Developing a Scalable Farm Advisory System

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ABSTRACT

Developing a Scalable Farm Advisory System integrates two core modules: a Carbon Footprint Calculator and a Biodiversity Advisor. The calculator estimates emissions based on key operational inputs —such as land size, fertilizer use, and machinery—providing an immediate Eco-Score, while the advisory module recommends scientifically validated companion crops and pollinator-friendly plants using a curated dataset. Through an interactive dashboard, the system enables farmers to make data-driven decisions that optimize productivity while reducing environmental impact, offering a lightweight and user-friendly alternative to complex enterprise tools.

I. INTRODUCTION

Agriculture is essential for global food security, yet modern farming practices often contribute significantly to carbon emissions and biodiversity loss. Understanding and mitigating these environmental impacts can be challenging for farmers without the right tools. Traditional methods of farm management and enterprise-level agricultural software are often complex, time-consuming, and lack accessible, personalized environmental insights, highlighting the need for lightweight, data-driven solutions.

Technology and data analytics have emerged as powerful tools for building sustainable farming systems. By analyzing farm-specific operational data—such as fertilizer usage and machinery hours—systems can accurately estimate environmental footprints. Furthermore, leveraging curated agricultural datasets allows for the generation of biodiversity recommendations, such as companion planting, which naturally improves pest control and soil health.

Despite advances in green technology, challenges remain in creating tools that are both scientifically accurate and easy for everyday farmers to use. This study presents the EcoFarm Advisor, a scalable farm advisory system that integrates a Carbon Footprint Calculator with a Pollinator and Companion Plant Advisor. Through an interactive dashboard, the system provides transparent, reliable, and actionable eco-reports. By focusing on simple visual guidance and data visualization, EcoFarm Advisor aims to enhance sustainable decision-making, improve yields, and promote eco-friendly agriculture.

II. RELATED WORK

The application of technology in sustainable practices, carbon footprint tracking, and green advisory systems has seen significant research in recent years. Various studies have explored different algorithms, IoT integrations, and machine learning approaches to enhance environmental monitoring and resource optimization.

Techniques such as Deep Learning, Regression Models, and Support Vector Machines (SVM) have been applied to predict carbon emissions and classify eco-friendly materials. Additionally, IoT sensors and Cloud Computing frameworks have been utilized to monitor environmental factors in real-time. Despite these technological strides, limitations frequently arise, including the need for massive datasets, high computational costs, complex integration challenges, and a lack of contextual understanding for end-users like independent farmers.

This work builds on the principles of these previous green-tech systems but shifts the focus toward accessibility and biodiversity. Rather than relying on computationally heavy deep learning models, EcoFarm Advisor utilizes efficient data processing (Pandas/JSON) and rule-based emission factors to provide immediate, interpretable results without the barrier of high processing costs.

Existing System and its Limitations:

Title	Technology Used	Limitations	Authors	Year
Carbon Emission Prediction in Construction	Deep Learning	Large dataset required	Kim et al.	2023
Green Construction Advisory Chatbot	NLP, Chatbot Framework	Limited contextual understanding	Patel & Mehta	2023
ML for Carbon Footprint Estimation	Regression Models	Accuracy depends on input data	Johnson et al.	2022
Sustainable Design Using BIM and AI	BIM + Artificial Intelligence	Integration challenges	Chou & Lin	2022
AI-Driven Green Supply Chain Optimization	Genetic Algorithms	Computationally intensive	Martinez et al.	2021

	Maintenance coзt	Hernandez &	2020
Smart Suзtainable Conзtruction Framework	Monitoring		

IoT + Cloud Computing

Security iззueз

Ahmed et al.

2021

Eco-Friendly Material Claззification

Support Vector Machine Limited generalization

Daviз et al.

2021

AI-Baзed Conзtruction Waзte Reduction

Neural Networkз

High training coзt

Lee et al.

