IoT-Based Environmental Conditions Monitoring of a Sawtooth Greenhouse: A Foundation for Anomaly Detection and Computational Fluid Dynamics

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Abstract. There is a shortage of food production in the world, and the United Nations has predicted that if there is no conscious mitigation plan, the world may face food limitations in the future. One of the strategies adopted to mitigate the shortage of food production is the greenhouse intervention. However, it is necessary to understand the environmental conditions required to ensure optimal crop production in a typical greenhouse. A fourth industrial revolution technology, namely the Internet of Things was used to measure the internal environmental conditions (temperature, pressure, relative humidity, and CO_2) of a greenhouse. This was combined with climate data. The work was performed at a sawtooth-shaped greenhouse at a residential University in Gauteng. The high temperatures of $40\,^{\circ}C$ and the low relative humidity of 20% found during the day in some locations make the environment suitable only for crop varieties grown in dry climates. Tomatoes in hotter and drier locations were observed to have poorer health than in other locations. The measured data inside the greenhouse have larger temperature and humidity ranges than the ERA5-Land satellite data for the local environment. Spectrum analysis was also performed. The results indicate the need for a control system to manage the irrigation schedule, fertiliser treatment, and vent openings. The study is designed to progress onward to decision support by AI, informed by Computational Fluid Dynamics modelling. Ultimately there would be an optimisation of the various strategies for controlling the growth conditions.

1 Introduction

Due to the increase in population and severe climate change, Africa and the rest of the world face a persistent food shortage, and many citizens live in food insecurity [1]. Unpredictable weather patterns from the consequences of climate change, among others, further exacerbate the food production crisis [2]. Until now, farmers in Africa have relied mainly on traditional farming methods. The industrialisation of farming has resulted in significant mechanization, which results in higher fossil fuel usage and non-tailored agricultural practices to specific crops [3]. This also results in over-fertilising and watering based on uniform crop needs, which may sometimes lead to food waste, poor crop quality, and water waste [4], as well as run-off pollution to water sources [5]. As such, traditional farming methods are losing traction in the realm of smart agriculture [6].

Smart agriculture involves collecting data to generate insight into environmental conditions and their impact on the production of agricultural produce. Internet of Things (IoT) technologies such as microcontrollers and sensors can be used to collect data as they are capable of providing real-time monitoring of plant health, soil moisture, temperature, relative humidity, and CO2, which dictate crop growth quality [7]. This ensures improved crop health by incorporating data into a larger intelligent control ecosystem. In addition, it facilitates a significant reduction of water waste, efficient control of fertilizer resources, and an increase in crop growth yield and quality [8]. However, the installation of IoT is challenging to implement in large area farms, where there is no closed area or controlled climate. As such, greenhouses are gaining interest as a technology that is used to improve controlled farming systems by providing a controlled environment that is otherwise difficult to achieve in the outdoors. This level of control can provide suitable climate conditions for crop production. Controlling environmental conditions could be efficient if a well-assisted natural circulation is implemented through an effective vent design. Important factors in greenhouse design include the shape of the roof opening, which influences aerodynamics and consequently natural cooling, as well as the greenhouse cover material for solar absorption. These can be optimised through Computational Fluid Dynamics (CFD).

CFD is a numerical computer-aided method that provides numerical approximate solutions to the Navier-Stokes equations, including coupled physics such as heat and mass transfer [9]. CFD has been implemented to simulate various weather patterns in greenhouses, providing the efficient design of greenhouse environmental conditions and performance [10]. IoT, CFD, and novel Machine Learning (ML) techniques can be combined into a digital twin of a greenhouse fed on real-time data. The digital twin can predict changing weather patterns, help farmers increase crop yield, and reduce resource wastage. Recently, an environmental monitoring sensor which utilises electronic and fiber optic sensors has been deployed at CERN to monitor relative humidity and temperature distribution in ATLAS Inner Tracker [11]. This same analytical method and technology were deployed to a typical greenhouse to monitor its environmental conditions.

In this study, an in-house sensor was used to investigate the temperature and relative humidity profile of a novel sawtooth greenhouse. IoT techniques and data analysis were employed to determine the best placement for specific plant selection based on the measured internal greenhouse temperature, relative humidity, and pressure conditions. The results obtained form a starting point for CFD modelling, further incorporated into a digital twin of the greenhouse.

