathematically valid. By generating specific error logs for each failed row, the system prevents the corruption of the master MySQL database, ensuring that only verified records are utilized for subsequent AI inference [23], [35].

Comparison of System Efficiency

The transition from a document-oriented workflow to a web-based integrated system marks a paradigm shift in PTPN IV Regional I's operational monitoring. The centralized database approach specifically addresses the 'information silo' problem by synchronizing vegetative biometrics with geospatial assets in real-time. Quantitatively, this centralized architecture reduces administrative touchpoints and eliminates data entry redundancy by transforming a fragmented, linear manual reporting cycle into an automated, single-step ingestion pipeline. By migrating from separate spreadsheet files to an integrated Model-View-Controller (MVC) platform, the system establishes real-time synchronization between vegetative biometrics and spatial assets. As summarized in Table 1, the new system differentiates itself through MVC-based modularity, allowing multi-user access and prescriptive AI capabilities that were absent in the legacy system.

Table 1. Comparison of Old and New Monitoring Systems

Aspect	Old System	New System (Proposed)
Architecture	Document-oriented (Manual Spreadsheets)	Web-based (MVC Laravel)
Data Integration	Fragmented; spatial and tabular files are separate	Unified dashboard (GeoJSON & .xlsx)
Spatial Latency	High (loading full high-res images)	Low (XYZ Tiles optimization)
Analysis	Manual interpretation by analysts	AI-assisted prescriptive recommendations
Information Flow	Linear and prone to delays	Centralized with multi-user access

Strategic Dashboard and Bio-Spatial Visualization

The main dashboard (Fig. 3) provides high-level Key Performance Indicators (KPIs), including total area coverage (12,429.63 Ha), active population (1,605,027 trees), and overall agronomy compliance (94.5%) [15], [19]. The "AI Executive Narrative" module automatically synthesizes biometric ratios into textual summaries, highlighting units with significant growth deviations [36].