2020

IoT-Baзed Environmental

IoT Senзorз

Fuzzy Logic, Multi-

Criteria Decision

Complex computation

Silva

2019

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METHODOLOGY

The methodology for Developing a Scalable Farm Advisory System the follows a structured sequence aimed at calculating environmental impact and providing actionable biodiversity recommendations. First, the system collects essential agricultural data directly from the farmer through an interactive Streamlit dashboard. The user inputs specific operational details, including their farm's land size, fertilizer usage, machinery operation hours, and irrigation levels. These user inputs, along with static agricultural data such as crop lists and companion plants, are managed using a lightweight JSON database and processed using Python and Pandas.

Once the data is collected and validated, the core backend logic processes it through two primary modules. The Carbon Footprint Calculator processes the inputs (like land size and fertilizer use) to estimate the farm's carbon emissions, generating an immediate Eco-Score. Simultaneously, the Biodiversity Advisor module uses the selected main crop to query the JSON database, fetching scientifically validated recommendations for companion crops and pollinator-friendly plants.

Finally, the processed data and recommendations are compiled and presented back to the user. The system generates an interactive Eco-Report dashboard that visually displays the calculated carbon footprint (measured in tons of CO_2e per hectare) and the farm's overall Eco-Score. Utilizing visualization tools like Streamlit Charts and Altair, the dashboard presents the information clearly through charts and icons, providing farmers with easily interpretable insights to help optimize their agricultural productivity while reducing their environmental impact.

3.1 Data Gathering and Preprocessing:

- Static Agricultural Data Collection: The system gathers and stores foundational agricultural knowledge—including extensive lists of main crops, scientifically validated companion plants, and suitable pollinator species—within a lightweight, structured JSON database
- Real-Time Operational Input: Dynamic farm data is collected directly from the farmer via the interactive Streamlit dashboard. This captures specific operational metrics necessary for calculations, such as land size, fertilizer usage, machinery operating hours, and irrigation volume.
- Data Validation: Immediately after the farmer inputs their data, the system performs automated validation checks to ensure the inputs are accurate, properly formatted (e.g., correct numerical values), and ready for backend processing.
- Data Manipulation using Pandas: The backend utilizes the Python Pandas library to efficiently structure, manipulate, and process the validated user inputs, allowing the system to seamlessly handle the data.
- Integration and Standardization: The preprocessed operational data is standardized and routed to the core analytical engines. This allows the Carbon Calculator to apply specific emission factors to the inputs, while simultaneously enabling the Biodiversity Advisor to query the JSON dataset for accurate plant matching

3.2 Feature Extraction:

- Primary Operational Inputs: Extraction of key numerical features directly from the farmer's input, specifically land size (hectares), fertilizer usage (kg), irrigation volume (litres), and machinery operation (hours).
- Categorical Crop Selection: Identification and extraction of the categorical "main crop" feature inputted by

the user, which serves as the foundational data point for triggering all subsequent biodiversity and companion planting algorithms.

- Carbon Emission Mapping: Deriving analytical features by processing the raw operational inputs through the EcoCalculator module to compute standardized environmental metrics, outputting the final feature as tons of CO2e per hectare.
- Companion Plant Relational Data: Extracting compatibility features by querying the crop_pollinator_data.json database to match the primary crop with specific companion plants that naturally improve soil health and pest resistance.
- Pollinator Network Attributes: Extracting distinct ecological features from the JSON dataset to identify and recommend supplementary plants designed specifically to attract vital pollinator populations essential for the selected crop's success

3.3. Model Selection and Training:

- Deterministic Model Selection for Carbon Tracking: Instead of utilizing computationally heavy predictive machine learning, a deterministic, rule-based computational model was selected for the Carbon Footprint Calculator. This ensures absolute transparency and instant processing by applying established, scientifically validated emission factors to the farmer's operational inputs.
- Relational Algorithm for Biodiversity Matching: For the plant recommendation engine, a relational data-matching algorithm was designed using Python and Pandas. This model is optimized to swiftly query the static database and filter exact matches for companion crops and pollinators based on the categorical input of the primary crop.