2 Methodology

A greenhouse located at the Centre for Ecological Intelligence (CEI) at the University of Johannesburg Bunting Road Campus (Latitude -26.18955, Longitude 28.01157) was used for this study. It is 23 metres long and 18.65 metres wide, with a height of 6.3 metres. Various crops, including tomatoes, basil, eggplant, and radish, are cultivated in the greenhouse. As shown in Figure 1, the greenhouse is a double-roofed, sawtooth-type greenhouse where the roofs have a half-Rankine aerodynamic shape. The expectation is that when the wind flows over the roof, it creates vortices (shown as swirls on the vents) that refresh the internal air by bringing cool air into the interior (blue arrows) and sucking hot air out of the interior (red arrows).

Figure 1: (*left*) CEI Agrihub Sawtooth greenhouse at University of Johannesburg. Note the vents which form part of the aerodynamic roof shape. The swirls represent vortices that bring cool air into the greenhouse and flush out hot air, which is represented by red arrows, to the outside. (*right*) Internal structure of the greenhouse with various crops within the greenhouse.

Wio terminals are part of the SEEED Wio family [12]. It generally refers to a series of Internet of Things (IoT) development boards. The Wio terminal acts as a module that is designed for quick prototyping and easy integration into various IoT applications. These boards are particularly known for their wireless communication capabilities, compact design, and ease of use. The Wio terminals use an ATSAMD51 microcontroller and support an I2C connection. These Wio terminals, with their peripherals, were used as data logging devices with digital output BME280 dual temperature and relative humidity sensors. The terminals were connected via a WiFi network to a cloud that logs data remotely from the sensors to a ThingSpeak [13] dashboard that can be downloaded for analysis. The temperature and relative humidity readings were generated.

The sensors were used to log data over fifty days to obtain meaningful results of temperature and relative humidity fluctuations in the greenhouse in three primary locations over the length of a tomato crop along the greenhouse. The data collected was then passed through a series of data analysis steps to refine data quality and determine the temperature and relative humidity profiles. Once the data for a single location is downloaded, it is segmented into separate days, where each day's data is binned into minutes. The average temperature and relative humidity are then calculated for each bin to produce an average 24 h temperature and relative humidity profile of the greenhouse. Thereafter, the average profiles were calculated by taking the average of all three locations to produce a single profile for temperature and relative humidity. The data is filtered for outliers and smoothed using a Savitzky-Golay filter. The smoothed data is then treated as the null hypothesis in a likelihood fit (Chi Squared) of the data. The error bars are determined by linear scaling (with an offset) to achieve a reduced chi-squared value of unity where the smoothed curve forms the null hypothesis (pre-accepted by inspection). The results can be seen in Figure 2. The plot is compared to data from ERA5-Land [14] 2m near-surface air temperature (T_{2m}) and relative humidity data for trend verification. This comparison is also shown in Figure 2. A Fast Fourier Transform (FFT) is used to search for daily and any possible other frequency components.

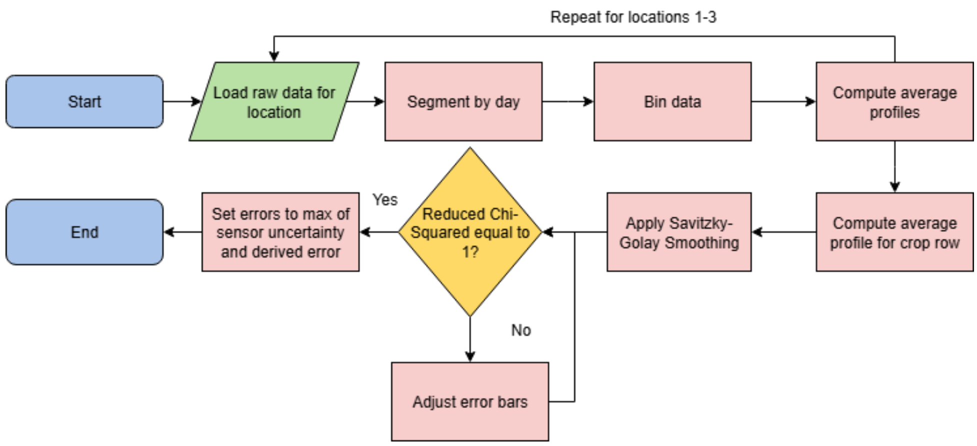

Figure 2: Data analysis process used in study to produce average temperature and relative humidity profiles.

