Decision Support for Sustainable Agriculture Using I2C Sensors

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***Abstract*—With the global population projected to reach nearly 10 billion by 2050, ensuring food security demands more efficient and sustainable agricultural practices. While emerging technologies hold great promise in addressing this challenge, their adoption among small-scale and urban farmers remains limited. A key barrier to that is that these technologies are often either too expensive or too complex for practical use at the small-farm level. On the other hand, developing new machine learning models to support these technologies often demands large volumes of high-quality data, which can be difficult to collect, manage, and process. This paper presents a technological setup designed to support precision agriculture without the typical financial or technical barriers, highlighting its potential to enhance sustainability and resource efficiency in urban and small-plot agriculture.**

***Index Terms*—Precision agriculture, ESP32, edge computing, environmental monitoring, Globus**

I. Introduction

MANY core practices in farming remain consistent over time, especially when it comes to how crops respond to environmental conditions. The optimal climate, soil, and care required for a given crop do not drastically change, which means that by collecting data on the conditions under which a crop is grown—along with any stress factors such as disease—and the yield it produces, we can begin to make informed predictions about future growing outcomes. This type of predictive insight can be especially powerful when applied over multiple growing cycles.

While there has been growing interest in using technology to support sustainable agriculture through environmental data collection, much of this work has relied on expensive and complex tools such as drones [1] or robotic systems [2]. Although effective, these solutions are often not well-suited to the realities of small-scale or urban farms. Many of these farms are unlikely to adopt unfamiliar technologies quickly, and the high costs associated with such tools can make long-term use impractical.

However, achieving meaningful results does not always require high-end or complicated systems. In this paper, we present a simple yet effective setup that collects basic numerical environmental data and provides actionable feedback. This setup supports both immediate responses—such as irrigation or shading adjustments—and longer-term insights that can guide decisions like altering soil composition or reconsidering crop selection. By focusing on simplicity, affordability, and usefulness, this approach offers a more accessible path to data-driven agriculture for small farms.

Our sensor dashboard is accessible at:
https://esp32-sensor-dashboard-j7mhbxmnr7eumvwwztpqbx.streamlit.app/

II. Implementation

A. Hardware Implementation

As with most agricultural sensing systems, our solution begins with data collection. We selected a set of low-cost, easy-to-integrate sensors: the BME280 for measuring temperature, humidity, and atmospheric pressure; the BH1750 for capturing light intensity (also used to estimate daily photoperiod); and a capacitive soil moisture sensor. These sensors are connected to an ESP32 microcontroller, which serves as the central hub for data aggregation and transmission.

The ESP32 was chosen due to its built-in Wi-Fi and Bluetooth capabilities, which make it highly suitable for IoT applications in agriculture. Unlike many traditional microcontrollers, the ESP32 can wirelessly transmit data without the need for additional communication modules. The entire setup is powered by a solar battery, making it well-suited for outdoor and remote environments such as small farms or urban plots. Solar power ensures long-term autonomous operation without frequent battery replacements, providing a sustainable and maintenance-light solution. Through this configuration, the system is capable of continuously monitoring key environmental parameters that influence crop health and productivity.

B. Software Implementation

On the software side, the ESP32 is programmed to read sensor values at 10-minute intervals and log the data to a Google Sheets file. Each ESP32 device writes to a dedicated sheet within the same spreadsheet file to maintain clear organization across multiple sensor nodes.

Despite the known limitations of Google Sheets, most important of which being the restricted storage capacity, this platform was chosen for several practical reasons:

- **Real-time Access:** It allows immediate access to sensor readings, enabling prompt intervention in case of abnormal values or device malfunction.
- **Data Preprocessing:** Using Google Apps Script, raw data can be cleaned, formatted, and modified as needed before further processing. Early-stage data cleaning helps prevent the accumulation of unusable data over time.
- **Remote Monitoring:** Data stored in Google Sheets can be accessed remotely, removing the need for on-site

data collection and offering convenience in monitoring conditions across different locations.

- **Ease of Integration:** The ESP32 can communicate directly with Google Sheets using standard HTTP requests, making it simple to log data without the need for complex intermediate systems or cloud infrastructure.

Despite these advantages, due to its limitations, Google Sheets is not suitable for long-term data storage. To address this, we implemented a daily offloading mechanism: the file is scheduled to offload its contents to a linked Google Drive folder at the end of each day. This not only prevents the sheet from reaching capacity and halting data collection, but also facilitates seamless data transfer using Globus for long-term storage and further processing.

C. Globus

To enable reliable and efficient transfer of collected data from Google Drive to high-performance computing (HPC) platforms, we incorporated Globus into our workflow. Globus was chosen for its ability to manage large-scale data transfers seamlessly across institutions, support automated workflows, and ensure secure, encrypted transmission. In our implementation, cleaned sensor data is temporarily stored in Google Drive and periodically offloaded to an institutional HPC cluster via Globus for further processing and long-term analysis. Beyond efficiency, Globus also enhances data privacy by enforcing secure authentication, encrypted data transmission, and access controls—ensuring that sensitive sensor information remains protected throughout the transfer process.

D. Processing

For data processing and model development, we utilize an institutional high-performance computing (HPC) cluster that offers scalable compute and storage resources suitable for our machine learning workflows. This infrastructure provides the flexibility to deploy custom software environments and handle large datasets efficiently.

III. System Functionality

A. Short-Term Feedback and Immediate Responses

The system utilizes the most recently collected sensor data to provide timely feedback on plant conditions. For example, if soil moisture remains below a critical threshold for an extended period or if high temperatures persist without observable improvement in other factors, the system flags these as issues. These conditions are immediately reflected in the farmer-facing dashboard, allowing for prompt awareness and action. This short-term feedback mechanism ensures that farmers can quickly respond to emerging problems before they impact plant health or yield.

B. Long-Term Insights and Decision Support

The system operates entirely on data-driven principles, relying on continuous input from environmental sensors to learn and improve over time. As more data accumulates across the growing season—capturing variations in environmental variables and crop response—the system's capacity to generate meaningful insights increases. In future collaborations, we aim to collect longitudinal datasets throughout complete crop cycles, enabling the development and training of machine learning models such as regression techniques for yield estimation, classification algorithms for stress detection, and clustering methods for identifying patterns across crop types. These models will support predictive analytics based on observed growing conditions. Ultimately, this will allow the system to transition from reactive feedback to proactive, evidence-based agricultural recommendations.

IV. Field Deployment

During our collaboration with an urban farm located in downtown Toledo, we tested our sensor-based monitoring system by collecting data from two plant beds—one where red cabbage was being grown and another where rosemary was cultivated. The system successfully recorded environmental variables such as temperature, humidity, soil moisture, and light intensity, and the collected data was accurately logged and transferred to our storage platform. In addition to data collection, we are developing a user-friendly dashboard designed to keep farmers informed in real time. This dashboard will not only display the collected sensor data in an accessible format but also provide actionable feedback and enable two-way communication between the system and the farmers. Sample data from this deployment is shown below.

V. Conclusion

This paper presents a practical, low-cost approach to supporting sustainable agriculture through sensor-based environmental monitoring and data-driven feedback. By leveraging widely available components such as the ESP32 microcontroller and integrating tools like Google Sheets and Globus, our system addresses key barriers—cost, complexity, and accessibility—that often prevent small-scale and urban farmers from adopting emerging technologies. The system not only enables immediate feedback on critical parameters like soil moisture and temperature, but also lays the groundwork for long-term insights through continuous data collection and high-performance computing resources. Field deployment at a local urban farm demonstrated the viability of this approach in real-world conditions.

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References

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