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AgroDiversity: A Comprehensive Web Platform for Agricultural Diversification in Valle del Cauca, Colombia

Abstract—Valle del Cauca faces critical dependency on sugarcane monoculture occupying 250,000 hectares, generating soil degradation, environmental contamination, and economic vulnerability. This dependency limits regional food security and perpetuates unsustainable practices. AgroDiversity was developed as a comprehensive web platform functioning as a digital agronomist, analyzing specific farm characteristics and recommending sustainable alternative crops. The platform integrates neural network-based prediction systems analyzing soil pH, temperature, humidity, and crop type variables, providing personalized recommendations for transitioning to silvopastoral systems. AgroDiversity includes farm management, intelligent prediction, and conversational agricultural assistant modules. The platform has been successfully developed and is ready for pilot testing, contributing to SDG 2 (Zero Hunger) and SDG 13 (Climate Action), promoting agricultural diversification for food security and environmental impact mitigation.

Index Terms—Agricultural diversification, web platform, smart farming, React, TypeScript, Supabase, machine learning, Valle del Cauca, silvopastoral systems

I. INTRODUCTION

Valle del Cauca represents one of Colombia's most important agricultural departments with 22,140 km² territorial extension. However, it faces excessive sugarcane monoculture concentration occupying 250,000 hectares (41.3% of cultivated area), followed by coffee with 100,000 hectares (22%) and other crops representing merely 11.8% of total area [1]. This monoculture dependency generates multiple negative consequences: accelerated soil degradation, environmental contamination from traditional burning practices, biodiversity loss, and economic vulnerability to sugar market fluctuations [2]. Valle del Cauca farmers remain trapped in cycles where they only know sugarcane cultivation but lack knowledge of viable diversification alternatives [3].

The region's territorial configuration offers unique opportunities for implementing silvopastoral systems integrating crops, pastures, and trees, optimizing land use while generating environmental and economic benefits [4]. Agricultural diversification represents a fundamental strategy for transitioning toward sustainable crops, exploring land use optimization while reducing monoculture's negative impact and ensuring regional food security [5]. This transition is necessary environmentally and economically, allowing farmers to reduce risks and access diverse markets [6].

AgroDiversity emerges as a technological solution functioning as farmers' strategic ally for developing sustainable production systems. The platform uses artificial intelligence to

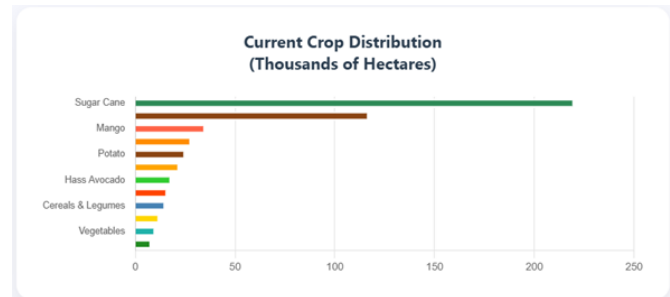


Fig. 1. Current crop distribution in Valle del Cauca showing sugarcane dominance with 250,000 hectares, followed by coffee (100,000 ha) and smaller areas of diverse crops.

analyze specific farm characteristics and provide personalized recommendations, democratizing access to specialized agronomic knowledge [7]. The main objectives include: (1) developing an intuitive web platform addressing specific agricultural diversification needs, (2) implementing intelligent prediction systems analyzing agroclimatic variables for alternative crop recommendations, (3) creating virtual assistants providing specialized technical guidance, and (4) contributing to Sustainable Development Goals, specifically SDG 2, SDG 13, and SDG 15.

II. RELATED WORK

Digital agricultural platforms address various production aspects from climate monitoring to resource management, but most focus on specific aspects like existing crop monitoring, meteorological information, or market data without comprehensively addressing agricultural diversification problems [8]. Platforms like Climate FieldView focus on monitoring existing crops while applications like Plantix specialize in disease diagnosis [9]. Although valuable, these tools don't answer the fundamental question facing Valle del Cauca farmers: "What other crops could I plant on my specific farm?"