3 Results and Discussions

The results of this study are divided into two components: temperature and relative humidity results obtained, and the FFT plots for analyzing the cyclical variations present in the greenhouse climate. The relative humidity (RH) for ERA5-Land was calculated from the dewpoint and the temperature using the Magnus formula [15]:

$$\gamma(T, RH) = \ln\left(\frac{R_H}{100}\right) + \frac{bT}{c+T}, \tag{1}$$

$$T_{d_p} = \frac{c\gamma(T, RH)}{b - \gamma(T, RH)}, \tag{2}$$

where the constants are $b = 17.625$ and c =243.04 °C. The ERA5-Land T_{2m} and the 2m dewpoint temperature represent the temperature (T) and the dewpoint temperature (T_{dp}), respectively, as input to equation 1 and equation 2 to solve for the RH.

3.1 Temperature and Relative Humidity distribution in the greenhouse

Figure 3 shows the average temperature and relative humidity profiles in the greenhouse. Furthermore, the plot of ERA5-Land for temperature and relative humidity was included. The sensor reading in the greenhouse suggests an increase in temperature during sunrise. However, during dawn, there was a drop in temperature. Similar behaviour was noticed for the ERA5-Land temperature distribution. However, the greenhouse retains a higher temperature than the outside around 00:00 hours. This is due to the greenhouse obtaining high solar gains in the daytime and retaining the heat. Additionally, the temperature increase is more pronounced than the outside, showing the efficacy of solar retention within the greenhouse. This is also noted from the longer heat retention shown from daytime to later, from 18:00 to 22:00 hours. The maximum temperature of $40\,^{\circ}\mathrm{C}$ is relatively high. This suggests that careful selection of plants that may not be adversely affected by high temperatures should be introduced into the greenhouse. For example, well-known crops that can tolerate high temperature $35\,^{\circ}\mathrm{C}$-$45\,^{\circ}\mathrm{C}$ such as okra (Abelmoschus esculentus) [16], eggplant (Brinjal/Solanum melongena) [17], sweet potato (Ipomoea batatas) [18], hot peppers/Chili (Capsicum spp.) [19], tomato and maize [20] should be candidates to thrive in the studied greenhouse. A drop in temperature was also noticed during the midday peak. Several factors are speculated to have contributed to this. For instance, the sensors may have suffered a drift due to overheating or improper solar shielding, leading to a dip in the temperature. Furthermore, during midday, there was an irrigation schedule, and due to the hot temperature, the water began to evaporate, which caused a fogging effect in the greenhouse. This is consistent with observations from Kumar *et al.* [21]. In addition, the roof shape and vent could also play a role in the dip in temperature because the roof provides a shading impact at this time. Future studies will be carried out using CFD to provide more insight into the temperature dip.

The sensor's relative humidity profile, obtained as shown in Figure 3, is consistent with ERA5-Land RH measurements. This suggests that the obtained data are accurate. There was a relatively high relative humidity at night. The effect of the high temperatures can be seen on the moisture and relative humidity conditions. The relative humidity distribution is as low as 10% during midday. Additionally, the rise in relative humidity at midday, complementary to the drop in temperature, can be seen, which supports the idea of evaporation creating the dip at these times. However, the vents do not appear to provide enough cooling in these locations, possibly due to the wind patterns during the data collection period.

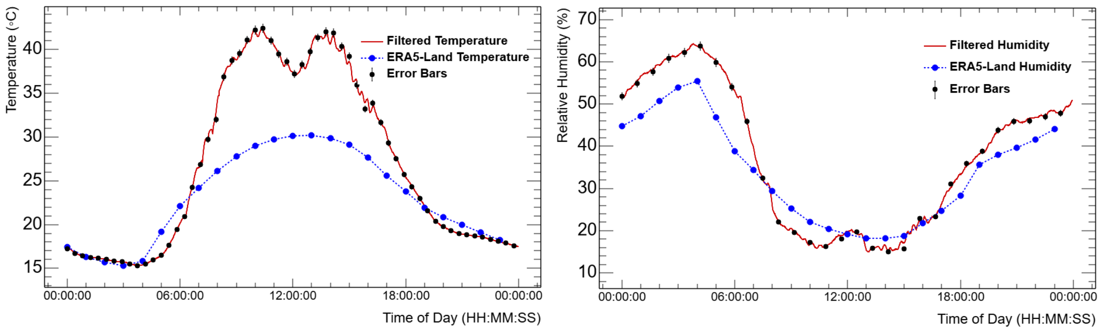

Figure 3: The plots of the average (*left*) temperature, and (*right*) relative humidity profiles for a single row in the greenhouse.