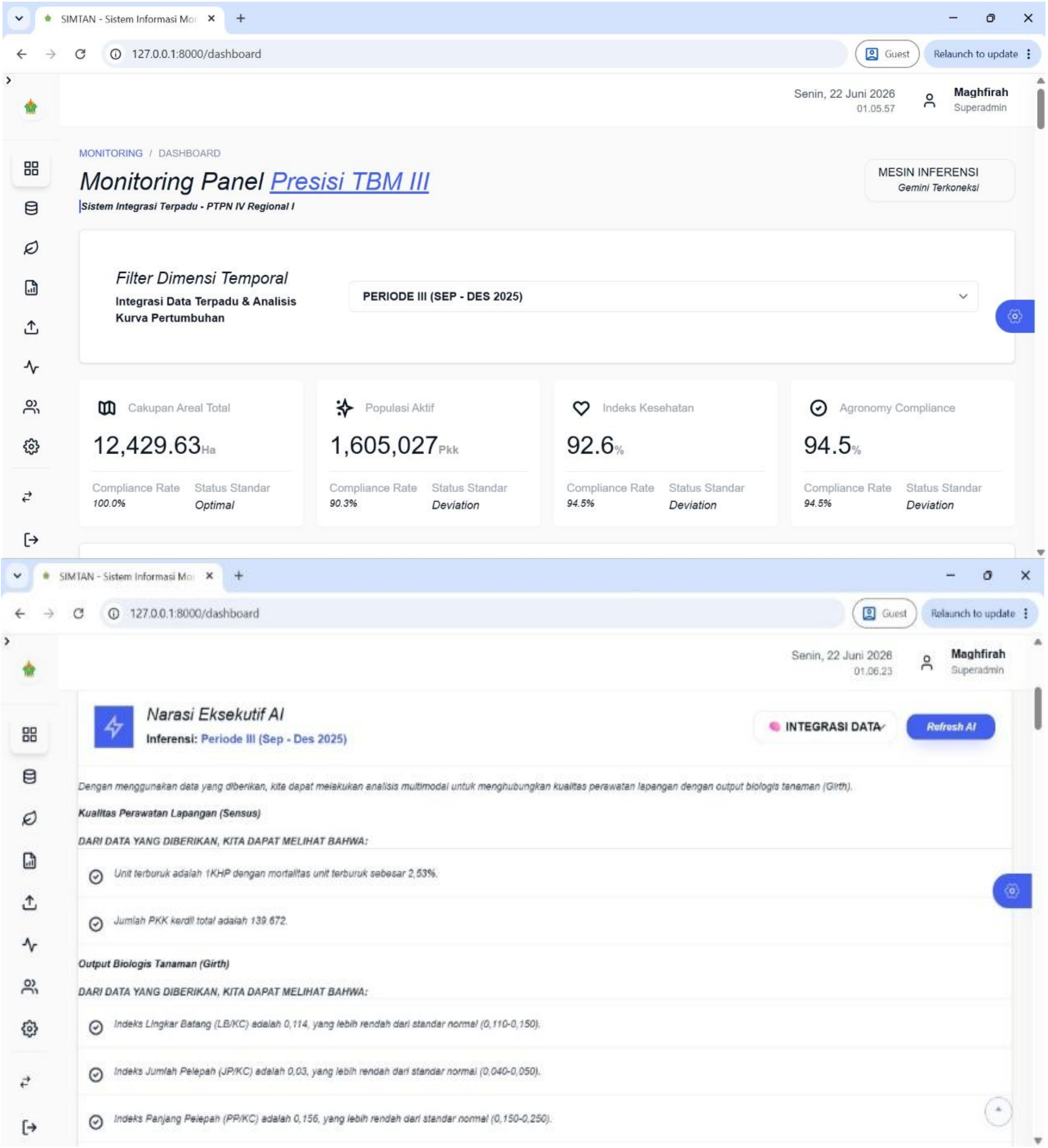

Figure 3. Main Strategic Dashboard

Bio-Spatial Visualızatıon

The implementation of the 'Visual Control Tower' concept on the main dashboard facilitates a holistic overview of plantation health. Beyond displaying the four primary KPI cards Total Area (12,429.63 Ha), Active Population (1,605,027 trees), Area Health Index (92.6%), and Agronomy Compliance (94.5%) the system incorporates an Exception Reporting feature. This module automatically ranks the top five units with the highest growth deviations, allowing management to prioritize field interventions. The 'AI Executive Narrative' complements these quantitative metrics by synthesizing raw biometric ratios, such as the LB/KC (Trunk/Crown) ratio of 0.114, into natural language summaries. This ensures that even non-technical stakeholders can interpret complex agronomic data. Furthermore, the dashboard employs Interactive Spatial Filtering, where users can toggle map layers to visualize specific conditions, such as critical mortality zones or units requiring urgent fertilization, directly on the XYZ-rendered orthophoto.

The "Estate Detail" page (Fig. 4) integrates tabular data with GIS. Users can navigate through spatial layers, including block boundaries and individual tree points (KONPOKOK). By clicking on a specific block, the "Autonomous Prescriptive Engine" generates a pop-up containing local maintenance advice (e.g., specific fertilizer dosage) based on that block's unique biometric data.