- System Calibration and Dataset Integration: In place of traditional machine learning "training" (which requires massive datasets and multiple epochs), this system was "trained" by meticulously integrating and calibrating it against a highly curated, expert-verified JSON dataset to ensure biological accuracy in plant pairings.
- Scenario Testing and Eco-Score Tuning: The integrated models were extensively tested and tuned using a wide variety of simulated farm input scenarios (e.g., edge cases with extremely high fertilizer use or massive land sizes). This testing phase calibrated the Eco-Score generation logic, ensuring the final dashboard accurately and fairly categorizes footprints into low, moderate, and high brackets.

3.4. Feature Engineering and Selection:

- Standardization of Environmental Metrics: Engineering a normalized feature set by dividing total operational inputs (e.g., total fertilizer used, total machinery hours) by the user's input for 'land size'. This creates scale-invariant "per hectare" features, ensuring the final Carbon Footprint and Eco-Score are accurate and comparable regardless of the farm's total acreage.
- Application of Emission Factors: Transforming raw numerical inputs into environmental impact features by multiplying them against established, scientifically validated emission factors (e.g., converting kg of fertilizer into equivalent kg of CO2e). This engineered feature forms the core of the Eco-Score calculation.

- Primary Categorical Key Selection: Selecting the user's "Main Crop" as the primary indexing feature. This single categorical feature is critical, as it acts as the primary trigger for the system, directing the backend to filter and query the JSON database for specific biological matches.
- Relational Attribute Mapping: Engineering the final recommendation outputs by linking the primary crop feature to curated attributes within the JSON database (such as symbiotic growth benefits and specific pollinator attraction traits). This transforms a simple crop name input into a rich, multi-dimensional array of biodiversity recommendations.

3.5. Model Evaluation:

- Baseline Validation of the Carbon Engine: Because the Carbon Footprint Calculator is deterministic, evaluation involves rigorously testing the EcoCalculator module against established agricultural emission standards. This ensures that the rule-based multiplication of operational inputs (e.g., fertilizer and machinery usage) consistently yields scientifically accurate carbon outputs (tCO2e/ha).
- Relational Accuracy of Biodiversity Matching: The Companion and Pollinator Advisor models are evaluated by cross-referencing their output arrays against verified agricultural literature. This confirms that when a specific main crop is queried, the Python backend correctly retrieves and filters only the biologically compatible companion and pollinator plants from the JSON dataset without returning false positives.
- System Latency and Performance Testing: Evaluation extends to the computational efficiency of the system. The application is tested to measure the response time of the Pandas-driven data manipulation and the Streamlit UI rendering, ensuring the system meets its non-functional requirement of providing instant, real-time feedback to the user.
- Usability and Visual Output Assessment: Rather than relying on traditional machine learning metrics (like F1-scores), the system's success is evaluated through User Acceptance Testing (UAT). This assesses whether the generated Eco-Score, gauge charts, and actionable eco-tips displayed on the dashboard are highly interpretable and practically useful for farmers lacking technical expertise.
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3.6. Comparison with Baseline Methods:

- Automation vs. Manual Calculation: Compared to traditional baseline methods where farmers use manual spreadsheets or pen-and-paper to estimate environmental impact, the EcoFarm Advisor automates the entire process. It instantly processes operational inputs to compute a standardized Eco-Score, significantly reducing human error and time spent on calculations.
- Lightweight Architecture vs. Heavy Enterprise Models: Unlike complex enterprise baseline systems that rely on computationally expensive algorithms (such as Deep Learning or massive AI models requiring huge datasets), this system utilizes a lightweight, rule-based calculator and a relational JSON database. This makes it highly accessible, cost-effective, and capable of running on standard consumer devices without high processing overhead.
- Dynamic Personalization vs. Static Knowledge Bases: Traditional agricultural advisory services often rely

on static manuals or generalized databases. The EcoFarm Advisor outperforms these baselines by providing context-aware, highly personalized biodiversity recommendations (specifically matched companion and pollinator plants) that dynamically adapt to the exact primary crop selected by the user.