3.2 FFT Analysis

Figure 4 shows the plots of the FFT of the ERA5-Land and sensor data collected from the greenhouse with amplitude in degrees Celsius. The ERA5-Land spectrum shows a strong peak at one cycle/day, which is the diurnal temperature variation expected from day/night variation. The higher order harmonics are resulting from harmonic distortion caused by a non-sinusoidal shape. The sensor's greenhouse FFT spectrum shows a strong peak at one cycle/day, which is coherent with the ERA5-Land data and expected from diurnal changes. Additionally, there is an indication of a 2-cycle/day peak, from the double peak resulting from the midday dip seen in the average temperature profile. The one cycle/day peak from the measured data is much higher than the ERA5-Land, showing the increased solar gain in the greenhouse as compared to the outside.

Overall, the greenhouse retains high temperatures in the day and high relative humidity at night. There is no evidence of the expected cooling effect from the vents. The results of this study are important as they will serve as the basis for future studies by applying CFD, which can then further support the strategic design of the greenhouse. Furthermore, IoT sensor technology has been used to monitor the temperature and relative humidity distribution in a greenhouse, and the likelihood of selected crops being cultivated in the greenhouse was proposed.

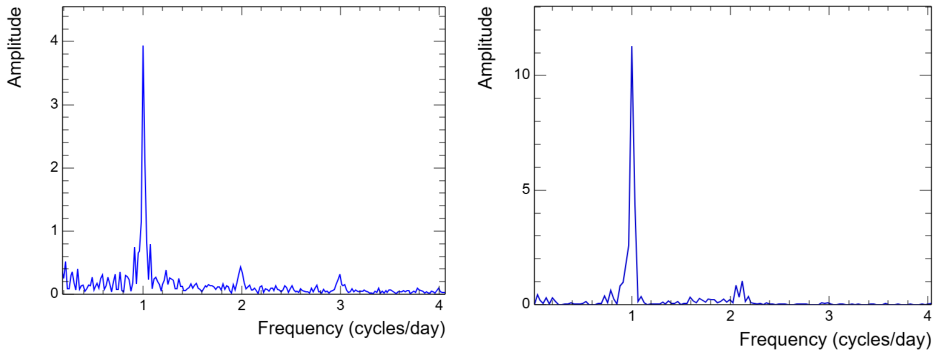

Figure 4: The FFT plots of (*left*) ERA5-Land data, and (*right*) data from the sensor in the greenhouse. The amplitude is in degrees Celsius

4 Conclusion

IoT sensors were used to quantify the temperature and relative humidity profiles. The temperature and relative humidity environmental conditions of the greenhouse were collected for fifty days. The obtained results show that during the day at midday, the temperature could rise to $45\,^{\circ}\mathrm{C}$, which is higher than the ERA5-Land maximum of $30\,^{\circ}\mathrm{C}$. This was reflected in the measured data FFT spectrum having a higher power magnitude than ERA5-Land. However, during the night the temperature was as low as $15\,^{\circ}\mathrm{C}$. The high temperature could be beneficial to the cultivation of heat-tolerant crops. The relative humidity levels in the position of the row of tomato crops were not consistent in higher temperature ranges, leaving the plants suitable for this area of the greenhouse limited to high-temperature-resilient crops. Future studies will build on this data and including companion CFD studies that will determine the optimal vent positions in the greenhouse for air circulation and cooling. An ML model that can predict internal weather patterns using weather station data and the current real-time data being collected will be deployed. This will lead to real-time decision-making tools for water schedules, to provide optimal water usage, and prevent crop wastage. Together with the CFD, this will form a digital twin of the greenhouse fed by real-time data, whilst using high-performance computing capabilities to infer plant health from environmental monitoring tools. This can provide the necessary information to help improve crop production.

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