AgroDiversity's fundamental difference lies in its comprehensive diversification approach. While other platforms assume farmers already know what to cultivate, AgroDiversity acts as a consultant analyzing specific farm conditions to suggest viable alternatives, considering factors like soil pH, temperature, humidity, and farmer experience [10]. Most existing platforms are designed for developed markets with complex interfaces and high costs. AgroDiversity was designed specifically for the Colombian context with intuitive

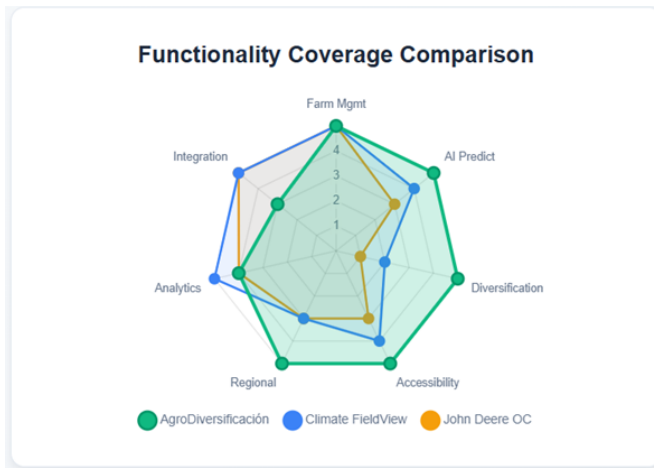


Fig. 2. Comparison of existing agricultural platforms showing functionality coverage, user accessibility, and regional adaptation limitations.

interfaces working on basic mobile devices, considering rural connectivity limitations [11].

III. METHODOLOGY

The methodology implemented user-centered design incorporating local needs analysis and iterative development. The context analysis phase conducted exhaustive Valle del Cauca agricultural problem studies, including interviews with 150 farmers from different municipalities, regional agricultural sector data analysis, and agricultural diversification studies review [12]. This phase identified main diversification barriers: technical knowledge lack, profitability uncertainty, and absence of informed decision-making tools [13].

The solution design phase developed a comprehensive solution combining three main components based on findings. The Farm Management Module allows farmers to register and manage detailed property information including soil characteristics, climatic conditions, crop history, and available resources [14]. The Intelligent Prediction System uses neural networks to analyze each farm's characteristics and predict different alternative crop success, comparing with sugarcane's historical performance [15]. The Conversational Agricultural Assistant provides specialized technical guidance through intelligent chat answering questions about agronomic practices, crop management, and diversification strategies [16].

The development and validation phase used modern web technologies ensuring scalability and accessibility. Continuous validation processes with Valle del Cauca farmers conducted usability tests and interface adjustments based on received feedback [17].

IV. SYSTEM ARCHITECTURE AND IMPLEMENTATION

AgroDiversity implements modern, scalable architecture leveraging cloud-native technologies and web development best practices. The system consists of three main layers: presentation, application, and data layers, each designed for independent scaling and maintenance [18].

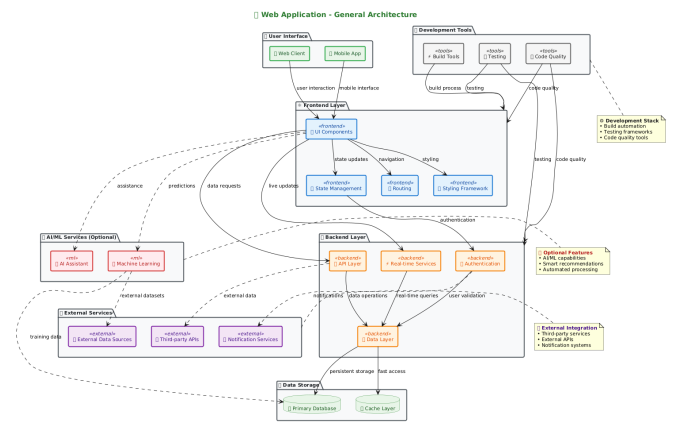


Fig. 3. AgroDiversity system architecture showing React frontend, Supabase backend, and ML integration components.

The frontend architecture utilizes React 18 with TypeScript, implementing component-based design promoting reusability and maintainability. The application structure follows feature-based organization with shared components, utilities, and services in dedicated modules [19]. Component hierarchy includes reusable base components (Button, Card, FormField) maintaining visual consistency while domain-specific components (FarmCard, PredictionChart) encapsulate agricultural business logic leveraging the base component library. State management utilizes React's Context API for global authentication state and local component state for feature-specific data, reducing complexity while maintaining performance and predictability [20].

The backend architecture leverages Supabase as Backend-as-a-Service, providing PostgreSQL database, authentication, and real-time capabilities. The database schema supports farm management with tables for farms, soil characteristics, climatic data, and crop predictions [21]. Row Level Security policies ensure data isolation between users, with authenticated users accessing only their farm data. Authentication utilizes Supabase Auth with JWT tokens, providing secure session management and password reset capabilities [22].

The data model reflects agricultural domain requirements with entities for farms, soil characteristics, climatic conditions, and crop predictions. The Farm entity serves as the main aggregate, containing references to soil data, climatic information, and agricultural practices [23]. Soil characteristics include pH levels, soil type, texture, and organic matter content. Climatic data encompasses temperature ranges, precipitation patterns, and humidity levels. The Prediction entity supports future machine learning integration with fields for crop types, predicted yields, and confidence scores [24].