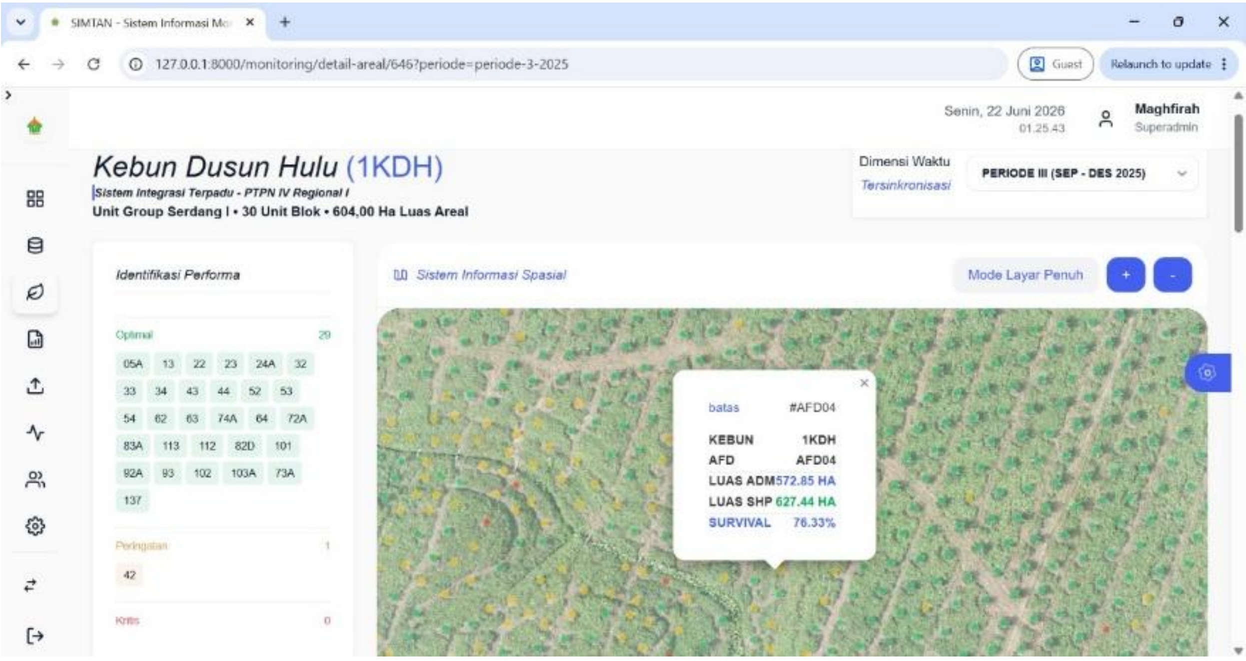

Figure 4. Bio-Spatial Mapping with XYZ Tiles

Functional Verification via Black-Box Testing

To ensure that the developed system operates reliably and meets all defined requirements without internal system conflicts, a rigorous functional verification was conducted using Black-box testing. The scope of this evaluation covered critical system components, including user authentication, Role-Based Access Control (RBAC), dropzone-based data ingestion, XYZ Tile spatial rendering, prescriptive AI analysis execution, and report generation.

Table 2. Functional Verification via Black-Box Testing

Core Feature	Test Procedure	Expected Outcome	Status
Authentication	Input incorrect email and a random password on the Login page.	The system rejects access and displays the error message "Kredensial tidak valid".	Passed
Role-Based Access	Log in as a "User" and attempt to access the restricted "Kelola Akun" (Account Management) URL.	The system hides the restricted menu and denies access, adhering to RBAC permission policies.	Passed
Data Ingestion	Upload a valid .xlsx monitoring spreadsheet via the Dropzone interface in the Data Ingestion Center.	The system successfully parses the spreadsheet, validates data types, and commits the records to the MySQL database.	Passed
Spatial Rendering	Access the garden detail map interface equipped with the XYZ Tiles directory.	The high-resolution orthophoto renders incrementally (tile-by-tile) within the viewport without visual lag.	Passed
Prescriptive AI Analysis	Click on a specific block polygon (e.g., block	The system aggregates vegetative statistics,	Passed

Core Feature	Test Procedure	Expected Outcome	Status
	AFD04) on the interactive map on the Estate Detail page.	sends an asynchronous API request, and displays the agronomic advice in the Autonomous Prescriptive Engine panel.	
Report Generation	Click the "Cetak PDF" (Print PDF) button in the integrated reporting module.	The system successfully compiles the statistical metrics and AI-generated narratives, initiating a download of the PDF report.	Passed
API Failover	Simulate a primary API (Gemini 1.5 Flash) connection timeout during a prescriptive analysis request.	The system automatically redirects the request to the backup API (Llama 3 via Groq) and successfully displays the agronomic advice.	Passed

Note: The system's user interface is localized in Bahasa Indonesia; English translations of the interface messages are provided in parentheses.