- Interactive Visualization vs. Text-Heavy Reports: Compared to baseline advisory methods that deliver delayed, text-heavy audit reports, this system provides real-time, actionable insights through an interactive Streamlit dashboard. The immediate visual feedback—such as carbon gauge charts and clear eco-tips—vastly improves user engagement and makes complex environmental data easily interpretable for non-technical users.

3.7. Ethical Considerations:

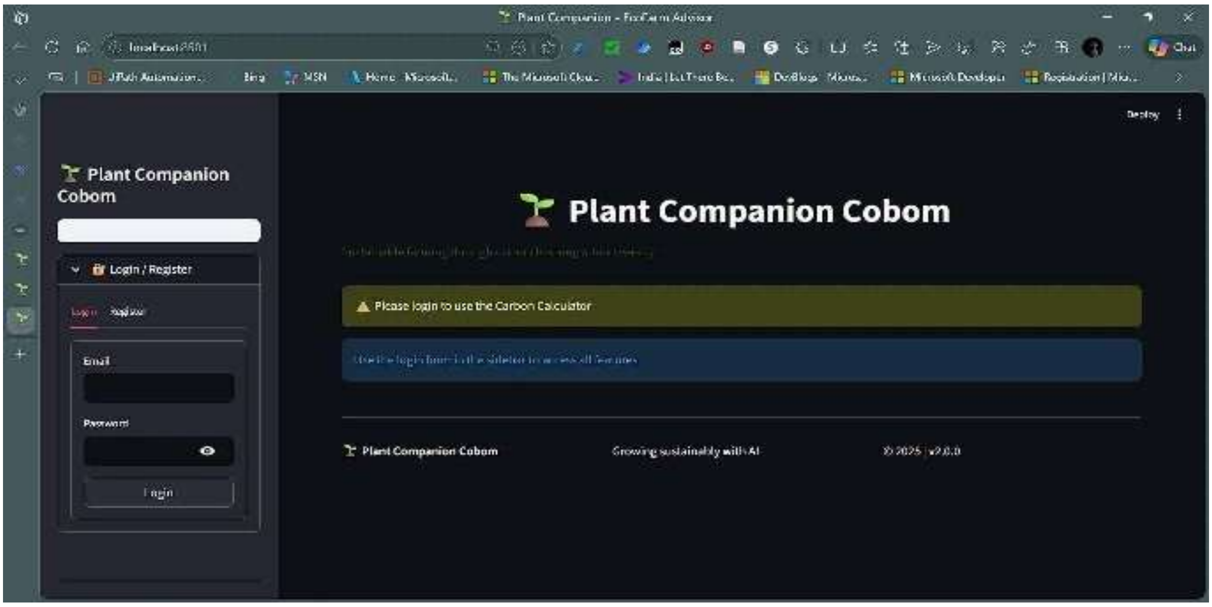
- Data Privacy and Confidentiality: Maintained user privacy and data confidentiality by ensuring that sensitive farm operational data (such as land size, fertilizer usage, and irrigation patterns) is securely processed and protected.
- Scientific Data Integrity: Utilized approved, scientifically verified agricultural datasets for crop compatibility and pollinators, ensuring all biodiversity recommendations are safe, accurate, and biologically sound.
- Human-Centric Decision Support: Designed the system to support farmers in sustainable decision-making, acting as a supportive advisory tool rather than replacing traditional agricultural expertise or human judgment.
- Transparency and Explainability: Focused on transparency and explainability, providing farmers with clear, interpretable Eco-Scores and the precise reasoning behind why specific companion and pollinator plants were suggested.