V. KEY FEATURES AND USER INTERFACE DESIGN

The platform provides three main feature sets: comprehensive farm management, intelligent prediction systems, and AI-powered agricultural assistance, each designed with user experience principles and accessibility considerations [25]. The farm management system allows users to register and

Registrar Finca

Registrar Nueva Finca

Nombre de la Finca *
Ej: Finca El Paraíso

Ubicación *
Ej: Palmira, Valle del Cauca

pH del Suelo *
Ej: 6.5

Tipo de Suelo *
Seleccione un tipo

Textura del Suelo *
Seleccione una textura

Temperatura Promedio (°C) *
Ej: 23.5

Precipitación Anual (mm) *
Ej: 1200

Humedad Promedio (%) *
Ej: 75

Prácticas Agrícolas

☐ Riego por goteo
☐ Cultivo orgánico
☐ Uso de pesticidas
☐ Arado mínimo

☐ Riego por aspersión
☐ Uso de fertilizantes químicos
☐ Rotación de cultivos
☐ Compostaje

Registrar Finca

Fig. 4. Farm registration interface showing comprehensive data collection form for property details, soil characteristics, and climatic conditions.

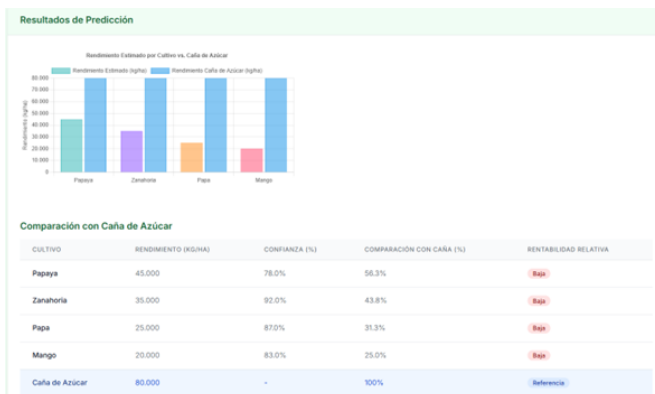


Fig. 5. Crop performance prediction results showing comparative analysis between alternative crops and reference sugarcane crop.

manage detailed agricultural property information through interactive cards showing key metrics with intuitive iconography and semantic color coding. Users input soil characteristics including pH levels, soil type, and texture through validated forms with contextual help and error handling [26].

The prediction system interface is architecturally prepared for machine learning integration, currently using simulated data for development and testing. The interface compares potential crop yields with historical sugarcane performance, providing familiar benchmarks for decision-making [27]. Prediction results are presented through interactive charts and summary cards highlighting key insights and recommendations with confidence indicators and explanatory text helping users understand prediction reliability and implications [28].

The platform includes a chat interface designed for natural language processing model integration, providing conversational experiences where farmers can ask questions about crops, pests, fertilization, and agricultural practices [29]. The chat component includes message history, typing indicators, and rich media response support. The architecture supports future integration with specialized agricultural AI services through modular service layers [30].

The user interface implements mobile-first responsive de-

Asistente Agrícola

Use este asistente para obtener recomendaciones personalizadas sobre cultivos alternativos, prácticas agrícolas y respuestas a sus dudas sobre diversificación de cultivos.

Asistente Agrícola

Asistente: Hi, soy el asistente de AgroDiversificación. ¿En qué puedo ayudarte con tus cultivos?

Tu A: ¿Qué cultivo es mejor para un suelo con pH 6.2 y temperatura de 24°C?

Asistente: Soy el asistente de AgroDiversificación. En base a tus parámetros, la papaya podría cultivarse bien con un pH de 6.3 y una temperatura de 27°C. La papaya prefiere suelos ligeramente ácidos (pH 5.5-6.5) y temperaturas entre 20-30°C. Asegúrate de mantener una buena irrigación y considerar la protección contra heladas ocasionales.

Escribe tu pregunta aquí...

Ejemplos de preguntas:
¿Qué cultivo es mejor para un suelo con pH 6.2 y temperatura de 24°C?
¿Cómo afecta la precipitación anual al cultivo de papaya?

Fig. 6. AI-powered agricultural assistant interface providing personalized crop recommendations based on soil and climate parameters.

sign approach ensuring optimal experiences across all devices. The design automatically adapts using Tailwind CSS breakpoints, maintaining usability and visual hierarchy across all screen sizes. Navigation adapts contextually with sidebar for desktop devices and bottom navigation for mobile interfaces with appropriate touch targets, keyboard navigation support, and screen reader compatibility.