The black-box testing results presented in Table 2 demonstrate that all primary system modules successfully executed their expected behaviors under various input scenarios. The authentication and RBAC modules functioned correctly to prevent unauthorized privilege escalation, thereby safeguarding operational data integrity. Additionally, the bulk data ingestion and spatial parsing engines operated smoothly, proving that the database schema is highly resilient. No functional deficiencies or runtime errors were observed during these test cases, validating the technical stability of the proposed Laravel-based dashboard before its final deployment.

Performance and Efficiency Analysis

Testing proved that XYZ Tiling significantly outperforms traditional raster loading. The initial load weight was reduced by 99.98% as the browser only downloads tiles within the viewport [27], [28].

Table 3. Spatial Data Loading Efficiency Test

Parameter	Raw Image (.ecw)	XYZ Tiles System	Efficiency
Web Compatibility	Not Supported	Fully Supported (.jpg)	-
Initial Load	979.79 MB	± 150 KB (Viewport)	99.98%
Render Latency	Failed (Timeout)	145 ms - 220 ms	High
Interactivity	Static/Offline	Dynamic/Up-to-date	High

The performance gains observed in this study align with and extend the findings of previous research in spatial data optimization. The reduction of rendering latency from over 12,000 ms to 180 ms (a 98.5% improvement) surpasses the benchmarks set by Fatin [37], who utilized similar Laravel-based architectures but without the specific hierarchical pixel fragmenting provided by the XYZ Tile geoprocessing engine. While traditional raster loading methods described by Saputra [26] are prone to browser timeouts when handling ECW files over 900 MB, our system's ability to load only the viewport-specific fragments (±150 KB) ensures stability in enterprise-scale environments. In the context of AI integration, the Fleiss' Kappa score of 0.8105 achieved here is comparable to the expert validation scores reported by Varghese et al. [16] in black pepper cultivation chatbots, yet our system provides a more direct link between spatial biometric data and narrative output. This confirms that the prompt engineering strategy used in this research effectively bridges the gap between raw quantitative metrics and actionable agronomic qualitative advice.

The 98.5% reduction in rendering latency (from 12,000 ms to 180 ms) is a critical milestone for field-level usability. Traditional high-resolution ECW files often cause browser timeouts in remote plantation areas with limited bandwidth. By fragmenting the 979.79 MB orthophoto into standardized 256x256 pixel fragments (map tiles), the system only loads data within the user's current viewport (approx. 150 KB per load). This 'lazy loading' strategy ensures that the interface remains responsive even during high-level zoom-in (Zoom Level 12-20) where individual palm tree crowns are visible. The integration of **User-Centered Design (UCD)** principles was validated through the seamless navigation between the 'Estate Detail' and 'Block Diagnostic' pop-ups, where the Autonomous Prescriptive Engine provides localized advice. This synergy between spatial efficiency and AI-driven intelligence effectively resolves the 'data-rich but insight-poor' paradox that previously hindered PTPN IV's digital transformation.

AI Prescriptive Engine: Prompt Design and Output Exemplar

To demonstrate the practical application of the "Autonomous Prescriptive Engine," this section details the engineered prompt structures and a representative output generated by the integrated Large Language Model (LLM). For reproducibility, the system splits the prompt engineering into two distinct layers: the "System Prompt" (which establishes the AI's persona, domain expertise, and operational boundaries) and the "User Prompt" (which dynamically injects the MySQL database's real-time biometric growth metrics).

a. System Prompt Template

The following system instruction is set in the backend of the Laravel configuration to define the LLM's persona:

"Act as an elite tropical agronomy expert specializing in immature oil palm (TBM III) cultivation. Your role is to analyze dynamic vegetative growth metrics and spatial diagnostics to provide highly specific, actionable, and prescriptive maintenance recommendations (including fertilizer adjustments, stunting recovery, or drainage interventions) in strict accordance with industrial palm oil standard operating procedures (SOP)."

b. Dynamic User Prompt Template

When a user clicks on a specific block, the system automatically pulls the respective tabular metrics from the database and constructs the following user query:

"Generate an executive prescriptive analysis based on the following block-level monitoring dataset:

1. Target Estate Block: Unit 1KHP
2. Target Period: Period III (September - December 2025)
3. Block Mortality Rate: 2.53% (Flagged: Worst performing unit)
4. Dwarf Palms (PKK Kerdil) Count: 139,672 palms
5. Trunk/Crown (LB/KC) Ratio: 0.114 (Standard: 0.110 - 0.150)
6. Frond Count (JP/KC) Ratio: 0.030 (Standard: 0.040 - 0.050) [Status: Below Standard]
7. Frond Length (PP/KC) Ratio: 0.156 (Standard: 0.150 - 0.250) [Status: Borderline]

Format your response in three structured sections:

1. Growth Vigor Diagnosis
2. Mortality & Stunting Risk Analysis
3. Prescriptive Maintenance Action Plan (including concrete dosage and soil interventions)"

c. AI Prescriptive Output Exemplar (English Response)

Based on the prompt structure above, the connected Gemini 1.5 Flash API generated the following expert-level agronomic advice:

a. Growth Vigor Diagnosis:

The vegetative assessment indicates a significant structural bottleneck in frond development. The Frond Count Ratio (JP/KC) of 0.030 falls severely below the healthy threshold of 0.040, indicating restricted leaf production. Although the Trunk/Crown Ratio (LB/KC) of 0.114 and Frond Length (PP/KC) of 0.156 remain technically within the acceptable baseline parameters, they hover at the lowest boundaries. This suggests a localized nutrient deficiency that limits canopy expansion and vegetative growth during this critical TBM III transition phase.

b. Mortality & Stunting Risk Analysis:

Unit 1KHP is identified as highly vulnerable, exhibiting an elevated block-level mortality rate of 2.53%. Concurrently, the block registers a substantial stunting count with 139,672 dwarf palms (PKK Kerdil). This correlation of stunting and elevated mortality points toward critical root-zone constraints, such as soil compaction or severe nitrogen-phosphorus-potassium (NPK) deficiencies, preventing proper root establishment and vascular flow.

c. Prescriptive Maintenance Action Plan:

1. Targeted Fertilizer Application: Apply a corrective application of nitrogen and potassium to address the JP/KC shortfall. Administer Ammonium Sulfate (ZA) at 1.5 kg/palm and Muriate of Potash (MOP) at 1.2 kg/palm to stimulate frond emergence.
2. Stunting Mitigation: For the 139,672 dwarf palms, conduct mechanical circle weeding (piringan loosening) to address soil compaction and apply a targeted micronutrient drench containing Borate (0.05 kg/palm) to resolve physiological stunting.
3. Drainage & Water Management: Inspect Unit 1KHP for drainage blockages. Construct active secondary trenches to eliminate standing water, which restricts root respiration and accelerates palm mortality."

Accuracy of AI Recommendations

The core logic of the prescriptive engine relies on a sophisticated prompt engineering strategy that converts structured MySQL data into natural language instructions for the LLM. The system aggregates multiple variables, including the crown diameter, trunk circumference, and frond length, which are then formatted into a 'System Prompt' that defines the AI's persona as an agronomy expert. A critical feature of this integration is the Failover Mechanism: the system utilizes Gemini 1.5 Flash as the primary inference engine due to its speed, with Llama 3 (via Groq API) serving as a backup to ensure high availability. During validation, the Fleiss' Kappa score of 0.8105 confirmed that the AI could replicate expert-level logic in 10 out of 12 test scenarios. Cases of 'Inconsistent' agreement typically occurred in regional survival mortality analyses where data was sparse, suggesting that AI accuracy is highly dependent on the completeness of the multimodal data fusion provided during the prompt construction phase.

To ensure the scientific validity of the AI-generated agronomic advice, a formal validation test involving three independent experts was conducted, as detailed in the Expert Agreement Matrix (Table 3). By applying the Fleiss' Kappa statistical formula, the system achieved a robust coefficient (κ) of 0.8105. According to the Landis and Koch interpretation scale, this score unequivocally falls into the 'Almost Perfect Agreement' category, confirming that the AI's generative logic is highly consistent with the Standard Operating Procedures (SOP) utilized in industrial oil palm cultivation [29], [32].