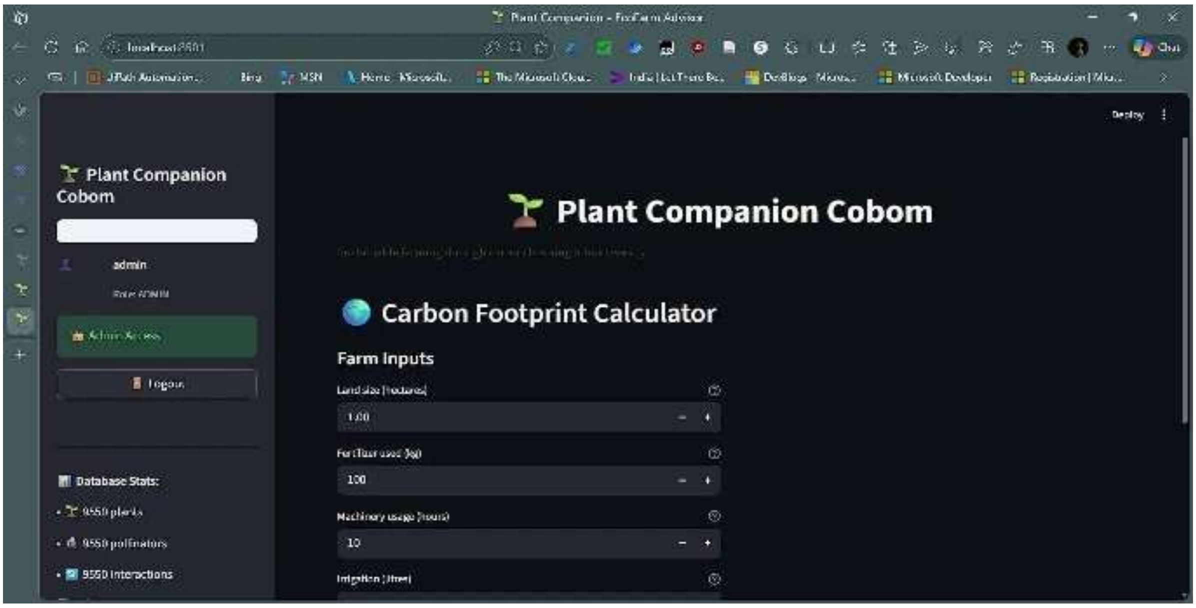
3.8. Result:

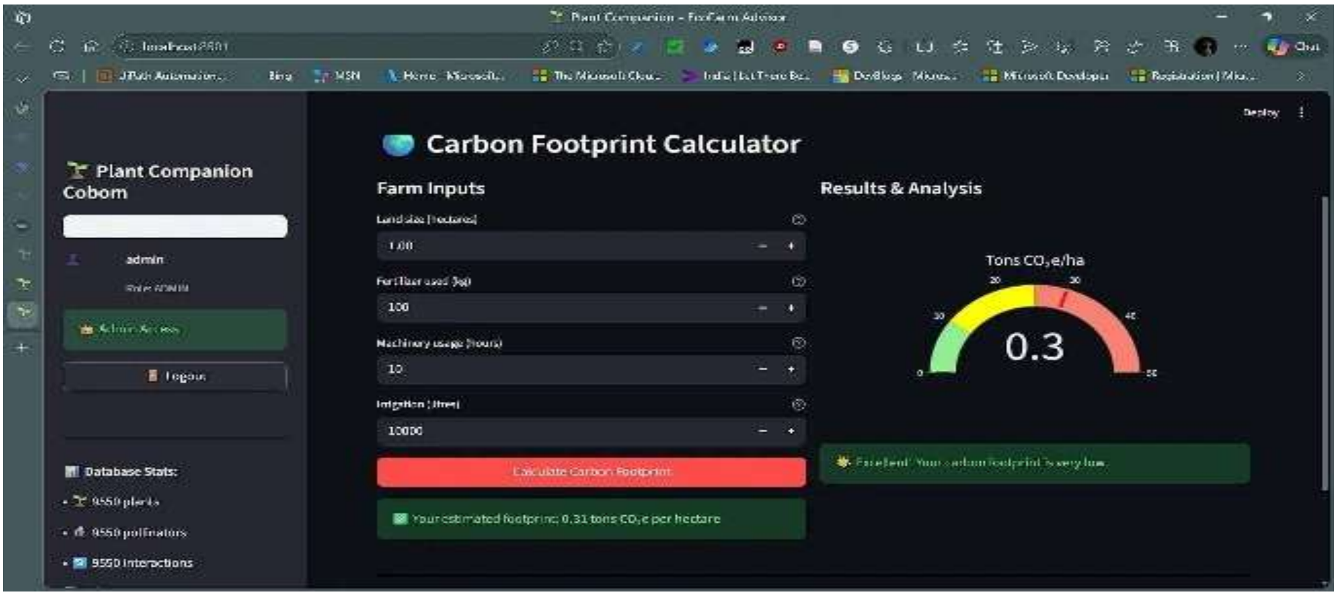
- Comprehensive Dashboard Interface: The system successfully launched a secure, user-friendly Streamlit dashboard (named "Plant Companion Cobom") where farmers can easily log in to access all advisory tools from a central navigation panel.
- Interactive Carbon Tracking: The system effectively captures user inputs (like 1.00 hectares of land, 100 kg fertilizer, 10 hours of machinery, and 10000 litres of irrigation) to generate a dynamic, color-coded gauge chart displaying the estimated carbon footprint (e.g., 0.31 Tons CO_2e/ha) along with immediate qualitative feedback (e.g., "Excellent! Your carbon footprint is very low").
- Targeted Biodiversity Suggestions: Upon selecting a main crop (like Tomato) from the Pollinator & Companion Plant Advisor, the system successfully outputs a curated checklist of verified companion plants (Basil, Carrot, Onion, Marigold) and pollinator plants (Sunflower, Marigold, Lavender, Borage).
- Integrated EcoFarm Report: The platform compiles user data into a clean, comprehensive "EcoFarm Report" screen that simultaneously displays the total Carbon Footprint, the selected Main Crop, and an aggregated Eco Score (e.g., 70/100, broken down into Carbon and Biodiversity metrics).
- Actionable Qualitative Advice: Alongside numerical metrics, the system delivers immediate, context-specific "Growing Tips" (e.g., "Tomatoes need full sun and consistent watering") and

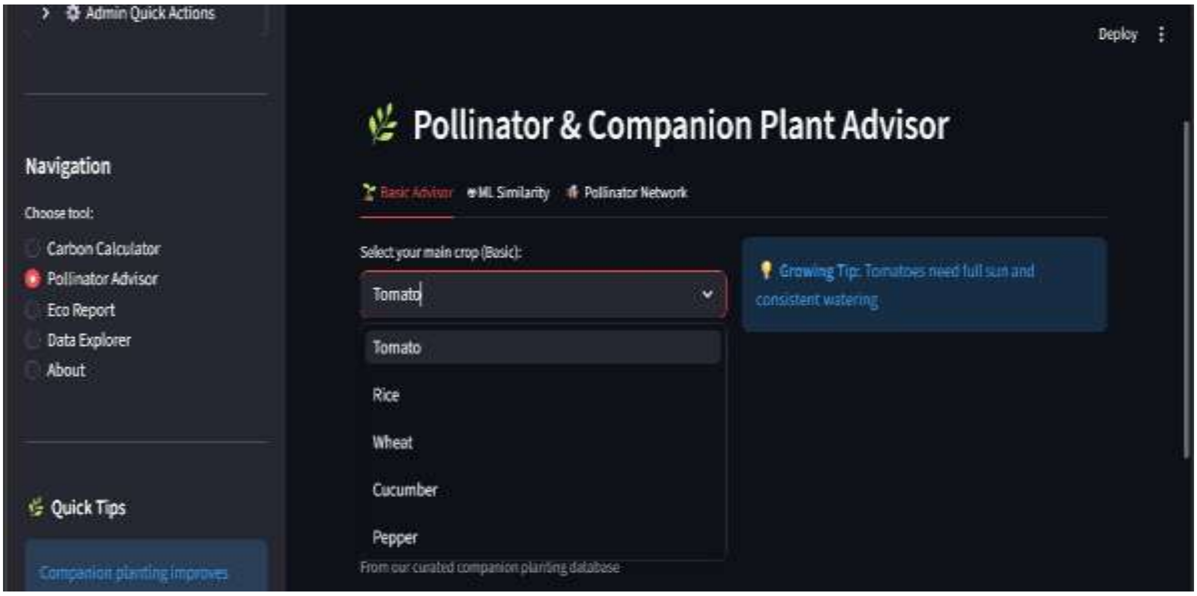
"Carbon Reduction Tipз" outlining how to maintain good practiceз and improve зuзtainability.