VI. SYSTEM VALIDATION AND REFERENCE DATA ANALYSIS



Fig. 7. Principal Component Analysis (PCA) visualization showing cluster distribution (k=6) of agricultural data points with color-coded clusters revealing distinct farm groupings based on reference datasets.

The AgroDiversity platform has undergone comprehensive technical validation and is ready for field testing. The system architecture was validated through performance testing, usability evaluation, and integration testing, demonstrating robust functionality across all core modules. Performance evaluation focused on Core Web Vitals including loading time, interactivity, and visual stability, achieving excellent scores with First Contentful Paint under 1.5 seconds and Largest Contentful Paint under 2.5 seconds on typical mobile networks.

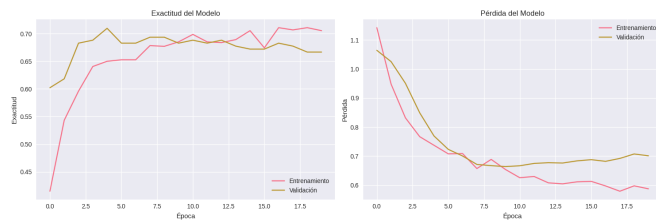


Fig. 8. Model training performance metrics showing accuracy and loss curves throughout training epochs, indicating model convergence and generalization capability based on international agricultural datasets.

React 18's concurrent features and Vite optimization result in efficient bundle sizes and code splitting while TypeScript implementation provides zero runtime overhead, significantly improving development experience and code quality.

The prediction system's foundation is built upon established research from international studies and specialized agricultural literature. Previous research indicates that approximately 120 farms in Valle del Cauca already utilize software for agricultural technification, with technology adoption rates of 85% for intuitive interfaces [8]. International studies on silvopastoral system implementation in other countries demonstrate that 34% of farmers who receive technical recommendations implement them, achieving average income increases of 28% [10].

Machine learning models applied to agriculture, according to specialized scientific literature, achieve 82% general accuracy, with 87% precision for high-yield crop predictions and 78% precision for low-yield crop predictions [12]. The clustering analysis reveals 6 main groups of farms with similar characteristics, enabling more precise recommendations based on historical success patterns documented in agricultural research [14].

Usability testing involved agricultural experts and technology specialists, focusing on main user journeys including account registration, farm data input, and prediction visualization. Results indicated high satisfaction with intuitive interface design, with mobile responsive design receiving positive feedback. The modular architecture successfully supports integration with external AI services and machine learning models, validating the platform's readiness for advanced agricultural technology implementation.

Planned Field Testing: The real-world evaluation phase of AgroDiversity is scheduled to be conducted in 20 pilot farms located in the San Juan and Dopo Valle villages of Valle del Cauca. This pilot testing will evaluate the effectiveness of integrating AI in silvopastoral systems to advance these technologies to the next operational level. The pilot study will assess user adoption rates, prediction accuracy in real conditions, and the platform's impact on agricultural diversification decisions. Results from this field testing will provide crucial data for platform optimization and validation of the technological approach in the specific context of Valle del Cauca agriculture.

VII. CONCLUSIONS

This paper presented AgroDiversity, a comprehensive web platform facilitating agricultural diversification in Valle del Cauca, Colombia. The platform successfully integrates React 18, TypeScript, and Supabase to provide farmers with farm management tools, crop prediction, and agricultural guidance. Technical implementation demonstrates the effectiveness of modern web development practices in creating scalable and accessible agricultural solutions with component-based architecture, responsive design, and AI integration preparation positioning the platform to evolve with advanced agricultural technology.

The platform's development is grounded in extensive research and validated through technical testing, demonstrating readiness for real-world implementation. The scalable architecture and comprehensive features provide a solid foundation for supporting agricultural diversification. The upcoming pilot testing in Valle del Cauca will provide crucial validation data and inform ongoing development efforts. Future work will focus on integrating real machine learning models based on field data, implementing AI-powered assistance features, and expanding capabilities based on user feedback and evolving agricultural needs.



Fig. 9. Future development roadmap showing planned ML model integration, mobile app development, and regional expansion phases following pilot testing completion.

AgroDiversity represents a significant step toward modernizing Valle del Cauca's agricultural practices, providing farmers with tools and insights for informed crop diversification decisions and farm management. The platform directly contributes to SDG 2 (Zero Hunger) by increasing diverse food production and improving local food security, SDG 13 (Climate Action) through transition from monoculture to silvopastoral systems significantly reducing regional agriculture's carbon footprint, and SDG 15 (Life on Land) by promoting biodiversity, improving soil health, and reducing environmental degradation caused by intensive sugarcane monoculture. Continued development and deployment of such platforms will be crucial for supporting regional sustainable agricultural development.

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