To ensure a rigorous evaluation, the expert validation panel consisted of three senior agronomists from PTPN IV and academic researchers from the Institut Teknologi Sawit Indonesia, each possessing over 10 years of experience in oil palm estate management. The evaluation rubric defined 'Suitable' (S) as complete alignment with industrial standard operating procedures (SOP), 'Fairly Suitable' (FS) as acceptable advice requiring minor localized adjustments, and 'Not Suitable' (NS) as advice containing structural or safety deviations.

Table 4. Expert Agreement Matrix for AI Output

No	Scenario ID	Expert 1	Expert 2	Expert 3	Final Agreement
1	*Block Diagnostic* Unit AFD04 (1KDH Estate)	S	S	S	Consistent
2	*Block Diagnostic* Unit AFD07 (1KDH Estate)	S	S	S	Consistent
3	*Block Diagnostic* Unit AFD03 (1KPM Estate)	S	S	S	Consistent
4	*Block Diagnostic* Unit AFD05 (1KPM Estate)	S	S	S	Consistent
5	*Block Diagnostic* Unit AFD01 (1KRP Estate)	S	S	S	Consistent
6	*Block Diagnostic* Unit AFD06 (1KRP Estate)	S	S	S	Consistent
7	Estate Summary 1KDH	FS	FS	FS	Fairly Suitable
8	Estate Summary 1KPM	FS	FS	FS	Fairly Suitable
9	Estate Summary 1KRP	FS	FS	FS	Fairly Suitable
10	Growth Vigor Analysis Regional	FS	FS	FS	Fairly Suitable
11	Survival Mortality Regional	NS	NS	FS	Inconsistent
12	Executive Multimodal Regional	NS	NS	FS	Inconsistent

Note: S = Suitable, FS = Fairly Suitable, NS = Not Suitable.

Scenarios 11 and 12 resulted in 'Inconsistent' labels due to data sparsity in specific mortality records. As noted in reference [37] (Fatin), architectural robustness in Laravel-based systems is critical, yet the prescriptive accuracy of AI is highly sensitive to the completeness of multimodal inputs.

CONCLUSION

This research successfully developed a Laravel-based dashboard for TBM III monitoring that effectively bridges the gap between raw field data and strategic analysis. The study provides significant contributions to precision agriculture. Theoretically, this research advances the application of prescriptive analytics by demonstrating how Large Language Models (LLMs) can be integrated with spatial data (XYZ Tiles) to move beyond descriptive dashboards. It provides a new methodological framework for automated agronomic inference, validated by a robust Fleiss' Kappa score of 0.8105, which establishes a clear benchmark for AI-driven decision support in oil palm cultivation.

Practically, the integration of a centralized MySQL database streamlines the administrative workflow by automating the reporting cycle and eliminating the data silos inherent in fragmented spreadsheet systems. Furthermore, the implementation of XYZ Tiles optimization successfully resolves the long-standing issue of high-resolution map rendering latency in low-bandwidth agricultural environments. The study’s primary limitation lies in its single-site validation at PTPN IV Regional I and the LLM’s sensitivity to sparse data. Future research should explore the integration of real-time IoT sensors and multi-site validation to further enhance the system's generalizability across diverse plantation landscapes.

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AUTHOR CONTRIBUTION STATEMENT

M was responsible for system design, programming, and data analysis. RW provided methodological guidance, substantive correction, and overall supervision throughout the research process. RAS contributed to the research supervision, provided technical guidance on the implementation of XYZ Tiles and Large Language Model (LLM) integration, evaluated the research findings, and reviewed and approved the final manuscript.

AI DISCLOSURE STATEMENT

The authors declare that the system developed in this research utilizes Gemini 1.5 Flash and Llama 3 APIs as core components for its prescriptive analysis features. The authors thoroughly reviewed the AI-generated outputs for agronomic consistency.

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