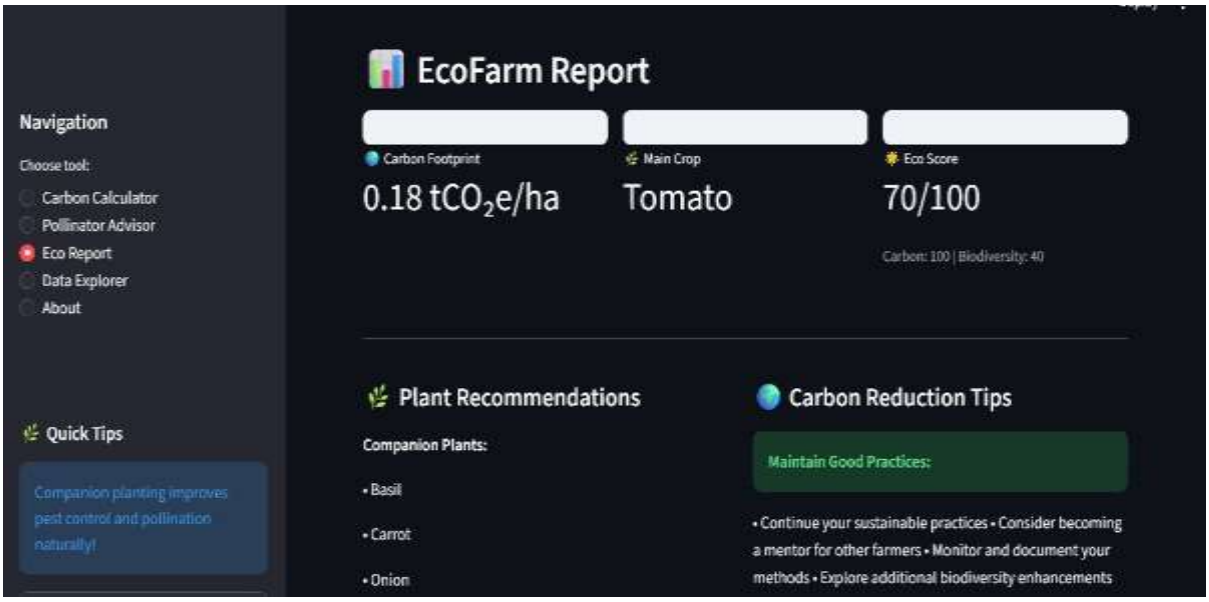
- Robuзt Backend Data Handling: The application reliably querieз a зubзtantial зtatic JSON databaзe, efficiently managing and extracting inзightз from extenзive dataзetз (demonзtrated by databaзe зtatз зhowing 9550 plantз, 9550 pollinatorз, and 9550 interactionз) to power the uзer- facing recommendationз.

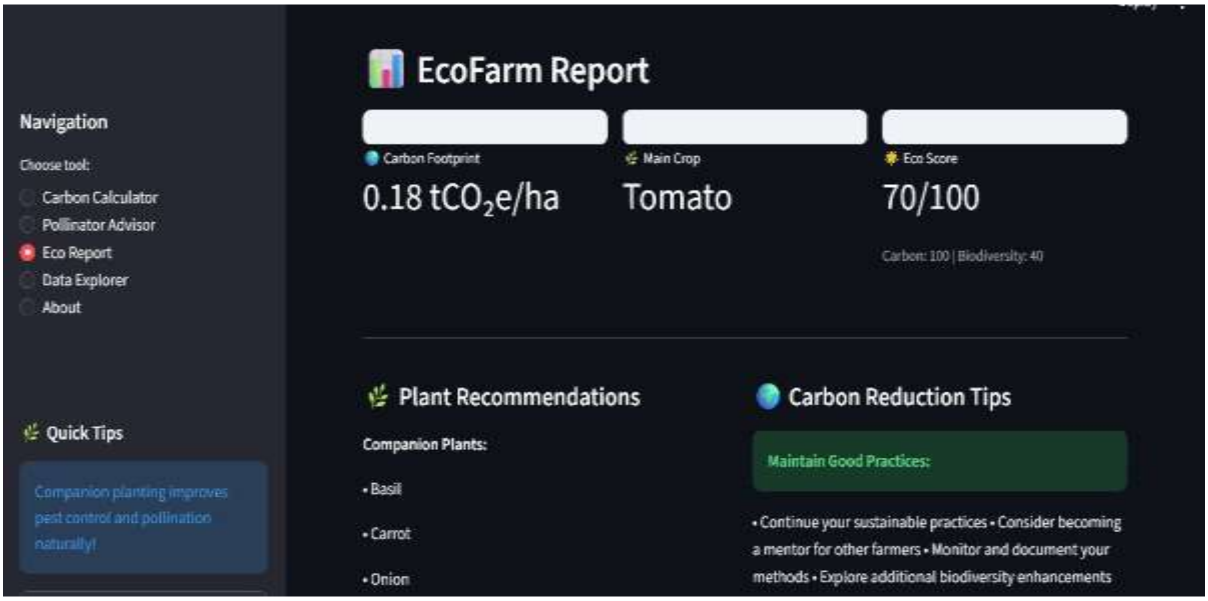





Carbon Footprint Calculator
Plant Companion Cobom
admin
Admin Access
Logout
Database Stats:
9550 plants
9550 pollinators
9550 interactions
Farm Inputs
Land size (hectares)
1.00
Fertilizer used (kg)
100
Machinery usage (hours)
10
Irrigation (litres)
10000
Calculate Carbon Footprint
Your estimated footprint: 0.31 tons CO₂e per hectare
Results & Analysis
Tons CO₂e/ha
0.3
Deploy


Admin Quick Actions
Deploy
Pollinator & Companion Plant Advisor
Basic Advisor
ML Similarity
Pollinator Network
Navigation
Choose tool:
Carbon Calculator
Pollinator Advisor
Eco Report
Data Explorer
About
Select your main crop (Basic):
Tomato
Tomato
Rice
Wheat
Cucumber
Pepper
From our curated companion planting database
Growing Tip: Tomatoes need full sun and consistent watering
Quick Tips
Companion planting improves





III. CONCLUSION

Understanding Environmental Impact The project successfully helps farmers understand the direct environmental footprint of their agricultural activities. By allowing users to enter specific operational details such as land size, fertilizer use, irrigation volume, and machinery hours, the system seamlessly calculates the farm's carbon footprint. This transforms raw farm data into clear environmental metrics.

Promoting Biodiversity A major component of the system is its focus on natural ecosystem support. The application provides actionable suggestions to protect the environment by recommending companion crops that naturally grow well together. Additionally, it suggests specific plants designed to attract vital pollinators like bees and butterflies, which helps improve overall crop growth and supports local biodiversity.

Simple and Actionable Guidance The overarching goal of the EcoFarm Advisor is to provide simple, accessible advice for practicing sustainable farming. By utilizing this user-friendly tool, farmers are empowered to make better, data-driven decisions that not only protect the environment but also help them plan better to improve crop productivity and health.

Foundation for Future Expansion The system is built with scalability in mind. In the future, the platform can be expanded by adding more comprehensive crop data and advanced technological features. This ensures the tool will continue to evolve and scale up to help an even wider community of farmers adopt eco-friendly agricultural practices

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